

Article

Forecasting Rainfall IDF Curves Using Ground Data and Downscaled Climate Projections to Enhance Flood Management in Punjab, Pakistan

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Abstract

Urban flooding poses an escalating threat to riverine cities in Southern Asia's tropical regions, primarily driven by rapid urban expansion. This study develops future projections of Intensity–Duration–Frequency (IDF) curves for major urban centers in Punjab, Pakistan, utilizing downscaled satellite-derived precipitation data. Baseline IDF curves were established using historical rainfall records from multiple meteorological stations. Among eight General Circulation Models (GCMs) assessed, EC-Earth3-Veg-LR demonstrated the highest skill in capturing extreme rainfall patterns relevant to the region. Future precipitation projections from this model were downscaled using the Equidistant Quantile Matching (EQM) technique and applied to generate IDF curves under two CMIP6 scenarios: SSP2-4.5 and SSP5-8.5. The results reveal a substantial increase in extreme rainfall intensities, particularly under the SSP5-8.5 scenario, with projected 100-year return period rainfall intensities rising by approximately 30–55% across key cities. The downscaled projections reveal more pronounced variations than the raw GCM outputs, emphasizing the importance of high-resolution climate data for accurate regional hydrological risk evaluation and effective urban flood resilience planning.

Keywords: future IDF; probability distribution; downscaling; IDF projections; flood management



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1. Introduction

Climate change is significantly altering natural processes worldwide, particularly the water cycle [1]. This is evident from the increasing frequency and intensity of extreme hydrological events such as floods and droughts [2]. The latest Sixth Assessment Report (AR6) developed by the Intergovernmental Panel on Climate Change (IPCC) highlighted a rise of 3.1 to 5.1 °C in temperature by the start of the year 2100 in comparison to the base period of 1986 to 2005. Relatively higher changes are expected in tropical and subtropical

regions based on the findings stated in AR6. Rising temperatures primarily affect rainfall distribution, a key element of the hydrological cycle [3]. Combined with rapid urbanization and population growth, climate change presents an urgent challenge [4].

Hydrological data, including temperature, humidity, and especially rainfall intensity, are essential for the planning and designing of water resource infrastructure [5]. Accurate rainfall assessment helps predict natural hazards, such as flash floods, which have caused significant loss of life and economic disruption globally [1,6]. Therefore, analyzing rainfall data with future variability in mind is vital for sustainable planning, efficient infrastructure design, and reducing the impact of extreme events [7].

Punjab, highly vulnerable to climate change, has faced severe floods from 2021 to 2023 [4,8]. IDF curves, based on probability distributions like Normal (N), Weibull (W2), Log Normal (LN2), Log Pearson (LP3), and Gumbel (GUM), are essential for analyzing rainfall extremes and designing stormwater systems [9,10]. Given the rising frequency of extreme events, analyzing historical and projected rainfall is vital for climate-resilient water resource planning [4,11–14].

A major limitation in hydrological studies is the assumption of stationarity, which limits projections of future extremes under climate change [15,16]. GCMs address this by simulating non-stationary future scenarios using Shared Socioeconomic Pathways (SSPs) developed under IPCC guidance [10]. Commonly used pathways include SSP2-4.5 (moderate emissions) and SSP5-8.5 (high emissions, worst-case) [17]. SSP1-2.6, though optimistic, is less suitable for extreme event analysis due to its strong mitigation assumptions [15,17]. SSPs enable more realistic future climate simulations.

Despite significant progress, several gaps remain. First, most IDF-related studies in Pakistan rely solely on gauge-based datasets, which suffer from spatial limitations and incomplete records, thereby reducing their accuracy in assessing extremes. Second, while GCM-simulated data are increasingly used globally to address data scarcity, their potential for developing localized IDF curves in Pakistan remains underexplored. Third, existing studies often assume stationarity and overlook the necessity of bias correction and downscaling, leading to uncertainties in projecting future extremes. Finally, very few attempts have been made to integrate observed rainfall data with downscaled GCM projections to generate IDF curves under multiple SSP scenarios. Addressing these gaps is crucial for advancing flood resilience and climate-adaptive water management in Pakistan.

Researchers have increasingly used CMIP6 GCM outputs under different SSP scenarios to assess future climate impacts, particularly on extreme rainfall. For instance, studies across the U.S. have shown that future projections under various SSPs indicate increased storm intensity for given return periods and durations [18]. Such analyses support climate adaptation strategies by informing resilient infrastructure planning. Similarly, Rohat et al. highlighted that rising rainfall extremes under SSP scenarios have major implications for stormwater system design [19]. Several studies worldwide have applied SSP-based projections to develop future IDF curves, aiding in the evaluation of climate change impacts on regional hydrology.

Research on climate change impacts requires datasets aligned with global change scenarios [20]. GCMs are numerical climate model simulations for atmospheric patterns based on user-defined parameters. High-resolution satellite-derived data are increasingly used due to their greater accuracy and accessibility compared to gauge-based observations, which have spatial and temporal limitations [21]. While IDF curve development relies on long-term rainfall records, observational data are often insufficient, making satellite-derived data a reliable alternative [4,20,22,23]. Global studies have validated satellite-derived data's accuracy in hydrological research [18,24,25], but they have yet to be widely used for IDF curve development and extreme rainfall analysis in Pakistan.

A key limitation of GCM outputs is their coarse spatial resolution, requiring preprocessing for localized studies [26,27]. Since IDF curves are sensitive to spatial variability, accurate input data are crucial for reliable estimates [16]. Studies have shown discrepancies between IDF curves developed using satellite-derived data and those based on ground stations, with satellite-derived data often overestimating or underestimating extreme rainfall events [23,28]. To address this, bias correction through downscaling improves GCM-simulated data by integrating ground observations to correct spatial and temporal inconsistencies [10,28]. Downscaling enhances data resolution and incorporates local climatic characteristics, improving regional applicability [29,30]. Statistical downscaling, due to its computational ease and precision, is widely preferred [31]. Methods like the delta method, bias-correction, and bias-correction-disaggregation are commonly used to refine datasets before analysis [32]. Studies on IDF curves typically show rising intensity patterns for both low and high return periods [31,33], though outputs for long-duration events can be inconsistent [34]. Bias-correction-disaggregation methods are considered computationally efficient with good outputs [10].

Earlier methods, hindered by complex computations, error propagation, and stationarity issues, were not widely accepted. Li et al. (2010) proposed the EQM method to adjust GCM-simulated datasets for future climate variations, addressing these challenges [15]. Unlike previous methods that used unmodified cumulative distribution functions (CDFs), EQM adapts these functions to account for non-stationarity [15,35]. It applies both temporal downscaling (evaluating distributional changes) and spatial downscaling of GCM-simulated annual maximum precipitation [10]. This study uses EQM to develop future rainfall IDF curves, focusing on spatial downscaling to the sub-daily station scale and temporal downscaling to capture distributional fluctuations.

Existing IDF curves are based on stationary extreme values using simple analysis of historical data [36]. However, global climate variability is intensifying extreme events [23]. It is therefore crucial to reassess IDF curves using future climate scenarios to better account for rising risks and support sustainable water infrastructure planning. While similar studies have been conducted in Brazil, none have been reported for Pakistan [37]. This study aims to develop future IDF curves under SSP2-4.5 and SSP5-8.5 for major cities in Punjab, located within the Indus Basin—an essential Asian watershed with potential for sustainable water resource development and regional economic improvement.

To address these shortcomings, the present study combines several novel elements. First, it applies a Taylor diagram-based ranking framework to identify the most reliable GCM for the region, ensuring improved accuracy of projections. Second, it employs EQM bias correction to enhance the reliability of downscaled rainfall data, which has rarely been used for IDF curve development in Pakistan. Third, this study generates probabilistic IDF curves for five major cities under two future climate scenarios (SSP2-4.5 and SSP5-8.5), providing the first set of city-specific empirical equations that can be directly used in hydrological design and flood risk management. These contributions collectively strengthen the methodological robustness of the analysis and enhance its practical value for planners and policymakers.

2. Data and Study Area

This research concentrates on five principal cities in Punjab, identified from historical records as high-risk zones prone to extreme climatic events. Past heavy rainfall has caused flooding, resulting in loss of life and economic disruption. Table 1 lists significant rainfall-induced floods, showing a clear rise in their frequency and intensity [38–41]. Given their susceptibility, assessing future climate impacts on rainfall intensity in these cities is essential.

Table 1. Recent hazardous rainfall-driven floods in Punjab province.

Extreme Rainfall and Floods	Month and Year	Impact
Heavy flooding due to rain	April 2024	21 deaths, 5 injuries, significant damage to houses and crops
Catastrophic flooding	August 2022	Over 33 million individuals were affected, with around 1.7 million homes destroyed and close to 1400 lives lost
Monsoon rains and flooding	June–August 2022	Widespread flooding, particularly impacting Punjab, Khyber Pakhtunkhwa, Balochistan, and Sindh
Severe flooding	September 2014	Millions were affected, causing significant damage to infrastructure and agriculture
Heavy monsoon rains	August 2011	Severe and widespread flooding led to significant loss of life and extensive destruction of property and agricultural land
Massive floods	July 2010	One of the worst floods in Pakistan’s history, affecting Punjab and other regions, causing massive destruction and loss of life

This study focuses on five major cities in Punjab—Lahore, Sialkot, Multan, Bahawalpur, and Sargodha—to analyze rainfall patterns and develop strategies to mitigate future climate change impacts. These cities were selected due to their historical exposure to rainfall-induced floods. The spatial distribution of the selected sites across Punjab, along with relevant geographic details, is illustrated in Figure 1. Elevated values represent mountainous terrain, whereas lower values correspond to plains and low-lying regions.

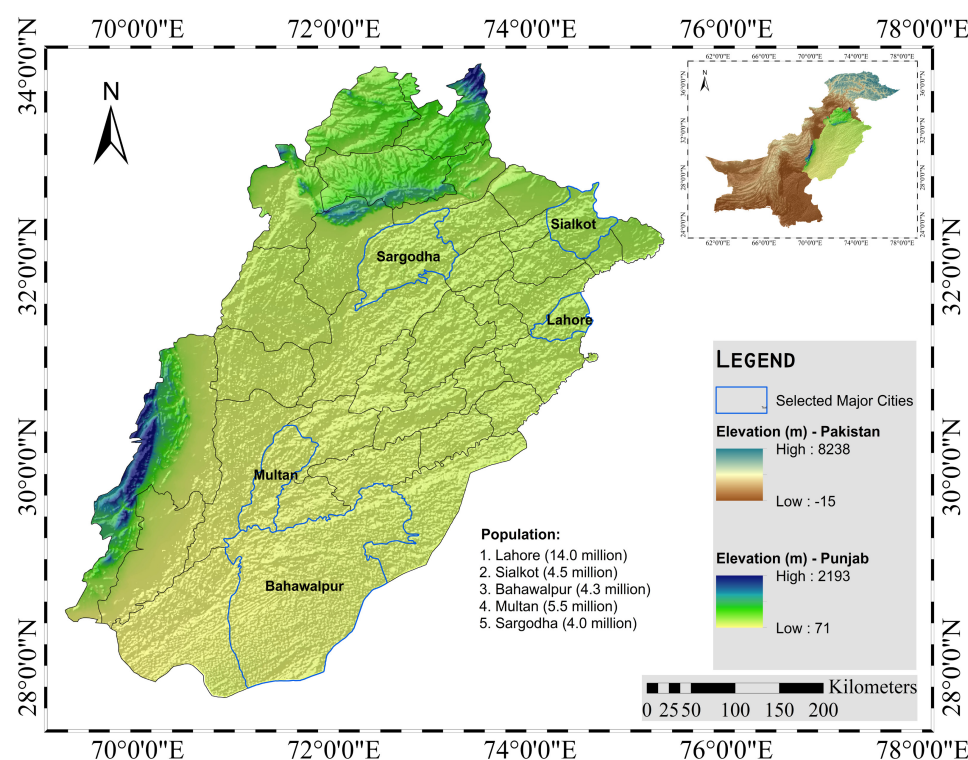


Figure 1. Spatial map of Punjab province (highlighted in green) within Pakistan, overlaid with a Digital Elevation Model (DEM, in meters), illustrating provincial and district boundaries, approximate population distribution, and the locations of the five selected urban centers: Lahore, Sialkot, Multan, Bahawalpur, and Sargodha.

In addition to their historical exposure to extreme rainfall and flooding, the five selected cities—Lahore, Sialkot, Multan, Bahawalpur, and Sargodha—were chosen based on

data completeness, spatial representativeness, and climatic diversity across Punjab. Each of these cities has a long-term, high-quality rainfall record obtained from the Pakistan Meteorological Department (PMD) with minimal missing data, ensuring statistical robustness. Collectively, they capture the province's climatic and physiographic diversity: Sialkot represents the humid sub-mountainous zone of northern Punjab, influenced by monsoon activity; Lahore and Sargodha reflect the semi-humid central plains; while Multan and Bahawalpur represent the arid to semi-arid southern region, characterized by infrequent but intense rainfall. This selection thus ensures comprehensive spatial coverage and reliable representation of the major rainfall regimes within Punjab.

This study uses two data sources. Observational daily rainfall data (1984–2022) were obtained from the PMD. Satellite-derived data were sourced from the Climate Data Store (CDS) by the Copernicus Climate Change Service (C3S) under the EU's Copernicus Program [15]. In this study, the Global Precipitation Climatology Project (GPCP) satellite-derived dataset was used to obtain daily precipitation. GCM simulation models are part of the IPCC's AR6 framework [42–44], providing historical and future projections (2024–2100) based on defined SSPs. In this study, precipitation projections were obtained from CMIP6 GCMs, which are physically based numerical simulations of the coupled atmosphere–ocean system. A total of eight GCMs were initially evaluated for their performance in simulating historical rainfall over Punjab using multiple statistical metrics (RMSE, R^2 , K–S, and A–D).

GCM-simulated precipitation data for Punjab's major cities were extracted by setting parameters such as temporal resolution, experiment type, variables, models, time range, and coordinates. Table 2 lists the details of the eight selected CMIP6 GCMs. Due to differing CMIP6 model resolutions, outputs were interpolated to a $0.5^\circ \times 0.5^\circ$ grid using bilinear interpolation, and a regional shapefile masked both reference and GCM precipitation data over Pakistan.

Table 2. General circulation models (GCMs) used in this research.

Model Name	Country	Modelling Centre	Horizontal Resolution (lon × lat)
BCC-CSM2-MR	China	Beijing Climate Center	$1.1^\circ \times 1.1^\circ$
CNRM-CM6-1	France	Centre National de Recherches Météorologiques, Centre Européen de Recherche et de Formation Avancée en Calcul Scientifique	$1.4^\circ \times 1.4^\circ$
CNRM-ESM2-1			
EC-Earth3-Veg-LR	Europe	EC-EARTH consortium, published at the Irish Centre for High-End Computing	$1.1^\circ \times 1.1^\circ$
HadGEM3-GC31-MM		Met Office Hadley Centre	$0.83^\circ \times 0.55^\circ$
MIROC6	United Kingdom	Atmosphere and Ocean Research Institute (The University of Tokyo), National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology	$1.4^\circ \times 1.4^\circ$
MRI-ESM2-0	Japan	Meteorological Research Institute	$1.1^\circ \times 1.1^\circ$
Nor-ESM2-MM	Norway	Bjerknes Centre for Climate Research, Norwegian Meteorological Institute	$1.25^\circ \times 0.9^\circ$

Various studies have evaluated climate models for regional applicability. For Pakistan, models like EC-Earth3-Veg, MRI-ESM2-0, and NorESM2-MM have proven effective in simulating precipitation extremes and replicating historical events [26,45,46]. Another research identified HadGEM3-GC31-MM, EC-Earth3-Veg-LR, and CNRM-ESM2-1 as top-

performing models [46]. Studies in Southeast Asia and Pakistan have further supported models such as EC-Earth3, MIROC5, CNRM-CM5, and GFDL-CM3 [28,47–51]. While no single model excels universally, those consistently ranked highly were selected: BCC-CSM2-MR, CNRM-ESM2-1, CNRM-CM6-1, EC-Earth3-Veg-LR, HadGEM3-GC31-MM, MIROC6, MRI-ESM2-0, and NorESM2-MM. Each model's performance in reproducing historical rainfall over Punjab was evaluated using multiple statistical tests (K–S, A–D, RMSE, and R^2) and summarized through ranking and Taylor diagram analyses. The best-performing GCM for forecasting rainfall extremes was identified using a ranking approach and validated via a Taylor diagram. This selection was also based on its performance across all stations and was considered suitable for developing future IDF curves. While an ensemble mean could have been used, the single best-performing model was preferred to preserve the spatial and temporal variability of rainfall extremes, which ensemble averaging can often smooth out.

3. Methodology

3.1. Research Steps

This study aims to develop improved IDF curves under future climate change scenarios for key cities in Punjab, Pakistan. Figure 2 illustrates the methodology used to achieve this goal. The process involved the following steps:

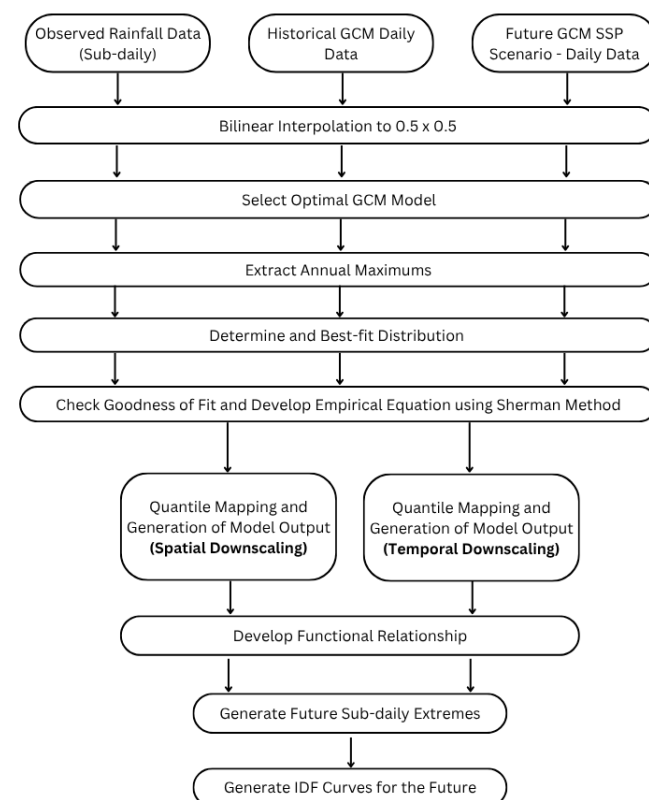


Figure 2. Flowchart for the procedure of generating the updated IDF curves.

1. Obtain observed and satellite-derived daily rainfall data for the selected cities. Extract GCM numerical simulations for the historical period and future scenarios.
2. Perform bilinear interpolation and extract annual maxima for the obtained rainfall datasets
3. Estimate short duration rainfall (1-h, 2-h, 3-h, 4-h, 6-h, 12-h, and 24-h periods)
4. Identify the optimal GCM model using a ranking method approach and the Taylor diagram

5. Determine the best-fit probability distribution (LP3, GUM, and LN2) for estimating rainfall intensity for the required durations and return periods, using the ranking method and goodness of fit tests.
6. Develop IDF curves for all locations and generate its empirical relations using the Sherman equation.
7. Downscale the satellite-derived dataset using the EQM Method in accordance with the best-fit probability distribution.
8. Generate future projections of updated IDF curves and empirical equations using the downscaled dataset for the defined climate scenarios SSP 2-4.5 and 5-8.5.

3.2. Estimating Short Duration Rainfall

Multiple short durations can be derived from the daily maximum dataset to compute the corresponding rainfall intensities. To obtain the required short-duration rainfall data series, the mostly used formula developed by the Indian Meteorology Department (IMD), also known as the reduction formula, was applied, as shown in Equation (1). Multiple researchers have used this formula for the computation of short-duration data series from daily maximum series [4,7,52–54].

$$P_d = P_{24} \left(\frac{d}{24} \right)^{1/3}, \quad (1)$$

where P_d represents the depth of rainfall in millimeters for a d -hour duration. The term P_{24} denotes the maximum daily rainfall depth in millimeters. In this study, short durations of 1 h, 2 h, 3 h, 4 h, 6 h, 12 h, and 24 h were computed using the annual maximum series.

3.3. Selection of Optimal GCM Model

Selecting the most suitable GCM model for downscaling satellite-derived data is crucial [55]. To identify the most suitable GCM for downscaling and future projection, a comprehensive ranking procedure was applied across all candidate models [56]. For each city, the simulated precipitation outputs from the eight selected GCMs were compared with observed datasets for the baseline period (1984–2022). The comparison involved three statistical goodness-of-fit tests (K–S, A–D, and RMSE), where lower test statistic values indicate better model performance. Based on these statistics, each GCM was assigned a rank for every test, with the lowest statistic receiving Rank 1, and so forth. The cumulative rank for each GCM was then computed by summing its individual ranks across the three tests to derive a composite performance score for each city. The GCM with the lowest total rank was considered the most accurate for that location. This procedure was repeated for all five study cities, after which an overall ranking was derived by aggregating the ranks across cities. Additionally, the coefficient of determination (R^2) values were computed separately from scatter plots between observed and simulated rainfall data to assess model fidelity. These R^2 values were reported alongside the final ranking table, as they were not directly used in the cumulative ranking. The rank-based evaluation was entirely derived from the statistical test performance metrics. These tests assess the model's goodness of fit, as detailed in Table 3.

The Taylor diagram was used to evaluate the spatial accuracy of the models by comparing satellite-derived and observed patterns [46,57]. It displays three error statistics: the correlation coefficient (R), the centered root mean square error, and the standard deviation (σ). The model with the highest correlation, the lowest error, and a standard deviation closest to that of the observations is considered the most reliable. The Taylor diagram is widely used for assessing climate model performance.

Table 3. Test statistics for goodness-of-fit tests.

Goodness-of-Fit Test	Test Statistics	Details
Kolmogorov–Smirnov (K–S)	$S_n(x) = 0; \text{ if } X < X_1$ $S_n(x) = \frac{k}{n}; \text{ if } X_k \leq X < X_{k+1}$ $S_n(x) = 1; \text{ if } X > X_n$ $D_n = \max F_x(x) - S_n(x) $ $P(D_n \leq D_n^\alpha) = 1 - \alpha$	$S_n(x)$ = Empirical cumulative frequency $F_x(x)$ = Cumulative density function of the hypothetical distribution D_n^α = Critical value
Anderson–Darling (A–D)	$A^2 = -\frac{\sum[(2i-1)\ln F_X(x_i) + \ln[1 - F_X(x_{n+1-i})]]}{n} - n$	A^2 = Quadratic category of EDF
Root Mean Square Error (RMSE)	$RMSE = \sqrt{\frac{1}{n} \sum (x_i - X)^2}$	x_i = estimated value X = recorded data value

3.4. Selection of Best-Fit Distribution

Before computing intensities and developing IDF empirical equations, the best-fitting probability distribution for the rainfall datasets must be determined [10,58]. This study selected three distributions—Log-Normal Type II (LN2), Log-Pearson Type III (LP3), and Gumbel (GUM)—based on regional research [59–61], with previous studies identifying one as the best fit.

The process starts by evaluating the distribution parameters, which assist in computing the required probability distribution functions (PDFs) and cumulative distribution functions (CDFs) for the corresponding distribution. The required distribution parameters include the mean, standard deviation, and coefficient of skewness, calculated using the Equations (2), (3a), and (3b):

$$\text{Sample mean} = X_{\text{avg}} = \frac{\sum X_i}{n}, \quad (2)$$

$$\text{Standard deviation} = \sigma = \sqrt{\left[\frac{1}{n-1} \sum (X_i - X_{\text{avg}})^2 \right]}, \quad (3a)$$

and

$$\text{Coefficient of skewness} = \gamma = \frac{n \cdot \sum (X_i - X_{\text{avg}})^3}{(n-1)(n-2)S^3}. \quad (3b)$$

Here, n denotes the total number of recorded data points, i refers to the observation index, and X_i represents the i th value in the ordered dataset.

This study takes into account the following frequency/probability distributions:

(1) Log-Normal Distribution: LN2 is commonly utilized in the annual precipitation and surface runoff studies. Both mean and variance are the two parameters that are essential elements of this distribution. Equations (4) and (5) below characterize the PDF and CDF, respectively. In this case, the random variable “ x ” is defined over a range greater than zero.

$$f(x) = \frac{1}{x\sigma_Y\sqrt{2\pi}} \exp \left[-\frac{1}{2\sigma_Y^2} (\ln(x) - \mu_Y)^2 \right] \quad (4)$$

and

$$F(x) = \frac{1}{\sigma_Y\sqrt{2\pi}} \int_0^x \left(\frac{1}{x} \exp \left[-\frac{1}{2\sigma_Y^2} (\ln(x) - \mu_Y)^2 \right] \right) dx. \quad (5)$$

(2) Log-Pearson Distribution: LP3 is a frequency distribution similar to the gamma family. It depicts the log-transformed form of the Pearson Type-III distribution variables. Equations (6) and (7) characterize the PDF and CDF, respectively.

$$f(x) = \frac{1}{|\alpha|x\Gamma(\beta)} \left[\left(\frac{\ln(x) - \zeta}{\alpha} \right)^{\beta-1} \right] \exp \left[- \left(\frac{\ln(x) - \zeta}{\alpha} \right) \right] \quad (6)$$

and

$$F(x) = \frac{1}{|\alpha|\Gamma(\beta)} \int_0^x \frac{1}{x} \left[\left(\frac{\ln(x) - \zeta}{\alpha} \right)^{\beta-1} \right] \exp \left[- \left(\frac{\ln(x) - \zeta}{\alpha} \right) \right] dx. \quad (7)$$

With the help of the methods of the moments (MOM) estimators, the parameters—shape β , scale α , and position ζ —are calculated using Equations (8), (9), and (10), respectively as shown below.

$$\beta = \frac{4}{\gamma^2}, \quad (8)$$

$$\alpha = \frac{\sigma\gamma}{2}, \quad (9)$$

and

$$\zeta = \mu - \frac{2\sigma}{\gamma}. \quad (10)$$

(3) Gumbel Distribution: The GUM distribution, classified as Type-I extreme value distribution, is commonly used to estimate the maximum values within a dataset, such as peak discharge. It is widely recognized as one of the most suitable distributions for flood frequency analysis and related hydrological assessments. The corresponding PDF and CDF are presented in Equations (11) and (12) below.

Moreover, the scale parameter α and location parameter β of the distribution are expressed in Equations (13) and (14) below. For the GUM distribution, these parameters are derived through the MOM estimation technique.

$$f(x) = \left(\frac{1}{\alpha} \right) \exp \left[- \left(\frac{x - \beta}{\alpha} \right) - \exp \left(- \left(\frac{x - \beta}{\alpha} \right) \right) \right], \quad (11)$$

$$F(x) = \exp \left[- \exp \left(- \frac{x - \beta}{\alpha} \right) \right], \quad (12)$$

$$\alpha = 0.7797\sigma, \quad (13)$$

and

$$\beta = \mu - 0.5772\alpha. \quad (14)$$

After determining the PDFs and CDFs, goodness-of-fit tests validated the selection process. These included empirical distribution function (EDF) tests, which compare the actual and theoretical datasets [62]. The K-S, A-D, and RMSE tests were applied to identify the optimal probability distribution representing the study area [63,64]. The most suitable probability distribution for each city and rainfall duration was identified separately through a combination of goodness-of-fit evaluations. The distribution with the highest overall ranking across these tests was selected as the best fit for that specific city and rainfall duration. This city-specific approach ensured that the probabilistic representation of rainfall extremes reflects local climatic variability, rather than being averaged across regions. The test statistics, detailed in Table 3, assess the suitability of a distribution for the dataset.

Finally, after the goodness-of-fit tests, the ranking method was applied to determine the best-fitting probability distribution for the rainfall dataset of Punjab cities. The distributions were ranked based on the lowest test statistics, with the distribution showing the best fit being selected.

3.5. Generating IDF Curves and Sherman Equation

IDF curves require data on rainfall intensity (I), duration (D), and return period (F). The rainfall depth data, based on short-duration series calculated using the IMD formula, were used for this. IDF curves for various durations and return periods were developed for each major city in Punjab. Rainfall intensity (I) was first calculated using the rainfall depth (P_d) in millimeters and duration (d) in minutes, as shown in Equation (15):

$$I = 60 \left(\frac{P_d}{d} \right). \quad (15)$$

After computing the intensity values, the recurrence interval (T) was computed. This was calculated for the available rainfall dataset using the California method, which has been recommended by many researchers for its precise results [33,55,58]. The formula for calculating return period value using the California method is shown in Equation (16):

$$T = \frac{N}{m}, \quad (16)$$

where (N) is the number of years for which rainfall data are available, (m) is the rank of the events, and (T) is the return period value calculated in years.

To produce the IDF curves, return periods of 2, 5, 10, 25, 50, and 100 years were specified for this study. Corresponding to these return periods and the earlier defined rainfall durations, rainfall intensities were extracted from the dataset, and the IDF curves for the observed dataset were plotted. After developing the IDF curves for all major cities under consideration using the best-fitting probability distributions, the next step was to formulate the empirical relation/equation for the selected distribution for all cities in the study region. Equations (17) and (18) are known as the Sherman equation, which is considerably accurate and simple to use for the computation of rainfall intensity using a few parameters.

$$i = \frac{a}{t^m} = \frac{kT^x}{t^m} \quad (17)$$

and

$$a = kT^x, \quad (18)$$

where i is rainfall intensity (mm/hr), t is the storm duration (minutes), T is the return period (years), and k , x , and a are constants (rainfall intensity parameters, regression parameters, or Sherman coefficients). The coefficient (a), depending on T , is shown in Equation (18). To develop the empirical relation for Punjab's cities using the Sherman equation, the coefficient values are determined. Equation (17) is linearized (Equation (19)) by applying a logarithmic function ($\log_{10}$ for i and t). A straight-line graph is plotted with $\log$ intensity on the y -axis and $\log$ duration on the x -axis. The slope gives parameter (m), and the y -intercept gives ($\log a$). Different lines are plotted for return periods (2, 5, 10, 25, and 50 years), varying ($\log a$) while keeping (m) constant. Equation (19) is further linearized (Equation (20)) to account for the frequency factor (a).

$$\log I = \log a - m \log t \quad (19)$$

and

$$\log a = \log k + x \log T. \quad (20)$$

Similarly, a straight-line graph for Equation (20) is plotted, with $\log a$ on the y -axis and $\log T$ on the x -axis. The $\log a$ values are obtained from the graph of Equation (19), and the

corresponding logT values are used to generate this graph. The slope of this straight line represents the value of parameter x , and the y-intercept gives the value of $\log k$. Following the defined procedure, the unknown parameters (k , a , and x) can be computed, and the empirical equations for a city can be developed. The procedure is repeated for each major city in the Punjab province, so that a unique and valid empirical equation is developed for each city.

3.6. Downscaling

CMIP6 GCM-simulated data, which provide coarse-resolution projections of future climate, require statistical downscaling to generate localized rainfall estimates suitable for IDF curve development. Such downscaling is particularly important in regions with sparse or unevenly distributed ground stations, where raw GCM outputs may misrepresent local rainfall extremes [65]. To improve the reliability of these projections, GCM-simulated data were corrected using observed station data. Various statistical downscaling methods have been applied globally to enhance the accuracy of climate projections, but many are limited by computational demand, methodological complexity, or higher associated uncertainty [66–69]. In this study, the EQM method [15] was adopted, as it effectively corrects distributional biases and enables consistent statistical downscaling across multiple emission scenarios [56,69].

3.7. EQM Method Algorithm

One of the essential parts of this study is the downscaling of GCM-simulated precipitation data to ensure an accurate downscaled dataset for the development of future IDF projections. For this purpose, the EQM method was adopted, which is presented stepwise as follows:

1. Select the appropriate GCM model for the study area and obtain the daily maximum rainfall using the historical GCM-simulated daily dataset.

$$X_{\max}^{\text{GCM}} = \begin{bmatrix} X_{1,\max}^{\text{GCM}} \\ X_{2,\max}^{\text{GCM}} \\ X_{3,\max}^{\text{GCM}} \\ \vdots \\ X_{N,\max}^{\text{GCM}} \end{bmatrix}, \quad (21)$$

where the values in the matrix, represented by $X_{i,\max}^{\text{GCM}}$, are the maximum daily rainfall values from historical GCM-simulated dataset for the i th year, and N is the number of years for which the dataset is available. It is important to note that for the formulation to work effectively, the same time span (number of years) should be used from the observed rainfall dataset.

2. Using the station/observed rainfall dataset for a location, acquire the sub-daily (1 h, 2 h, 3 h, 4 h, 6 h, 12 h, and 24 h) maximum rainfall values.

$$X_{\max}^{\text{STN}} = \begin{bmatrix} X_{1,\max}^{\text{STN},1\text{hr}} & X_{1,\max}^{\text{STN},2\text{hr}} & \cdots & X_{1,\max}^{\text{STN},24\text{hr}} \\ X_{2,\max}^{\text{STN},1\text{hr}} & X_{2,\max}^{\text{STN},2\text{hr}} & \cdots & X_{2,\max}^{\text{STN},24\text{hr}} \\ X_{3,\max}^{\text{STN},1\text{hr}} & X_{3,\max}^{\text{STN},2\text{hr}} & \cdots & X_{3,\max}^{\text{STN},24\text{hr}} \\ \vdots & \vdots & \vdots & \vdots \\ X_{N,\max}^{\text{STN},1\text{hr}} & X_{N,\max}^{\text{STN},2\text{hr}} & \cdots & X_{N,\max}^{\text{STN},24\text{hr}} \end{bmatrix}, \quad (22)$$

where the values in the matrix, represented by $X_{i,\max}^{\text{STN},j}$, are the maximum sub-daily rainfall values for a particular location/city (STN) from station/observed rainfall dataset for the j th rainfall duration in the i th year, and N is the number of years for which the dataset is available.

3. Acquire the daily maximum rainfall using the future GCM-simulated dataset for the defined climate scenarios (i.e., SSP 2-4.5 and 5-8.5).

$$X_{\max}^{\text{GCM,Fut}} = \begin{bmatrix} X_{1,\max}^{\text{GCM,SSP2-4.5}} & X_{1,\max}^{\text{GCM,SSP5-8.5}} \\ X_{2,\max}^{\text{GCM,SSP2-4.5}} & X_{2,\max}^{\text{GCM,SSP5-8.5}} \\ X_{3,\max}^{\text{GCM,SSP2-4.5}} & X_{3,\max}^{\text{GCM,SSP5-8.5}} \\ \vdots & \vdots \\ X_{N_f,\max}^{\text{GCM,SSP2-4.5}} & X_{N_f,\max}^{\text{GCM,SSP5-8.5}} \end{bmatrix}, \quad (23)$$

where the values in the matrix, represented by $X_{\max}^{\text{GCM,Fut}}$, are the maximum daily rainfall values from the future GCM-simulated precipitation dataset for the defined climate scenarios, and N_f is the number of years considered in the future dataset.

4. Determine the best-fitting probability distribution representing the daily maximum values obtained from the GCM-simulated (historical and future) dataset and the observed rainfall datasets.

$$\text{PDF}^{\text{GCM}} = f\left(\frac{\theta^{\text{GCM}}}{X_{\max}^{\text{GCM}}}\right), \quad (24a)$$

$$\text{PDF}_j^{\text{STN}} = f\left(\frac{\theta^{\text{STN},j}}{X_{\max}^{\text{STN},j}}\right), \quad (24b)$$

and

$$\text{PDF}^{\text{GCM,Fut}} = f\left(\frac{\theta^{\text{GCM}}}{X_{\max}^{\text{GCM,Fut}}}\right), \quad (24c)$$

where PDF represents the probability distribution function, and θ is the critical parameter of the best-fitting distribution.

5. Extract the GCM-simulated sub-daily dataset, $Y_{\max,j}^{\text{STN}}$, represents a statistical linkage between the sub-daily dataset and the cumulative probability distribution of the GCM simulation using the quantile mapping methodology. This is also known as spatial downscaling of the historical GCM-simulated dataset to the sub-daily observed rainfall dataset.

$$Y_{\max,j}^{\text{STN}} = \text{CDF}\left(\left(\text{invCDF}\left(X_{\max}^{\text{GCM}}/\theta^{\text{GCM}}\right)\right)/\theta^{\text{STN},j}\right), \quad (25)$$

where CDF represents the cumulative probability distribution function, and invCDF is the inverse of corresponding CDF. $Y_{\max,j}^{\text{STN}}$ is the sub-daily maximum dataset statistically downscaled for the corresponding j th duration.

6. With a similar approach, model the variation between the scenario-based future GCM dataset and the historical GCM-simulated dataset using the quantile mapping methodology, which helps extract the downscaled scenario-based future GCM projections, $Y_{\max}^{\text{GCM,Fut}}$ for the dataset. This is known as temporal downscaling of future GCM projections to the baseline historical GCM rainfall dataset:

$$Y_{\max}^{\text{GCM,Fut}} = \text{CDF}\left(\left(\text{invCDF}\left(X_{\max}^{\text{GCM}}/\theta^{\text{GCM}}\right)\right)/\theta^{\text{GCM,Fut}}\right), \quad (26)$$

where $Y_{\max}^{\text{GCM,Fut}}$ is the temporally downscaled dataset for the future GCM projections and the historical GCM simulated dataset for the corresponding period.

- Form a suitable function/expression to develop a mathematical relationship between $Y_{\max,j}^{\text{STN}}$ and $X_{i,\max}^{\text{GCM}}$. Few studies [10,70] suggest a linear relationship between the two quantities, providing a reasonably accurate relationship. However, this is not valid for all distribution functions. Previous studies have used the Gumbel CDF for this relationship. In this study, the LP3 distribution was identified as the best fit, so its CDF (Equation (29)) is used to develop the first-order linear equation for the two CDFs for the region.

$$Y_{\max,j}^{\text{STN}} = f(X_{\max}^{\text{GCM}}), \quad (27)$$

$$Y_{\max,j}^{\text{STN}} = a_1 X_{\max}^{\text{GCM}} + b_1, \quad (28)$$

and

$$F(x) = \frac{\gamma\left(k, ke^{-\frac{\ln(x)-\mu}{\beta}}\right)}{\Gamma(k)}, \quad (29)$$

where $\gamma(k)$ is the lower partial gamma function, $\Gamma(k)$ is the complete gamma function, k is the shape parameter, and μ and β are the location and scale parameters.

- Following the same approach, determine the function that links $Y_{\max}^{\text{GCM,Fut}}$ and $X_{i,\max}^{\text{GCM}}$

$$Y_{\max}^{\text{GCM,Fut}} = f(X_{\max}^{\text{GCM}}) \quad (30)$$

and

$$Y_{\max}^{\text{GCM,Fut}} = a_2 X_{\max}^{\text{GCM}} + b_2. \quad (31)$$

- To develop future projections of the dataset, combine Equations (17) and (19) along with the replacement of $X_{i,\max}^{\text{GCM}}$ with $Y_{\max}^{\text{GCM,Fut}}$ in Equation (17).

$$X_{\max,j}^{\text{STN,future}} = a_1 \left[\frac{X_{\max}^{\text{GCM,future}} - b_2}{a_2} \right] + b_1. \quad (32)$$

- Finally, produce IDF curves for the downscaled future projection dataset and compare it with the observed/station-based IDF curves to determine variations in intensities.

4. Results and Discussion

The first step involved selecting the most suitable GCM by evaluating how well various models simulated historical rainfall over the study area. GCM simulation outputs were compared with observed data, and the results, shown in Figure 3 as a heat map, rank the models for Punjab's major cities based on goodness-of-fit tests. The figure outlines the ranking criteria, emphasizing the need for region-specific assessments due to the spatial variability in GCM performance.

Figure 3 shows a heat map ranking GCMs based on their ability to replicate rainfall patterns in Punjab's major cities; lighter shades and lower ranks indicate better performance. The EC-Earth3-Veg-LR model was selected for its consistent top ranking. Choosing region-specific GCMs reduces uncertainty in projections [71]. The comparative assessment of GCMs (Figure 3) shows that EC-Earth3-Veg-LR consistently performed best across all five cities, yielding the highest correlation coefficients ($R^2 = 0.973$ – 0.992) and the lowest RMSE values (1.37–7.72 mm). BCC-CSM2-MR ranked second, with comparable R^2 values (0.924–0.968) but slightly higher RMSE. In contrast, models such as MIROC6 and CNRM-

ESM2-1 exhibited higher errors ($RMSE > 8$ mm) and weaker correlations ($R^2 < 0.90$). Overall, EC-Earth3-Veg-LR reduced RMSE by about 65–80% compared with the least accurate models, confirming its superior ability to reproduce observed rainfall characteristics across Punjab. Accordingly, EC-Earth3-Veg-LR and BCC-CSM2-MR were selected for EQM bias correction and subsequent IDF development. Figure 4's Taylor diagram further summarizes model performance, ensuring the most reliable GCM is used for accurate downscaling and future projections.

Test	GCM	Major Cities of Punjab									
		Bahawalpur		Lahore		Multan		Sargodha		Sialkot	
		Statistic	Rank	Statistic	Rank	Statistic	Rank	Statistic	Rank	Statistic	Rank
K-S Test	BCC-CSM2-MR	0.031	2	0.015	2	0.068	6	0.018	1	0.035	4
	CNRM-CM6-1	0.034	3	0.015	2	0.015	1	0.052	8	0.036	5
	CNRM-ESM2-1	0.031	2	0.023	4	0.016	2	0.050	7	0.050	7
	EC-Earth3-Veg-LR	0.020	1	0.012	1	0.015	1	0.022	2	0.019	2
	HadGEM3-GC31-MM	0.044	5	0.021	3	0.035	4	0.033	4	0.045	6
	MIROC6	0.086	6	0.032	6	0.016	2	0.043	5	0.016	1
	MRI-ESM2-0	0.044	5	0.021	3	0.058	5	0.047	6	0.028	3
	NorESM2-MM	0.037	4	0.028	5	0.034	3	0.028	3	0.028	3
A-D Test	BCC-CSM2-MR	0.677	4	2.849	3	0.156	1	2.753	2	0.085	2
	CNRM-CM6-1	6.807	6	2.849	3	3.138	6	10.730	8	0.081	1
	CNRM-ESM2-1	8.335	8	2.334	2	3.791	7	10.141	7	5.576	7
	EC-Earth3-Veg-LR	4.085	5	4.205	4	3.138	6	4.527	3	1.157	4
	HadGEM3-GC31-MM	0.473	3	5.360	6	1.384	4	5.229	5	3.415	6
	MIROC6	0.259	1	1.218	1	2.369	5	0.294	1	0.818	3
	MRI-ESM2-0	0.441	2	4.695	5	0.293	2	9.378	6	1.362	5
	NorESM2-MM	7.679	7	8.073	7	0.775	3	4.937	4	1.362	5
RMSE Test	BCC-CSM2-MR	3.509	3	11.350	6	2.789	3	12.531	6	10.425	3
	CNRM-CM6-1	4.141	4	7.696	2	5.904	6	24.647	8	12.616	4
	CNRM-ESM2-1	4.364	6	10.850	5	6.907	7	8.884	5	14.085	5
	EC-Earth3-Veg-LR	1.374	1	7.721	1	2.531	2	3.596	1	6.734	1
	HadGEM3-GC31-MM	2.939	2	8.576	4	13.372	8	6.021	2	14.526	6
	MIROC6	9.703	8	8.268	3	1.711	1	6.239	4	29.840	7
	MRI-ESM2-0	6.244	7	19.635	8	5.540	4	16.192	7	7.976	2
	NorESM2-MM	4.260	5	10.277	7	5.757	5	6.106	3	7.976	2
Models' Ranking:		1									8
Final Rank	GCM	Rank	R ²	Rank	R ²	Rank	R ²	Rank	R ²	Rank	R ²
	BCC-CSM2-MR	9	0.9241	11	0.9397	10	0.9795	9	0.9632	9	0.9678
	CNRM-CM6-1	13	0.9575	7	0.9397	13	0.9219	24	0.955	10	0.9666
	CNRM-ESM2-1	16	0.9797	11	0.9023	16	0.9717	19	0.8584	19	0.9247
	EC-Earth3-Veg-LR	7	0.9729	6	0.9917	9	0.9219	6	0.9932	7	0.9904
	HadGEM3-GC31-MM	10	0.9089	13	0.9499	16	0.6101	11	0.9438	18	0.9308
	MIROC6	15	0.6737	10	0.951	8	0.9528	10	0.9649	11	0.9015
	MRI-ESM2-0	14	0.8690	16	0.952	11	0.9058	19	0.967	10	0.9574
	NorESM2-MM	16	0.9653	19	0.9573	11	0.9356	10	0.9584	10	0.9574
		Low								High	
Best Fit GCM		EC-Earth3-Veg-LR		EC-Earth3-Veg-LR		MIROC6		EC-Earth3-Veg-LR		EC-Earth3-Veg-LR	
Second Best Fit GCM		BCC-CSM2-MR		CNRM-CM6-1		EC-Earth3-Veg-LR		BCC-CSM2-MR		BCC-CSM2-MR	

Figure 3. Heat map of global climate model ranking for major cities in Punjab.

Figure 4 shows the statistical performance of climate models via Taylor diagrams for Bahawalpur, Lahore, Multan, Sargodha, and Sialkot. The results confirm that EC-Earth3-Veg-LR consistently outperforms others, with the highest correlation, lowest RMSE, and standard deviation closest to the observed values. This model was selected for further analysis. A visual summary of GCM performance and rankings across Punjab's major cities is shown in Figure 5.

The comprehensive GCM ranking presented in Figure 5 highlights the consistent superiority of EC-Earth3-Veg-LR, which attained the lowest overall rank across all stations, indicating the smallest cumulative error and the best rainfall simulation capability. BCC-CSM2-MR followed closely as the second-best model, while MIROC6 and CNRM-ESM2-1 ranked lowest due to higher deviations from observed data. The inter-city ranking confirms that EC-Earth3-Veg-LR achieved top-three performances in all five cities, whereas models with weaker skill exhibited greater spatial inconsistency. Quantitatively, EC-Earth3-Veg-LR outperformed the ensemble average by approximately 60–70% in RMSE reduction and

5–20% in correlation (R^2), reaffirming its suitability for EQM bias correction and subsequent IDF curve development.

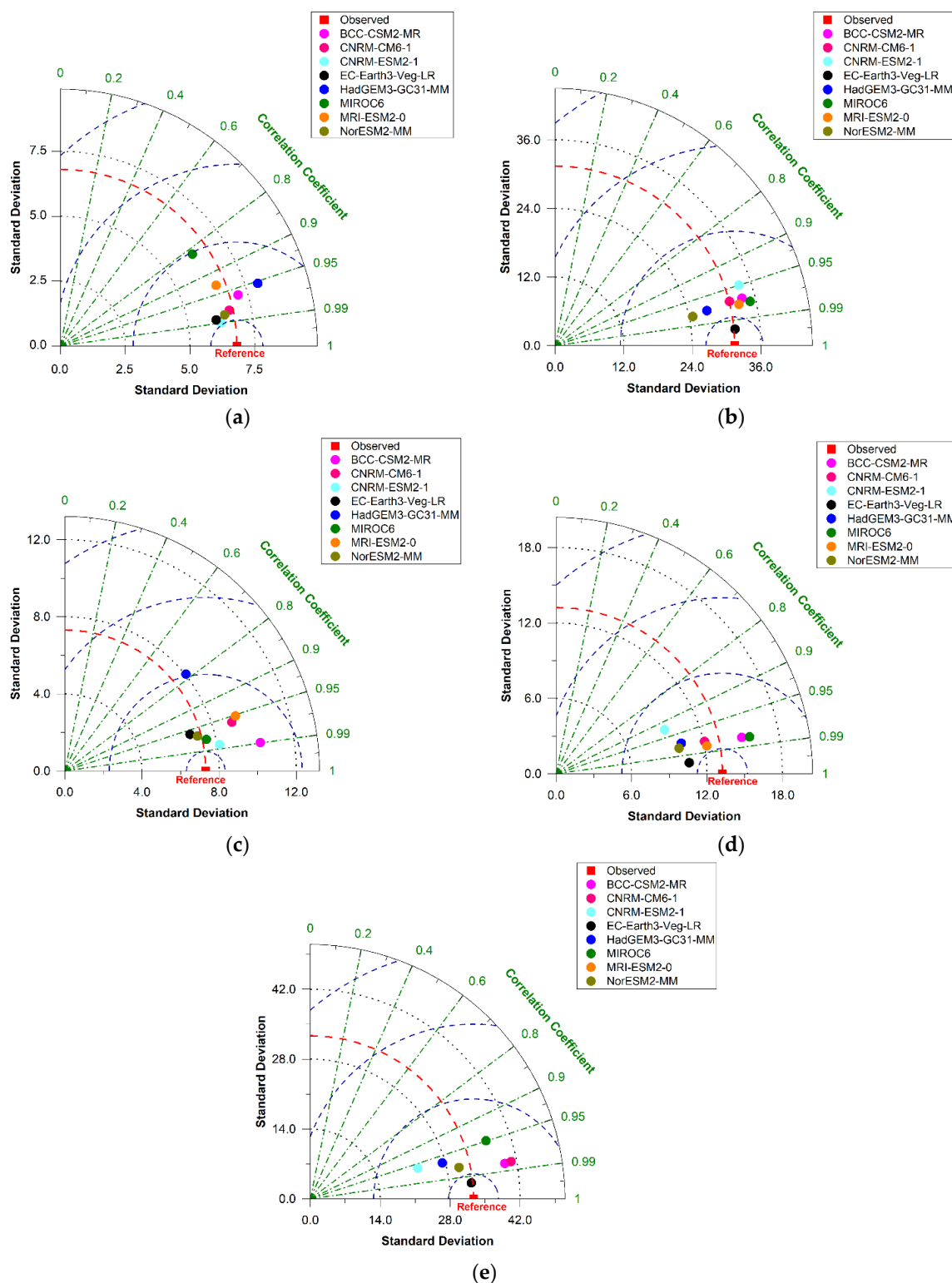


Figure 4. Taylor diagram of climate model statistical performance for (a) Bahawalpur, (b) Lahore, (c) Multan, (d) Sargodha, and (e) Sialkot.

The second step was to characterize the annual rainfall datasets by identifying the best-fitting probability distribution for the major cities of the province under consideration. The ranking method was adopted for this purpose, and the results are given in Table 4.

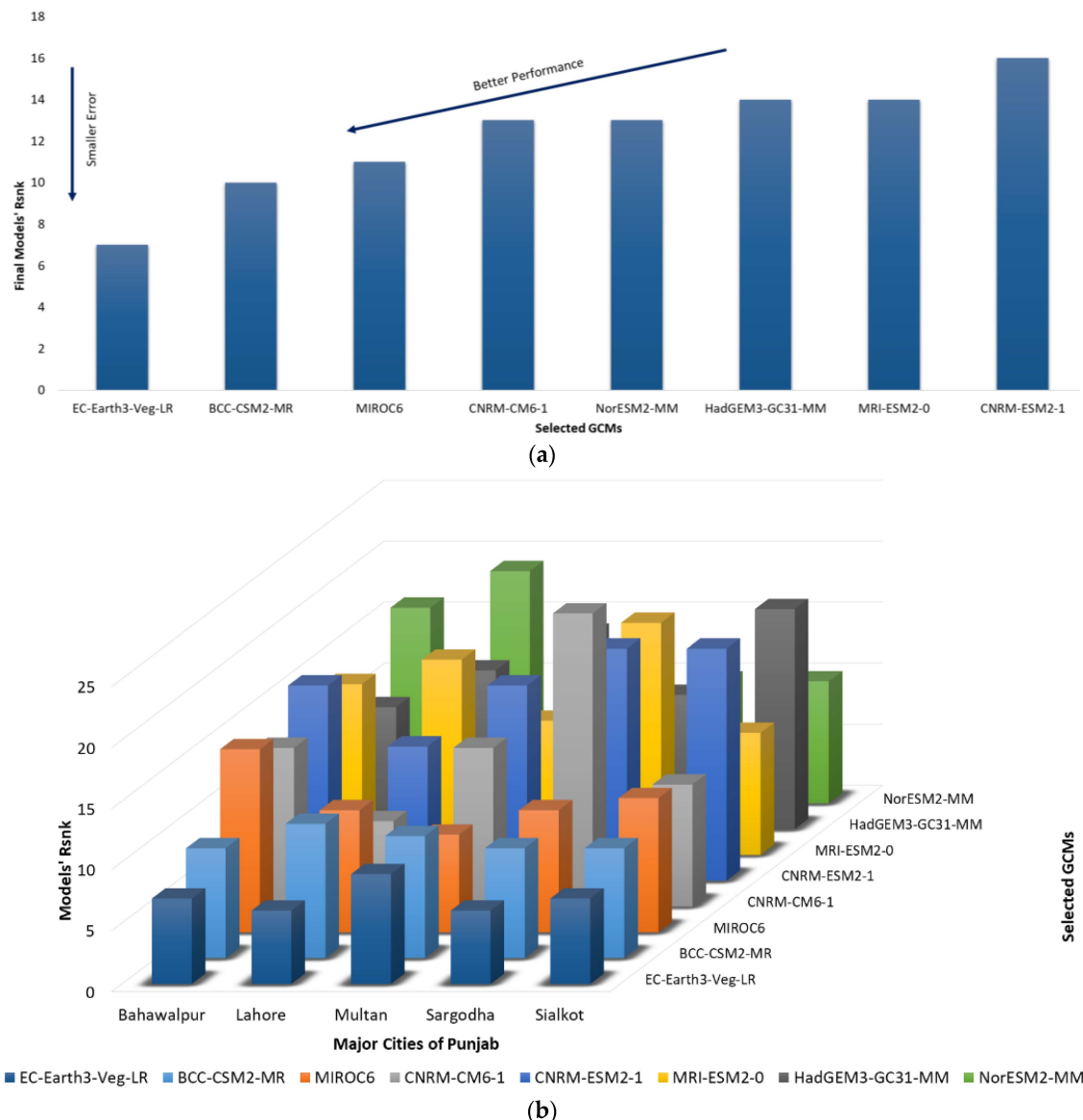


Figure 5. (a) Comprehensive ranking of GCM models based on their performance in simulating precipitation over major cities of Punjab; (b) Ranked performance of GCMs across the major cities in Punjab.

Table 4 summarizes the goodness-of-fit test results for ground/station, historical, and future GCM-simulate precipitation data for the major cities in Punjab. Based on the K–S, A–D, and RMSE tests, the LP3 distribution was found as the most suitable for modelling annual maximum rainfall in both historical and projected datasets [72,73]. For observed data, LP3 achieved the lowest K–S (0.010–0.030) and A–D (≈ 0.03 –0.08) statistics together with small RMSE values (0.89–6.20 mm). In the historical GCM-simulated series, LP3 again produced the best overall rank, with RMSE mostly between 1.6 and 3.8 mm, while alternative distributions such as LN2 and GUM yielded higher residuals. Under future projections (SSP2-4.5 and SSP5-8.5), LP3 maintained its superiority, keeping RMSE below ≈ 9 mm even in cases where other models exceeded 12–14 mm. Quantitatively, LP3 reduced RMSE by roughly 40–60% compared with the second-ranked distribution, demonstrating its robustness for both present and projected rainfall extremes in Punjab. Rainfall intensities for specified durations and return periods were estimated using the best-fitting distribution identified from the goodness-of-fit tests. As LP3 was optimal for the major cities, intensity

values were derived from the LP3 dataset. Table 5 summarizes the computed intensities for the defined durations and return periods.

Table 4. Goodness of fit test results.

Dataset Source	Name of City	Best-Fit Test Statistics Result			Highest Ranked Distribution (Sum of Ranks)
		K-S Test	A-D Test	RMSE Test	
Observed Data	Lahore	LP3 (0.010)	GUM (1.888)	LP3 (6.202)	LP3 (4)
	Multan	LN2 (0.017)	LP3 (0.307)	LN2 (1.303)	LP3 (6)
	Bahawalpur	LN2 (0.014)	LP3 (0.047)	LN2 (0.886)	LP3 (6)
	Sargodha	LP3 (0.016)	GUM (1.926)	LP3 (2.184)	LP3 (4)
	Sialkot	LN2 (0.015)	LP3 (0.327)	LN2 (5.346)	LP3 (4)
GCM Historical Data	Lahore	LN2 (0.021)	GUM (0.038)	LP3 (2.100)	LP3 (5)
	Multan	LP3 (0.021)	GUM (0.029)	LP3 (1.768)	LP3 (4)
	Bahawalpur	LP3 (0.067)	LP3 (0.036)	LP3 (7.183)	LP3 (3)
	Sargodha	LP3 (0.024)	GUM (0.009)	LP3 (1.574)	LP3 (4)
	Sialkot	LN2 (0.041)	LP3 (0.076)	LP3 (4.390)	LP3 (5)
GCM Future (SSP2-4.5)	Lahore	LP3 (0.064)	LP3 (0.001)	LN2 (8.615)	LP3 (4)
	Multan	LP3 (0.035)	LP3 (0.002)	LP3 (8.123)	LP3 (3)
	Bahawalpur	LP3 (0.070)	LP3 (0.001)	LP3 (8.660)	LP3 (3)
	Sargodha	GUM (0.029)	LP3 (0.001)	LP3 (3.036)	LP3 (5)
	Sialkot	LP3 (0.024)	LP3 (0.003)	LN2 (5.609)	LP3 (4)
GCM Future (SSP5-8.5)	Lahore	LP3 (0.049)	LP3 (0.001)	LN2 (5.337)	LP3 (4)
	Multan	LP3 (0.068)	LP3 (0.011)	LP3 (9.486)	LP3 (3)
	Bahawalpur	LP3 (0.076)	LP3 (0.001)	LP3 (13.117)	LP3 (3)
	Sargodha	LP3 (0.070)	LP3 (0.003)	LN2 (7.450)	LP3 (4)
	Sialkot	LP3 (0.041)	LP3 (0.004)	LN2 (14.292)	LP3 (4)

Table 5. Rainfall intensities (mm/hr) for different durations (hours) and return periods (years) estimated using the LP3 distribution for the regions under consideration.

Name of City	Dataset Source	Return Period (Year)	Rainfall Duration (hrs)						
			1	2	3	4	6	12	24
Bahawalpur	Observed Data	2	5.26	3.45	2.68	2.24	1.74	1.11	0.71
		5	12.89	7.31	5.29	4.21	3.07	1.82	1.09
		10	17.57	9.68	6.88	5.42	3.90	2.25	1.32
		25	21.82	11.83	8.33	6.52	4.64	2.64	1.53
		50	27.08	14.53	10.17	7.92	5.61	3.16	1.82
		100	35.20	18.88	13.22	10.30	7.29	4.10	2.36
	GCM Historical Data	2	2.41	1.94	1.63	1.42	1.15	0.79	0.52
		5	7.71	4.65	3.48	2.84	2.13	1.31	0.81
		10	13.81	7.78	5.61	4.46	3.25	1.92	1.15
		25	21.17	11.56	8.18	6.43	4.60	2.65	1.56
		50	31.05	16.65	11.66	9.10	6.46	3.66	2.12
		100	40.36	21.65	15.16	11.83	8.39	4.75	2.76
	GCM Future (SSP2-4.5)	2	2.50	1.60	1.27	1.10	0.90	0.64	0.46
		5	10.97	6.34	4.63	3.72	2.74	1.64	0.99
		10	25.36	12.33	8.66	6.76	4.79	2.70	1.55
		25	42.82	22.40	15.43	11.87	8.25	4.48	2.49
		50	54.56	28.37	19.45	14.92	10.32	5.57	3.07
		100	70.93	36.88	25.29	19.40	13.42	7.24	3.99
	GCM Future (SSP5-8.5)	2	2.80	2.00	1.70	1.48	1.24	0.90	0.62
		5	13.10	7.63	5.60	4.50	3.33	2.00	1.22
		10	27.67	13.75	9.73	7.64	5.47	3.13	1.83
		25	45.06	23.87	16.57	12.84	9.01	5.00	2.84
		50	56.81	29.89	20.66	15.96	11.15	6.14	3.46
		100	73.86	38.85	26.86	20.75	14.49	7.98	4.50

Table 5. Cont.

Name of City	Dataset Source	Return Period (Year)	Rainfall Duration (hrs)						
			1	2	3	4	6	12	24
Lahore	Observed Data	2	29.15	18.47	14.13	11.68	8.92	5.63	3.55
		5	41.53	25.85	19.63	16.17	12.30	7.73	4.86
		10	50.20	31.01	23.48	19.31	14.67	9.20	5.78
		25	58.62	36.03	27.23	22.36	16.97	10.63	6.67
		50	70.28	43.02	32.47	26.64	20.20	12.64	7.93
		100	91.36	55.93	42.21	34.63	26.25	16.43	10.31
	GCM Historical Data	2	23.50	14.85	11.34	9.37	7.16	4.51	2.84
		5	33.83	20.83	15.75	12.93	9.81	6.14	3.85
		10	39.73	24.25	18.26	14.96	11.33	7.07	4.43
		25	44.87	27.22	20.45	16.73	12.65	7.88	4.93
		50	52.01	31.42	23.56	19.26	14.54	9.05	5.66
		100	67.61	40.84	30.63	25.03	18.90	11.76	7.36
	GCM Future (SSP2-4.5)	2	23.66	15.31	11.81	9.82	7.55	4.80	3.04
		5	40.68	24.65	18.48	15.10	11.39	7.07	4.41
		10	55.86	31.64	23.48	19.06	14.26	8.77	5.44
		25	71.29	41.45	30.48	24.61	18.29	11.16	6.88
		50	82.62	47.78	35.05	28.25	20.96	12.75	7.85
		100	107.41	62.12	45.56	36.72	27.25	16.58	10.21
	GCM Future (SSP5-8.5)	2	26.49	17.11	13.20	10.96	8.42	5.35	3.38
		5	44.42	27.21	20.52	16.82	12.73	7.94	4.98
		10	61.72	35.36	26.42	21.54	16.21	10.04	6.26
		25	80.06	47.29	35.07	28.46	21.31	13.11	8.14
		50	93.50	54.97	40.67	32.97	24.64	15.13	9.39
		100	121.55	71.46	52.87	42.86	32.03	19.67	12.20
Multan	Observed Data	2	6.70	4.37	3.38	2.82	2.18	1.39	0.89
		5	14.42	8.30	6.06	4.86	3.57	2.14	1.30
		10	19.21	10.75	7.71	6.12	4.44	2.61	1.56
		25	23.59	12.98	9.23	7.28	5.23	3.03	1.79
		50	29.10	15.83	11.19	8.78	6.28	3.60	2.11
		100	37.82	20.58	14.54	11.41	8.16	4.68	2.75
	GCM Historical Data	2	4.44	3.04	2.40	2.03	1.59	1.03	0.67
		5	12.20	6.97	5.06	4.04	2.96	1.76	1.06
		10	17.54	9.67	6.89	5.43	3.91	2.26	1.33
		25	22.68	12.28	8.65	6.77	4.82	2.74	1.59
		50	29.11	15.58	10.89	8.48	6.00	3.37	1.94
		100	37.84	20.26	14.16	11.03	7.80	4.39	2.52
	GCM Future (SSP2-4.5)	2	3.00	2.00	1.60	1.38	1.12	0.80	0.57
		5	11.86	6.90	5.06	4.07	3.01	1.81	1.10
		10	26.24	12.89	9.09	7.12	5.07	2.88	1.66
		25	43.69	22.97	15.87	12.24	8.54	4.68	2.62
		50	55.48	28.97	19.92	15.32	10.63	5.77	3.20
		100	72.12	37.66	25.90	19.92	13.82	7.51	4.16
	GCM Future (SSP5-8.5)	2	3.50	2.40	1.90	1.63	1.34	0.97	0.67
		5	12.48	7.35	5.42	4.38	3.25	1.97	1.20
		10	26.86	13.34	9.46	7.44	5.33	3.05	1.78
		25	44.50	23.55	16.33	12.64	8.86	4.90	2.77
		50	56.47	29.66	20.48	15.80	11.01	6.04	3.39
		100	73.41	38.55	26.62	20.53	14.32	7.85	4.40

Table 5. Cont.

Name of City	Dataset Source	Return Period (Year)	Rainfall Duration (hrs)						
			1	2	3	4	6	12	24
Sargodha	Observed Data	2	12.02	7.74	5.96	4.95	3.80	2.41	1.53
		5	20.39	12.20	9.09	7.39	5.55	3.42	2.13
		10	25.83	15.10	11.12	8.99	6.69	4.08	2.52
		25	30.93	17.82	13.03	10.48	7.75	4.69	2.88
		50	37.61	21.45	15.60	12.51	9.22	5.55	3.39
		100	48.89	27.88	20.29	16.26	11.98	7.21	4.41
	GCM Historical Data	2	6.56	4.40	3.46	2.90	2.26	1.46	0.93
		5	14.43	8.47	6.25	5.05	3.75	2.28	1.40
		10	20.21	11.46	8.30	6.62	4.85	2.89	1.75
		25	25.97	14.44	10.34	8.20	5.94	3.49	2.09
		50	33.34	18.30	13.01	10.26	7.40	4.30	2.56
		100	43.34	23.79	16.92	13.34	9.61	5.59	3.32
	GCM Future (SSP2-4.5)	2	7.71	5.20	4.09	3.44	2.68	1.74	1.12
		5	22.34	12.58	9.06	7.20	5.23	3.07	1.83
		10	33.92	17.52	12.38	9.71	6.93	3.95	2.30
		25	44.93	23.98	16.73	13.00	9.16	5.11	2.91
		50	52.51	27.87	19.37	15.02	10.54	5.85	3.32
		100	68.27	36.24	25.18	19.52	13.71	7.60	4.31
	GCM Future (SSP5-8.5)	2	9.60	6.69	5.33	4.51	3.55	2.32	1.50
		5	23.88	14.11	10.44	8.45	6.30	3.84	2.37
		10	38.49	20.44	14.79	11.81	8.64	5.14	3.11
		25	54.44	29.99	21.37	16.88	12.18	7.10	4.23
		50	65.49	35.82	25.42	20.02	14.40	8.35	4.95
		100	85.14	46.57	33.04	26.02	18.71	10.85	6.43
Sialkot	Observed Data	2	24.85	15.76	12.06	9.97	7.62	4.81	3.03
		5	36.16	22.39	16.96	13.95	10.60	6.65	4.18
		10	43.60	26.74	20.19	16.56	12.56	7.85	4.93
		25	50.60	30.84	23.22	19.03	14.40	8.99	5.64
		50	60.21	36.53	27.45	22.47	16.99	10.59	6.64
		100	78.28	47.49	35.69	29.21	22.08	13.77	8.63
	GCM Historical Data	2	20.88	13.23	10.12	8.37	6.40	4.04	2.54
		5	31.63	19.46	14.71	12.07	9.16	5.73	3.60
		10	38.22	23.28	17.52	14.35	10.85	6.77	4.24
		25	44.19	26.74	20.07	16.41	12.39	7.71	4.82
		50	52.27	31.48	23.57	19.25	14.52	9.02	5.64
		100	67.96	40.93	30.65	25.03	18.87	11.73	7.33
	GCM Future (SSP2-4.5)	2	21.81	14.05	10.83	8.99	6.91	4.39	2.78
		5	37.87	22.63	16.86	13.71	10.28	6.33	3.93
		10	50.85	28.48	20.96	16.93	12.58	7.66	4.72
		25	63.33	36.24	26.41	21.19	15.63	9.42	5.76
		50	72.59	41.31	30.02	24.04	17.69	10.63	6.49
		100	94.37	53.70	39.02	31.25	23.00	13.82	8.43
	GCM Future (SSP5-8.5)	2	20.94	13.76	10.69	8.92	6.88	4.40	2.80
		5	36.21	22.05	16.58	13.56	10.24	6.37	3.98
		10	52.26	29.32	21.73	17.63	13.18	8.09	5.02
		25	70.03	40.44	29.63	23.86	17.68	10.74	6.60
		50	82.88	47.54	34.71	27.90	20.62	12.48	7.66
		100	107.74	61.80	45.13	36.27	26.81	16.22	9.96

The table shows rainfall intensities for five major cities of Punjab across six return periods and seven durations, based on observed and GCM-simulated data for historical and future scenarios. The results indicate a substantial increase in projected intensities, with 100-year events rising by 40–50% across cities. Intensities also increase notably for

shorter durations and higher return periods, emphasizing the need to revise IDF curves to reflect future climate-driven extremes and to guide infrastructure planning.

Using the information provided in Table 5, IDF curves for all major cities were prepared using only the ground/observed and GCM-simulated historical datasets, as shown in Figure 6. IDF curves developed using the GCM-simulated future datasets will be presented subsequently, once the corresponding datasets are downscaled, as mentioned earlier.

The pre-downscaling comparison of observed and historical GCM-based IDF curves (Figure 6) indicates that the GCM simulations generally underestimate rainfall intensities, particularly for higher return periods and shorter durations. Across all five cities, the mean underestimation of 100-year intensities is approximately 15–30%, with the largest discrepancies in Lahore and Sialkot, where 1-h observed intensities exceed GCM estimates by up to 25–35%. The differences gradually diminish for longer durations (>12 h), reflecting the GCMs' coarser temporal resolution and smoothing effect on extreme short-duration rainfall. Despite these deviations, the similarity in curve shapes and the consistent decline of intensity with duration confirm that the GCMs capture the general rainfall scaling behavior, validating their suitability for bias correction using the EQM method.

After developing IDF curves using the best-fitting probability distribution, empirical equations were formulated for each city using the Sherman equation. The required parameters were estimated via a logarithmic approach, as detailed in the methodology. Graphs of Equations (19) and (20) provided the necessary coefficients, which were then applied in Equation (17) to derive the final formulas. Table 6 summarizes the resulting rainfall intensity equations across all data sources, return periods, and durations. These equations, based on both observed and GCM-simulated data for historical and future scenarios, are essential for estimating future intensities and guiding climate-resilient infrastructure design [7].

The next crucial step involved downscaling GCM-simulated precipitation datasets for the SSP2-4.5 and SSP5-8.5 scenarios using the EQM method, as detailed earlier. This approach, validated by Srivastav et al. (2014), showed strong agreement between historical and adjusted IDF rainfall intensities [10]. Figures 7 and 8 present the results of spatial and temporal downscaling as an empirical CDF. Spatial downscaling (Figure 7) effectively mirrored the trend of the historical GCM-simulated dataset, while temporal downscaling (Figure 8) established a statistical relationship between historical and future GCM-simulated datasets, thereby improving rainfall IDF projections. Temporal downscaling of future GCM data was performed using the bias-corrected historical GCM distribution derived during spatial downscaling, following the EQM framework proposed by Srivastav et al. (2014) [10].

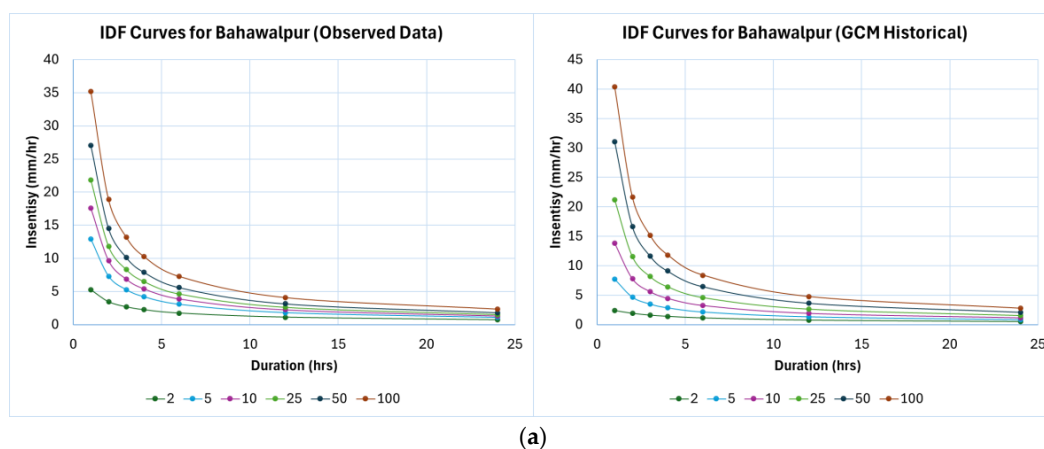


Figure 6. Cont.

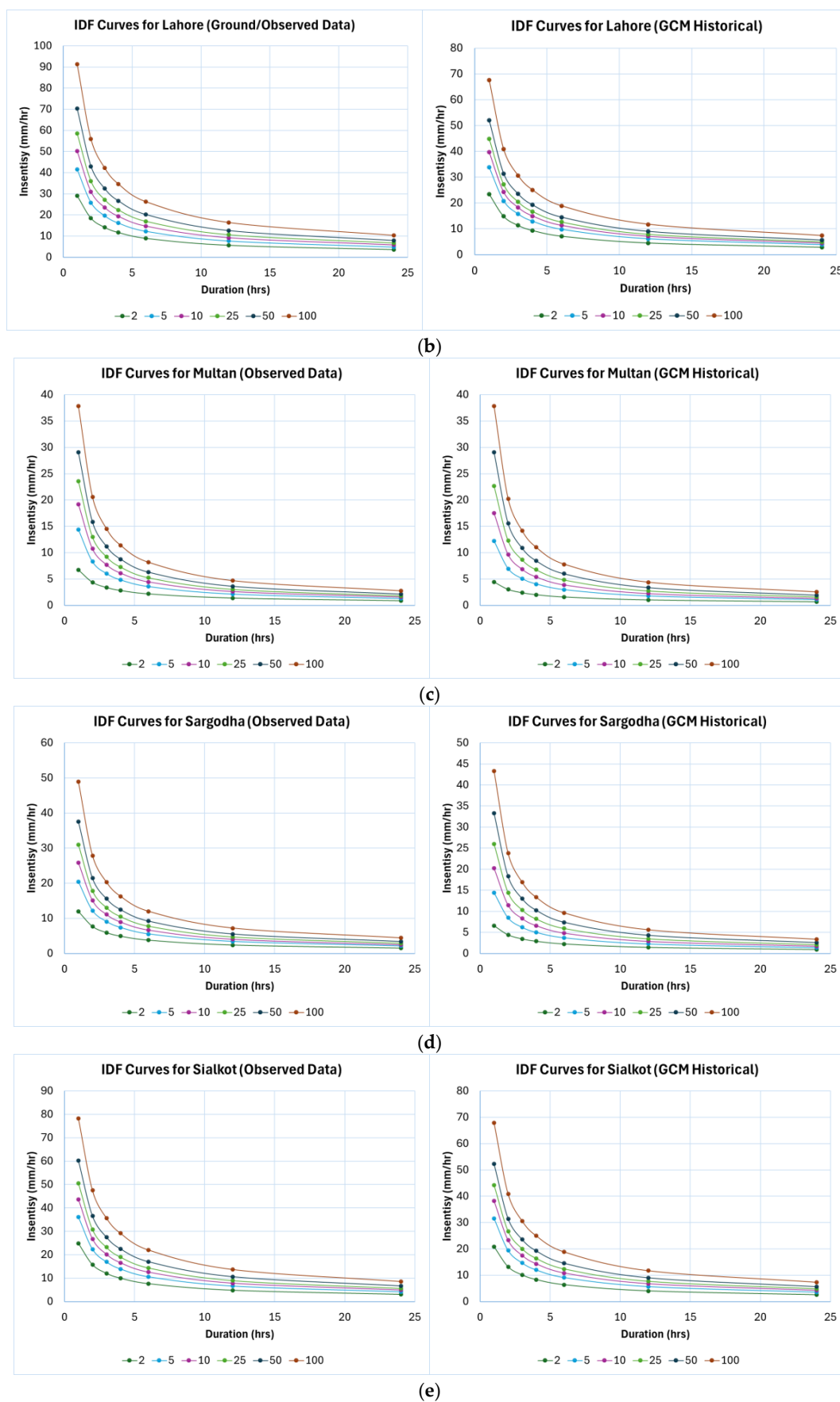
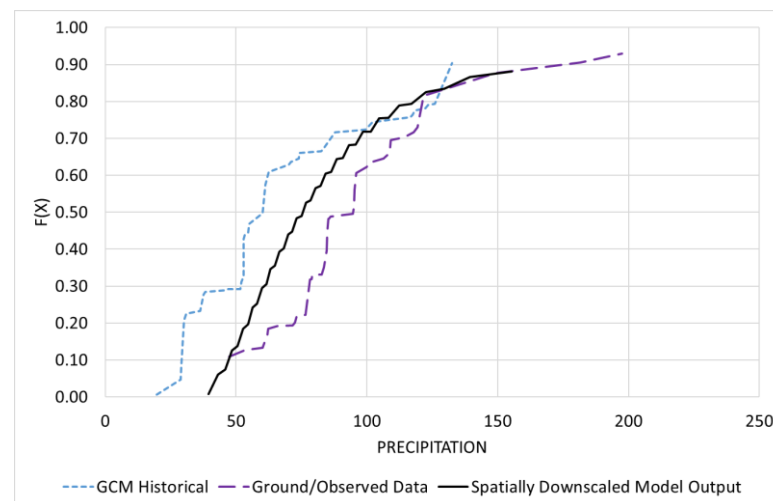
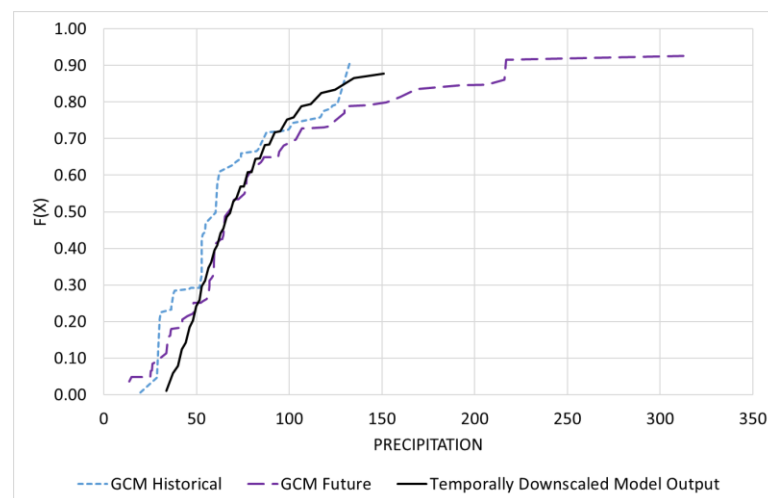


Figure 6. IDF curves using ground/observed data and historical GCM-simulated data for (a) Bahawalpur, (b) Lahore, (c) Multan, (d) Sargodha, and (e) Sialkot (return period in years).

Table 6. Empirical formulas of the selected probability distribution intended for all major cities in Punjab, corresponding to different data sources.

Name of City	Dataset Source			
	Observed Data	GCM Historical	GCM Future (SSP2-4.5)	GCM Future (SSP5-8.5)
Bahawalpur	$i = \frac{5.15T^{0.440}}{t^{0.797}}$ $R^2 = 0.9180$	$i = \frac{2.11T^{0.688}}{t^{0.746}}$ $R^2 = 0.9448$	$i = \frac{2.40T^{0.814}}{t^{0.822}}$ $R^2 = 0.9041$	$i = \frac{2.83T^{0.785}}{t^{0.788}}$ $R^2 = 0.8931$
Lahore	$i = \frac{25.42T^{0.272}}{t^{0.680}}$ $R^2 = 0.9839$	$i = \frac{21.23T^{0.245}}{t^{0.690}}$ $R^2 = 0.9696$	$i = \frac{21.10T^{0.364}}{t^{0.719}}$ $R^2 = 0.9660$	$i = \frac{23.16T^{0.371}}{t^{0.706}}$ $R^2 = 0.9725$
Multan	$i = \frac{6.37T^{0.403}}{t^{0.778}}$ $R^2 = 0.9353$	$i = \frac{4.35T^{0.500}}{t^{0.789}}$ $R^2 = 0.9178$	$i = \frac{2.82T^{0.776}}{t^{0.811}}$ $R^2 = 0.9111$	$i = \frac{3.21T^{0.747}}{t^{0.798}}$ $R^2 = 0.9196$
Sargodha	$i = \frac{10.83T^{0.331}}{t^{0.729}}$ $R^2 = 0.9670$	$i = \frac{6.01T^{0.448}}{t^{0.758}}$ $R^2 = 0.9490$	$i = \frac{7.86T^{0.507}}{t^{0.811}}$ $R^2 = 0.8945$	$i = \frac{8.90T^{0.526}}{t^{0.759}}$ $R^2 = 0.9335$
Sialkot	$i = \frac{21.95T^{0.271}}{t^{0.686}}$ $R^2 = 0.9796$	$i = \frac{18.75T^{0.276}}{t^{0.691}}$ $R^2 = 0.9724$	$i = \frac{19.86T^{0.349}}{t^{0.734}}$ $R^2 = 0.9588$	$i = \frac{18.05T^{0.402}}{t^{0.721}}$ $R^2 = 0.9728$

**Figure 7.** Statistical relation between GCM-simulated historical data and ground/observed data to develop the spatially downscaled model output.**Figure 8.** Statistical relation between GCM historical and future data to develop the temporally downscaled model output.

While EQM bias correction and LP3 frequency modelling have each been used previously in rainfall studies, their explicit coupling for regional IDF projection is uncommon. In this study, the EQM procedure first reduces systematic biases in CMIP6 daily precipitation, improving the fidelity of future projections at the station scale. The LP3 distribution subsequently provides a robust probabilistic framework to translate these bias-corrected projections into IDF relationships. The diagnostic identification of LP3 as the best-fitting distribution for most stations therefore directly reinforces the suitability of this combined approach: EQM improves the input data quality for frequency analysis, and LP3 reliably describes the statistical behavior of extremes in the corrected series. Therefore, this is the first study to integrate EQM downscaling with LP3-based IDF development for major districts in Punjab using CMIP6 projections, providing a practical pipeline from bias-corrected climate projections to usable, station-specific IDF equations for design and planning.

The spatial and temporal downscaling equations produced a first-order linear relationship, derived from the LP3 mapping functions, which are shown in Figures 9–11. The figures clearly demonstrate that, for all the major cities considered in this study, a linear relationship exists between the concerned variables for downscaling [70]. Figure 9 represents the relationship derived from the EQM method for spatial downscaling, whereas Figures 10 and 11 show the relationships for temporal downscaling under SSP 2-4.5 and 5-8.5, respectively.

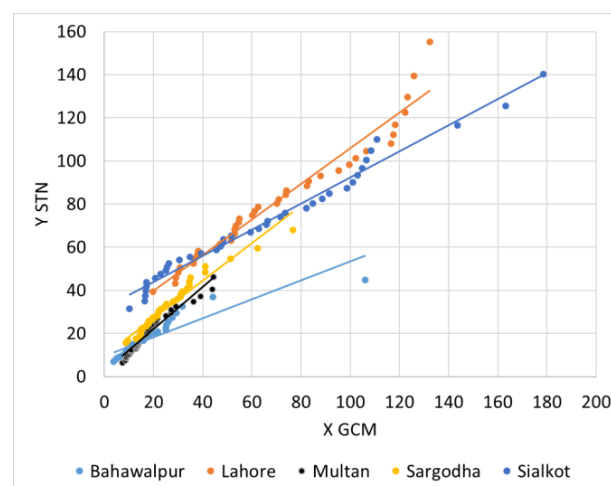


Figure 9. Linear relationship derived from the EQM method for spatial downscaling.

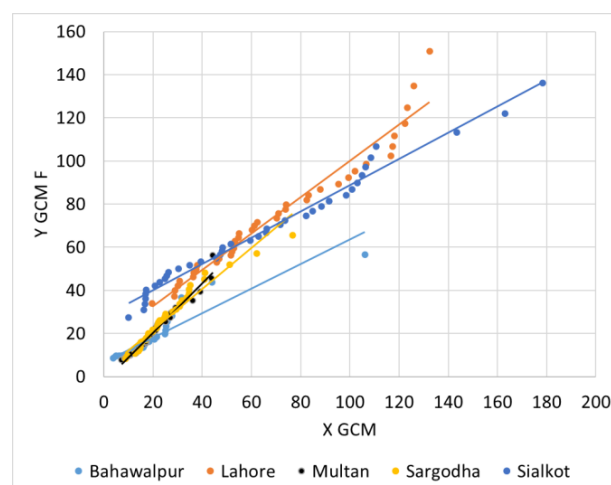


Figure 10. Linear relationship derived from the EQM method for temporal downscaling (SSP 2-4.5).

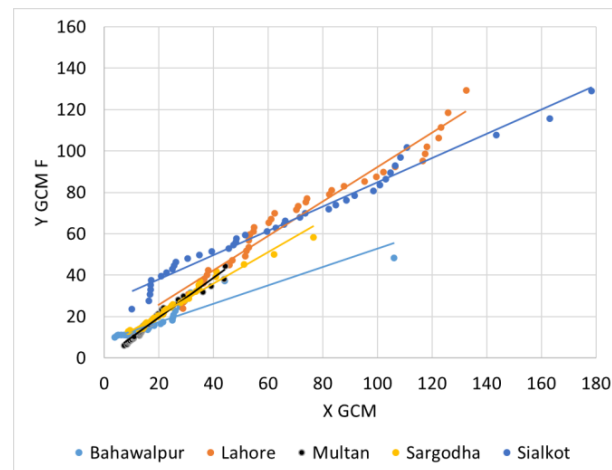


Figure 11. Linear relationship derived from the EQM method for temporal downscaling (SSP 5-8.5).

Following the defined procedure, the downscaled GCM-simulated datasets for both climate scenarios were obtained and validated through visual representation and statistical techniques, as presented earlier. Table 7 below shows an analytical summary of the computed downscaled maximum rainfall intensities intended for the defined duration of 1 h and multiple return periods for major cities in Punjab.

Table 7. Updated IDF curves and the relative percentage changes in intensities for future climate scenarios in the regions under consideration.

Name of City	Scenario	Dataset Source	Return Period					
			2	5	10	25	50	100
Bahawalpur	Historical	Observed Data	5.26	12.89	17.57	21.82	27.08	35.20
	SSP2-4.5	GCM Future	2.50	10.97	25.36	42.82	54.56	70.93
		Downscaled GCM Future	2.40	11.06	25.36	42.70	54.38	70.69
		Change in % to observed	−54.37%	−14.16%	44.31%	95.72%	100.80%	100.80%
		% effect of Downscaling	−4.00%	0.84%	0.00%	−0.27%	−0.33%	−0.33%
	SSP5-8.5	GCM Future	2.80	13.10	27.67	45.06	56.81	73.86
		Downscaled GCM Future	3.00	13.55	28.11	45.49	57.25	74.42
		Change in % to observed	−42.97%	5.14%	59.95%	108.5%	111.39%	111.39%
		% effect of Downscaling	7.14%	3.44%	1.58%	0.93%	0.76%	0.76%
Lahore	Historical	Observed Data	29.15	41.53	50.20	58.62	70.28	91.36
	SSP2-4.5	GCM Future	23.66	40.68	55.86	71.29	82.62	107.41
		Downscaled GCM Future	25.74	42.98	58.36	74.00	85.57	111.24
		Change in % to observed	−11.70%	3.48%	16.26%	26.23%	21.76%	21.76%
		% effect of Downscaling	8.76%	5.65%	4.48%	3.80%	3.56%	3.56%
	SSP5-8.5	GCM Future	26.49	44.42	61.72	80.06	93.50	121.55
		Downscaled GCM Future	32.38	51.28	69.51	88.84	103.23	134.20
		Change in % to observed	11.11%	23.47%	38.48%	51.56%	46.89%	46.89%
		% effect of Downscaling	22.27%	15.45%	12.63%	10.97%	10.40%	10.40%
Multan	Historical	Observed Data	6.70	14.42	19.21	23.59	29.10	37.82
	SSP2-4.5	GCM Future	4.84	9.85	16.86	34.33	58.78	100.65
		Downscaled GCM Future	3.50	12.34	26.66	44.04	55.81	72.55
		Change in % to observed	−47.76%	−14.42%	38.77%	86.69%	91.80%	91.80%
		% effect of Downscaling	−27.64%	25.31%	58.12%	28.30%	−5.06%	−27.92%
	SSP5-8.5	GCM Future	3.50	12.48	26.86	44.50	56.47	73.41
		Downscaled GCM Future	3.60	13.67	28.07	45.75	57.80	75.15
		Change in % to observed	−46.27%	−5.22%	46.11%	93.91%	98.67%	98.67%
		% effect of Downscaling	2.86%	9.47%	4.51%	2.81%	2.36%	2.36%

Table 7. Cont.

Name of City	Scenario	Dataset Source	Return Period					
			2	5	10	25	50	100
Sargodha	Historical	Observed Data	12.02	20.39	25.83	30.93	37.61	48.89
	SSP2-4.5	GCM Future	7.71	22.34	33.92	44.93	52.51	68.27
		Downscaled GCM Future	9.38	24.03	35.62	46.65	54.33	70.62
		Change in % to observed	−22.00%	17.84%	37.91%	50.83%	44.45%	44.45%
		% effect of Downscaling	21.63%	7.56%	5.03%	3.83%	3.46%	3.46%
	SSP5-8.5	GCM Future	9.60	23.88	38.49	54.44	65.49	85.14
		Downscaled GCM Future	13.84	28.61	43.73	60.23	71.86	93.42
		Change in % to observed	15.08%	40.32%	69.27%	94.74%	91.08%	91.08%
		% effect of Downscaling	44.14%	19.82%	13.62%	10.64%	9.73%	9.73%
	Historical	Observed Data	24.85	36.16	43.60	50.60	60.21	78.28
Sialkot	SSP2-4.5	GCM Future	21.81	37.87	50.85	63.33	72.59	94.37
		Downscaled GCM Future	23.04	39.23	52.32	64.91	74.30	96.59
		Change in % to observed	−7.29%	8.48%	20.00%	28.27%	23.39%	23.39%
		% effect of Downscaling	5.65%	3.60%	2.89%	2.49%	2.35%	2.35%
	SSP5-8.5	GCM Future	20.94	36.21	52.26	70.03	82.88	107.74
		Downscaled GCM Future	24.06	39.77	56.30	74.59	87.94	114.32
		Change in % to observed	−3.20%	9.98%	29.13%	47.40%	46.04%	46.04%
		% effect of Downscaling	14.89%	9.85%	7.73%	6.51%	6.11%	6.11%

Table 7 presents the percentage changes in rainfall intensities for future climate scenarios, before and after EQM downscaling. Across all cities, downscaling improved the agreement with observed values by reducing GCM bias by approximately 5–25%, depending on duration and return period. The effect was most notable for shorter durations (2–10 h), where raw GCM outputs typically underestimated intensities. Under the SSP2-4.5 scenario, EQM correction reduced underestimation in Bahawalpur and Multan by up to 27–30%, while in Lahore and Sialkot, intensities increased by 6–10%, aligning more closely with observations. In future projections, rainfall intensities are likely to increase by 20–45% under SSP5-8.5 relative to historical conditions, with the largest amplification in urban centers such as Lahore and Sargodha. These results demonstrate that EQM-based downscaling effectively corrects systematic GCM biases and captures the projected intensification of extreme rainfall under warming scenarios.

Figures 12 and 13 represent the updated IDF curves for Lahore city, corresponding to SSP 2-4.5 and 5-8.5 scenarios, for 25- and 100-year return periods. The effect of downscaling the future GCM datasets for the climate scenarios considered can be clearly seen from these figures.

The analytical summary in Table 7 presents several noteworthy findings:

1. The updated IDF curves show a consistent increase across intensifying SSP scenarios, with the highest changes under SSP5-8.5 [74].
2. Downscaled GCM datasets project a significant rise in rainfall intensities for major cities in Punjab, improving future projections' accuracy compared to raw GCM outputs.
3. Rainfall intensities increase more under the SSP5-8.5 scenario than SSP2-4.5 [75], highlighting the impact of greenhouse gas emissions.
4. The downscaling process significantly affected future projections, especially for extreme return periods; for Lahore, the 100-year intensity increased by about 10% under SSP5-8.5.
5. Rainfall intensities increased most in Multan, followed by Bahawalpur, Sargodha, Lahore, and Sialkot, with critical implications for infrastructure design [76]. Historical

rainfall intensities show typical trends for Punjab's major urban centers, with Lahore being the wettest and Bahawalpur the driest [76].

6. SSP5-8.5 shows a higher percentage change than SSP2-4.5 across rainfall durations. Bahawalpur's 50-year return period intensity increases by 95.72% under SSP2-4.5, and Lahore's by 26.23%.
7. Under SSP5-8.5, future projections show a larger increase, with Bahawalpur's 50-year return period intensity rising by 111.39%, and Lahore's by 51.56%.
8. Downscaled GCM projections are generally lower than raw data but show significant increases compared to historical observations [77].

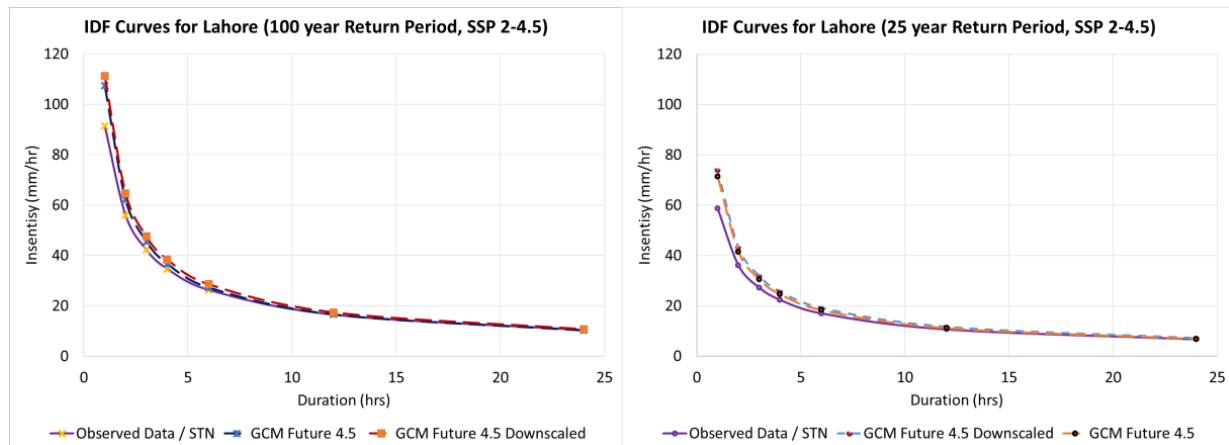


Figure 12. Updated IDF curves for Lahore city representing the downscaling effect on SSP 2-4.5 for 100-year and 25-year return periods.

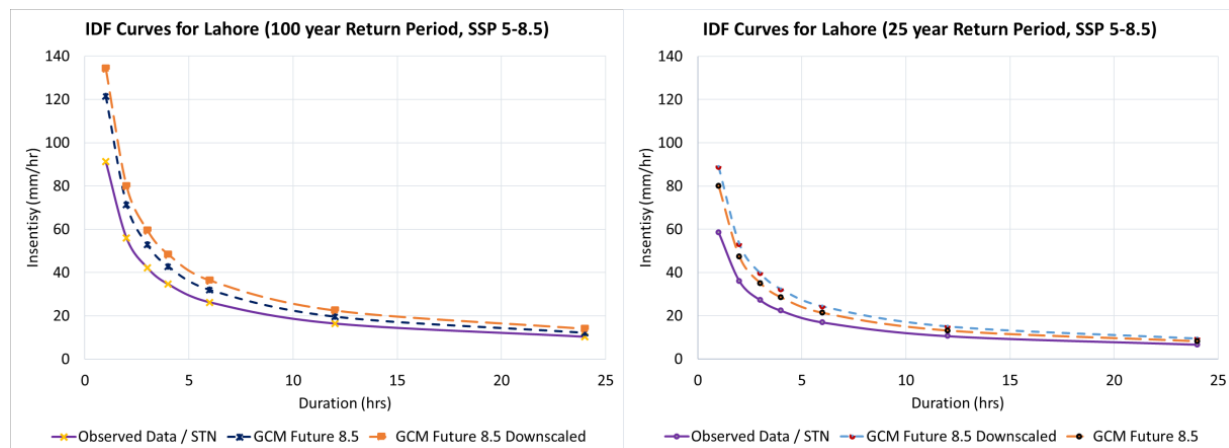


Figure 13. Updated IDF curves for Lahore city representing the downscaling effect on SSP 5-8.5 for 100-year and 25-year return periods.

These results suggest that cities in Punjab will face significant challenges due to increased rainfall intensities, requiring adaptation and mitigation strategies to protect water resources, agriculture, and infrastructure [74,76,78]. Downscaled GCM-simulated data are crucial for accurate climate impact studies, as satellite-derived datasets tend to overestimate changes. The findings indicate a significant increase in future rainfall intensities, especially under higher emissions scenarios, with implications for urban planning, infrastructure design, and water resource management [73,76,79]. Figure 14 presents the updated IDF curves, and Table 8 shows the updated rainfall intensity equations for downscaled GCM-simulated datasets, which can aid in designing and managing climate-resilient water infrastructure.

The table presents updated empirical formulas for rainfall IDF curves using down-scaled GCM-simulated datasets. The results show significant increases in rainfall intensities, especially under SSP5-8.5. For Lahore, the 100-year rainfall intensity is projected to rise by 25% under SSP2-4.5 and by 30% under the downscaled SSP2-4.5 scenario. Under SSP5-8.5, the increase is 44%, with a 55% rise for the downscaled projections. The downscaling process results in a 3% increase under SSP2-4.5 and an 8.5% increase under SSP5-8.5 [80–82].

The updated IDF curves presented in Figure 14 show a clear intensification of rainfall extremes across all five cities under future climate scenarios. Compared with historical conditions, projected 100-year rainfall intensities increase by approximately 20–35% under SSP2-4.5 and 35–55% under SSP5-8.5, with the most pronounced rise observed in Lahore and Sargodha. Short-duration storms (2–6 h) exhibit the strongest relative increase, indicating a potential escalation of flash-flood risk in urban areas. The curves for Bahawalpur and Multan, while showing smaller absolute intensities, still display consistent upward shifts of 10–25%, reflecting broader regional intensification trends. Overall, the downscaled IDF relationships capture both spatial and scenario-driven variations in rainfall extremes, underscoring the growing influence of a warming climate on hydrological design parameters in Punjab.

The downscaling process was crucial, yielding lower projected increases than raw GCM data, though changes are still substantial. These findings emphasize the importance of downscaled climate data for assessing local impacts of climate change. They underline the need for adaptation and mitigation strategies in Punjab’s major cities to address future increases in rainfall intensities. Spatial differences observed in the IDF curves across the five study cities can be attributed to both geographical and climatic factors. Cities located in the northern part of Punjab, such as Sialkot, are influenced by hilly terrain and orographic effects, which enhance precipitation intensity compared to the relatively flat and arid regions of southern Punjab, such as Multan and Bahawalpur. Additionally, variations in atmospheric water vapor availability contribute to these differences, as areas with higher humidity are more prone to short-duration extreme rainfall events. Under a warming climate—particularly under the SSP5-8.5 scenario—enhanced convective activity and the greater atmospheric moisture-holding capacity (approximately 7% per °C, following the Clausius–Clapeyron relation) lead to a disproportionate increase in short-duration rainfall intensities. These processes collectively help explain the differences in IDF curves across the study region and underscore the importance of considering both topographic and climatic drivers when developing future design standards.

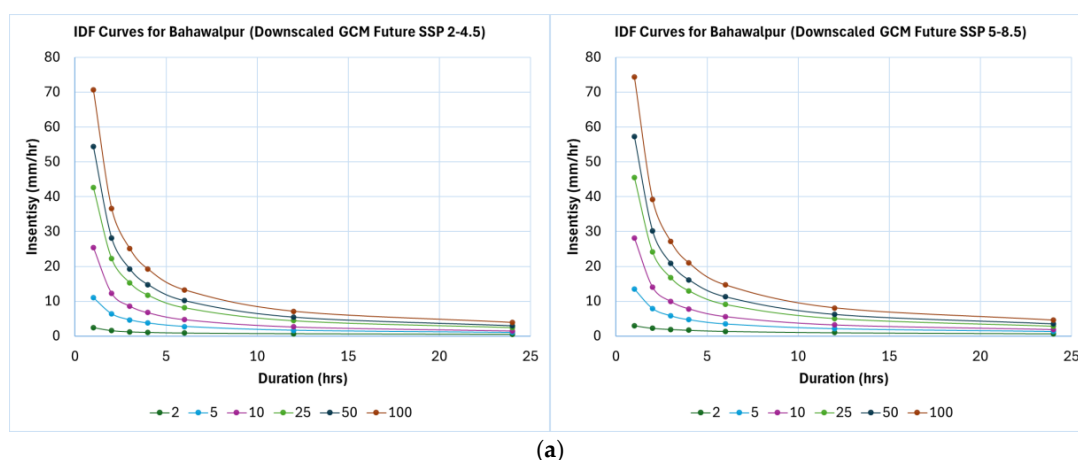


Figure 14. Cont.

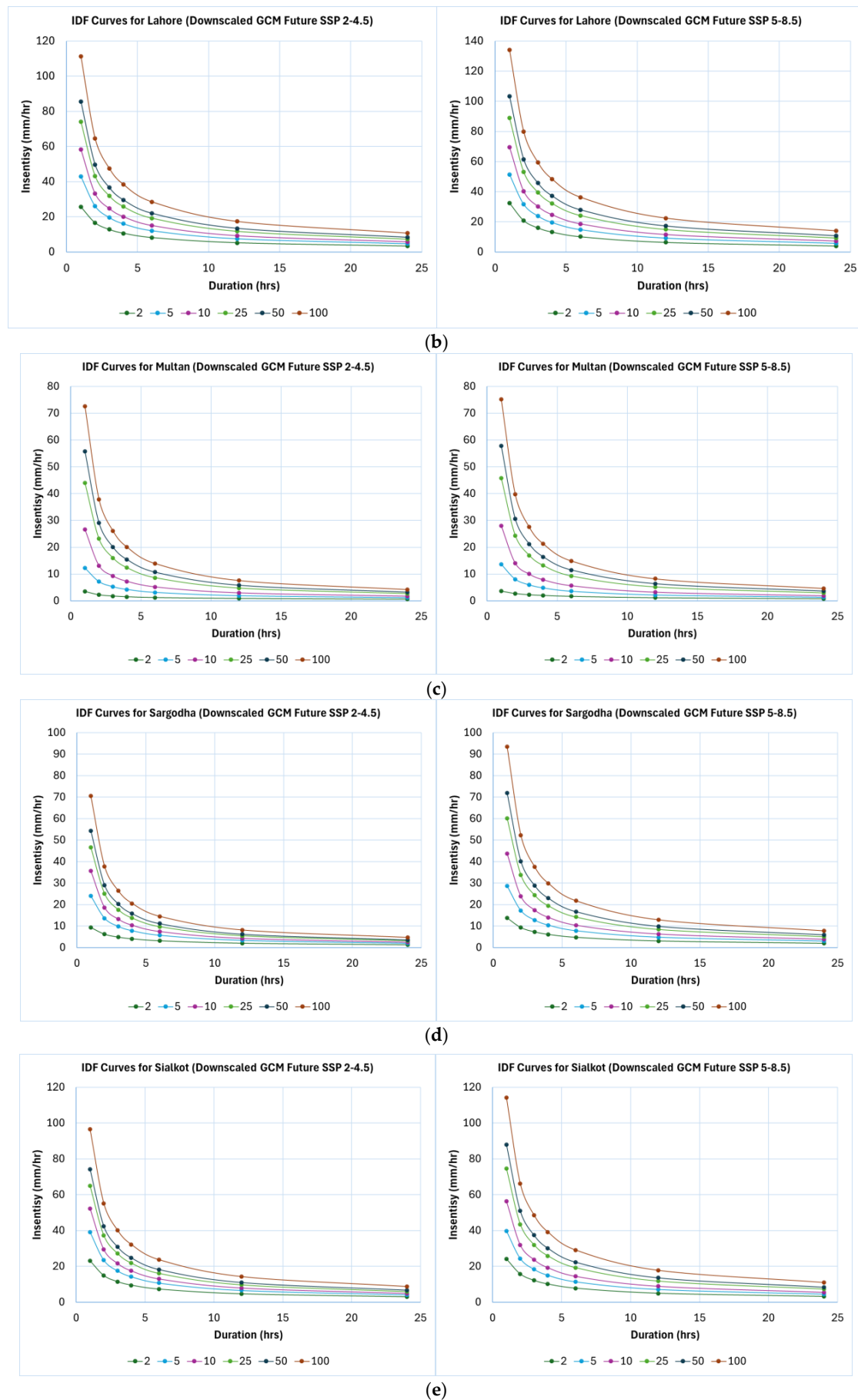


Figure 14. Updated IDF curves for (a) Bahawalpur, (b) Lahore, (c) Multan, (d) Sargodha, and (e) Sialkot.

Table 8. Updated empirical formulas of the selected probability distribution for downscaled GCM future projections.

Name of City	Dataset Source				
	Observed Data	GCM Future (SSP2-4.5)	Downscaled GCM Future (SSP2-4.5)	GCM Future (SSP5-8.5)	Downscaled GCM Future (SSP5-8.5)
Bahawalpur	$i = \frac{5.15T^{0.440}}{t^{0.797}}$ $R^2 = 0.9180$	$i = \frac{2.40T^{0.814}}{t^{0.822}}$ $R^2 = 0.9041$	$i = \frac{2.35T^{0.820}}{t^{0.819}}$ $R^2 = 0.900$	$i = \frac{2.83T^{0.785}}{t^{0.788}}$ $R^2 = 0.8931$	$i = \frac{3.02T^{0.770}}{t^{0.783}}$ $R^2 = 0.895$
Lahore	$i = \frac{25.42T^{0.272}}{t^{0.680}}$ $R^2 = 0.9839$	$i = \frac{21.10T^{0.364}}{t^{0.719}}$ $R^2 = 0.9660$	$i = \frac{22.85T^{0.353}}{t^{0.715}}$ $R^2 = 0.984$	$i = \frac{23.16T^{0.371}}{t^{0.706}}$ $R^2 = 0.9725$	$i = \frac{28.13T^{0.346}}{t^{0.699}}$ $R^2 = 0.978$
Multan	$i = \frac{6.37T^{0.403}}{t^{0.778}}$ $R^2 = 0.9353$	$i = \frac{2.82T^{0.776}}{t^{0.811}}$ $R^2 = 0.9111$	$i = \frac{3.20T^{0.744}}{t^{0.811}}$ $R^2 = 0.920$	$i = \frac{3.21T^{0.747}}{t^{0.798}}$ $R^2 = 0.9196$	$i = \frac{3.42T^{0.738}}{t^{0.777}}$ $R^2 = 0.912$
Sargodha	$i = \frac{10.83T^{0.331}}{t^{0.729}}$ $R^2 = 0.9670$	$i = \frac{7.86T^{0.507}}{t^{0.811}}$ $R^2 = 0.8945$	$i = \frac{9.28T^{0.472}}{t^{0.801}}$ $R^2 = 0.909$	$i = \frac{8.90T^{0.526}}{t^{0.759}}$ $R^2 = 0.9335$	$i = \frac{12.35T^{0.464}}{t^{0.741}}$ $R^2 = 0.953$
Sialkot	$i = \frac{21.95T^{0.271}}{t^{0.686}}$ $R^2 = 0.9796$	$i = \frac{19.86T^{0.349}}{t^{0.734}}$ $R^2 = 0.9588$	$i = \frac{20.91T^{0.341}}{t^{0.731}}$ $R^2 = 0.961$	$i = \frac{18.05T^{0.402}}{t^{0.721}}$ $R^2 = 0.9728$	$i = \frac{20.63T^{0.383}}{t^{0.714}}$ $R^2 = 0.977$

Although the results demonstrate clear and consistent trends, certain uncertainties should be acknowledged. Differences among CMIP6 models introduce inter-model variability, especially in simulating convective rainfall and short-duration extremes, which may contribute to the spread in projected intensities. The EQM bias correction, while effective in improving GCM performance, assumes stationarity in the bias structure and may not fully capture non-linear future changes in precipitation behavior. Additionally, the selection of the LP3 distribution and the limited number of high-quality rainfall stations could introduce regional uncertainty and potential overfitting in specific areas. Nevertheless, the use of multiple GCMs, rigorous validation, and the consistent agreement between observed and downscaled GCM-simulated datasets enhance the robustness of the projections and support the reliability of the derived IDF relationships.

This study aligns with previous research on climate change impacts on water resources in the Hindukush–Karakorum–Himalaya region [83] and rainfall erosivity in central India [76]. It contributes to the growing literature on climate change effects in South Asia, particularly Pakistan, showing significant future increases in rainfall intensities, especially under extreme emission scenarios. These findings are consistent with projections of increased runoff and water availability in the Indian subcontinent [80]. However, this study specifically focuses on updating rainfall IDF curves for Punjab’s major cities, offering localized insights for urban planning and water management.

5. Conclusions

This study projects future rainfall IDF curves for major cities in Punjab, Pakistan, using downscaled CMIP6 GCM-simulated data. Results show significant increases in rainfall intensities across all durations and return periods, especially under the higher emissions scenario (SSP5-8.5). The downscaled projections indicate a sharper rise in intensities compared to raw GCM data, emphasizing the value of high-resolution climate data for local impact assessments. The updated IDF equations can aid water resources planners, engineers, and policymakers in managing infrastructure under changing climate conditions. The spatial variability in the updated IDF curves also reflects the influence of topography and atmospheric moisture availability, with northern hilly regions experiencing stronger orographic effects than the drier plains. These insights reinforce the importance of incorporating both climatic and geographic factors when applying IDF projections for

design and planning. These findings are crucial for enhancing urban resilience to climate change-induced water challenges, such as frequent and intense flooding.

The projected escalation of rainfall extremes carries profound implications for Punjab's rapidly urbanizing landscape. Cities such as Lahore and Sialkot, characterized by dense populations and limited drainage capacity, face an elevated risk of severe urban flooding and infrastructure stress. In contrast, cities like Multan and Bahawalpur, though less densely populated, remain highly susceptible to stormwater accumulation due to flat terrain and slower runoff. Sargodha, with moderate population density, represents an intermediate vulnerability profile where both hydrological and infrastructural limitations converge. These contrasting urban dynamics underscore that the consequences of intensifying rainfall will not be uniform but instead will amplify existing disparities in resilience and preparedness across municipalities. Hence, the findings of this study provide an essential scientific foundation for developing city-specific adaptation frameworks, prioritizing climate-resilient infrastructure, and guiding evidence-based policymaking to safeguard the socio-economic stability of Punjab's urban centers under a changing climate.

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