

Projected Shifts in Rainfall Intensity-Duration-Frequency Curves under Climate Change Scenarios in Lampung, Indonesia

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Abstract

This study develops non-stationary Intensity–Duration–Frequency (IDF) curves for Lampung Province, Indonesia, using bias-corrected CMIP6 rainfall projections from the ACCESS-ESM1-5 model under SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5 (2015–2060). Quantile mapping was applied to daily rainfall observations (2012–2014) to reduce model bias. Post-correction performance improved substantially, with Nash–Sutcliffe Efficiency increasing to 0.87–0.97 and Kling–Gupta Efficiency reaching 0.93–0.98 across stations. Trend analysis indicates significant annual rainfall declines under high-emission scenarios (up to -12.77 mm/year, $p < 0.01$). Despite declining annual totals, short-duration extremes intensify markedly. For a 5-year return period, 1-hour rainfall intensity increases from 19 mm/hour (historical lowland baseline) to ~ 183 mm/hour under SSP5-8.5. At the 25-year return period, 1-hour intensities in high-elevation zones rise from 125 to 210 mm/hour ($\approx 68\%$ increase). In contrast, 24-hour intensities show comparatively moderate changes. Elevation-stratified analysis reveals stronger relative amplification in lowland regions, while highlands maintain the highest absolute intensities due to orographic enhancement. These findings demonstrate substantial upward shifts in future IDF curves and highlight limitations of stationary design assumptions for hydrological infrastructure in tropical regions.

Keywords: non-stationary IDF, CMIP6 projections, quantile mapping, extreme rainfall intensification, climate change adaptation

1. Introduction

Climate change has emerged as a critical global challenge, driving substantial shifts in temperature, atmospheric circulation, and hydrological extremes. One of the most profound consequences of these changes is the alteration in precipitation patterns, particularly the intensification of short-duration extreme rainfall events (Hoegh-Guldberg *et al.*, 2019; Martel *et al.*, 2021). In Southeast Asia, these shifts are further amplified by complex regional climate drivers such as El Niño–Southern Oscillation (ENSO), the Indian Ocean Dipole (IOD), and the Madden–Julian Oscillation (MJO), which modulate rainfall variability across the Maritime Continent (Aldrian & Susanto, 2003; Aslam & *et al.* 2025). Indonesia, situated at the core of these interactions, is therefore highly susceptible to changes in extreme rainfall behaviour and the resulting hydrometeorological hazards. Understanding how these changes translate into local-scale rainfall extremes is crucial for improving climate-resilient water infrastructure and disaster risk management in the region.

Lampung Province, located in the southern part of Sumatra, is particularly vulnerable due to its diverse topography and rapidly expanding urban areas. Elevation gradients, from highland regions to coastal lowlands, create substantial spatial variability in rainfall intensity, which can exacerbate flood risks, especially under the compounding influence of climate change (Ferguglia *et al.*, 2024; Pramono *et al.*, 2018). Consequently, accurately characterizing rainfall extremes is essential for regional hydrological planning, including dam safety, stormwater management, flood mitigation, drainage design, and climate resilience strategies (Cook *et al.*, 2020; Sun *et al.*, 2019).

A key tool for hydrological design is the Intensity–Duration–Frequency (IDF) curve, which defines statistical relationships between rainfall intensity, storm duration, and return period. However, conventional IDF curves are typically derived from stationary historical records and assume that the probability distribution of extreme rainfall remains constant over time. This assumption has been widely challenged, as increasing temperature and shifting atmospheric moisture conditions cause non-stationary behavior in both the intensity and frequency of extreme rainfall (Martel *et al.*, 2021; Westra & Fowler, 2014). As a result, relying solely on historical IDF curves can lead to the systematic underestimation of future rainfall extremes, resulting in undersized infrastructure and increased flood risk. In Indonesia, this issue has already manifested in several regions, including Lampung, where outdated

IDF estimates have contributed to drainage failures and recurrent flooding (Kurniawan & Pranoto, 2020). These challenges highlight the urgent need to update IDF curves using climate-change-informed approaches.

Despite its importance, studies developing future IDF curves for Lampung remain limited. Existing research in Indonesia often relies on historical observations or coarse-resolution climate models that do not adequately capture local-scale rainfall variability, especially across elevation gradients. Moreover, none of the prior studies for Lampung have incorporated CMIP6 high-resolution projections with bias correction to generate scenario-based future IDF curves. This represents a critical research gap, particularly given the region's topographic heterogeneity and rising climate risks. Addressing this gap is essential to ensure that future hydrological designs are robust under multiple climate change scenarios.

To address these limitations, this study aims to develop non-stationary, climate-informed IDF curves for Lampung Province based on bias-corrected CMIP6 climate projections. Specifically, the present study develops updated IDF curves for Lampung Province using bias-corrected rainfall projections from the ACCESS-ESM1-5 model under the CMIP6 framework. The projections are statistically downscaled using quantile mapping and analyzed across four elevation classes: high hills, hills, low hills, and lowlands-under four Shared Socioeconomic Pathway (SSP) scenarios. This integrated approach provides one of the first localized, elevation-based future IDF assessments for the region, offering valuable insights for infrastructure design, disaster risk reduction, and long-term climate adaptation planning. The results are expected to be directly relevant for water resource managers, urban planners, and policymakers involved in climate adaptation strategies in Indonesia.

2. Methodology

2.1 Study Area and Data

Lampung Province is located at the southern tip of Sumatra Island, Indonesia (approximately 3.75°–6.0° S and 103.0°–105.5° E), exhibits diverse topographic characteristics, ranging from coastal lowlands in its eastern and southern parts to mountainous highlands in the west, including sections of the

Bukit Barisan mountain range (Figure 1). Elevations vary from near sea level to more than 1,500 meters, creating pronounced spatial gradients in rainfall distribution driven by orographic uplift and local convection. These topographic variations significantly influence short-duration rainfall intensities and contribute to the occurrence of flash floods and landslide-prone areas. Climatically, Lampung is classified as a tropical monsoonal region, with distinct wet and dry seasons modulated by large-scale climate modes such as ENSO, IOD, and MJO. The province receives annual rainfall ranging from 1,800 to 3,500 mm, with high spatial variability linked to elevation and proximity to the coast.

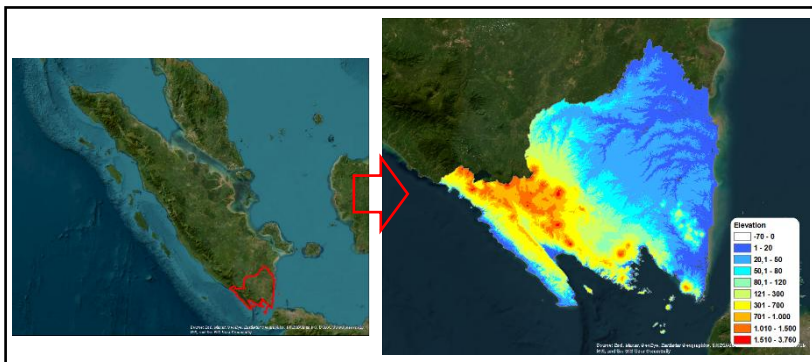


Figure 1. Study area map showing Lampung Province within Sumatra Island (left) and its topographic elevation distribution in meters (right)

This study employs two core datasets: ground-based observational rainfall data and climate model projections derived from global simulations. The observational data were provided by the Mesuji Sekampung River Basin Authority (BBWS Mesuji Sekampung) in Lampung, Indonesia, comprising daily rainfall records for the period 2012 to 2014. Four rain gauge stations were selected for their completeness and spatial representativeness: Kebon Tebu, Bukit Kemuning, Natar, and Way Jepara, spanning highland to lowland zones to represent the region's diverse topography. These stations span a range of topographic zones, from highlands to lowlands, enabling coverage of the region's diverse rainfall characteristics.

This research also incorporates future climate data from the NASA Earth Exchange Global Daily Downscaled Projections based on the Coupled Model Intercomparison Project Phase 6 (NEX-GDDP-CMIP6). The NEX-GDDP CMIP6 dataset was selected because its $0.25^{\circ} \times 0.25^{\circ}$ spatial resolution appropriate for resolving regional and topography-driven rainfall patterns

(Rao *et al.*, 2024). Among the available models, this study specifically utilizes the ACCESS-ESM1-5 model, developed by the Commonwealth Scientific and Industrial Research Organisation (CSIRO), which has demonstrated strong performance in simulating precipitation over Southeast Asia, particularly within the Maritime Continent region (Agiel *et al.*, 2024). The four SSP scenarios (SSP1-2.6, SSP2-4.5, SSP3-7.0, SSP5-8.5) represent a full range of plausible future socioeconomic and emissions pathways and were included to capture the uncertainty of future climate conditions relevant for infrastructure design and climate adaptation in Lampung Province. The model outputs cover two distinct periods: a historical baseline from 1985 to 2014 and a future projection period from 2015 to 2060.

The observational period (2012–2014) was selected to ensure temporal consistency with the CMIP6 historical simulations, as the ACCESS-ESM1-5 model provides historical outputs only up to 2014. Beyond this point, the model transitions to scenario-based projections (2015 onward) under the Shared Socioeconomic Pathways (SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5), which are driven by different forcing assumptions and are not directly comparable with observed historical conditions.

To represent a wide range of possible climate futures, the analysis is conducted under four Shared Socioeconomic Pathways (SSPs), which serve as standardized scenarios for global greenhouse gas emissions and socioeconomic development trajectories (Eyring *et al.*, 2016). The characteristics of SSPs are described in Table 1.

Table 1. Characteristics of shared socioeconomics pathways

No.	SSPs	CO ₂ Equivalent	Radiative Forcing	Rate of Change in Radiative Forcing	Characteristics
1	SSP1 - 2.6	450 ppm	2.6 W/m ²	Declining	• Economic growth • Fossil dominance
2	SSP2 - 4.5	650 ppm	4.5 W/m ²	Stabilizing	• Regional fragmentation • High barriers
3	SSP3 - 7.0	850 ppm	7.0 W/m ²	Stabilizing	• Moderate development • Stabilized emissions
4	SSP5 - 8.5	1350 ppm	8.5 W/m ²	Rising	• Sustainable mitigation • Global cooperation

The SSP scenarios influence the projected IDF curve shifts through differences in radiative forcing and atmospheric moisture. Low-emission pathways such as SSP1-2.6 produce relatively modest increases in extreme rainfall, while high-emission scenarios like SSP5-8.5 generate substantially larger intensifications, particularly for short-duration events. As a result, SSP5-8.5 yields the greatest upward shift in IDF values, highlighting the strong dependence of rainfall extremes on future emissions trajectories. The ACCESS-ESM1-5 model, under each SSP scenario, produces daily precipitation data used to examine projected rainfall intensities and long-term trends across Lampung.

2.2 Methods

2.2.1 Statistical Downscaling with Quantile Mapping

To enhance the applicability of climate model outputs for local-scale analysis, this study employs a statistical downscaling technique utilizing the quantile mapping method. The original resolution of the ACCESS-ESM1-5 model within the NEX-GDDP-CMIP6 dataset is $0.25^\circ \times 0.25^\circ$, which may not capture local rainfall characteristics accurately due to spatial averaging and inherent model biases. Therefore, quantile mapping is employed to align the statistical distribution of modelled rainfall data with that of observed data from selected rain gauge stations across Lampung Province. The quantile mapping method works by adjusting the cumulative distribution function (CDF) of the model data to match the observed data. The transformation is conducted using Equation 1.

$$P_o = F_o^{-1} (F_m(P_m)) \quad (1)$$

Where,

- P_m : Raw model output from ACCESS-ESM1-5 (precipitation value),
- $F_m(P_m)$: CDF of the modeled data for value P_m
- F_o^{-1} : Inverse CDF (quantile function) of the observed data, and
- P_o : Bias-corrected (downscaled) model valued

This method adjusts each value in the model dataset so that the overall frequency distribution matches the historical observed distribution, improving local relevance. It is particularly effective in correcting systematic errors in

both the mean and variability of rainfall simulations, and has been successfully used in previous studies on bias correction for rainfall projections (Kurnia *et al.*, 2020; Schober *et al.*, 2018).

2.2.2 Model Validation and Performance Metrics

To assess the accuracy of the climate model before and after applying quantile mapping, several statistical validation metrics are used. These include:

a) Root Mean Square Error (RMSE)

RMSE evaluates the average magnitude of the error between model and observed rainfall. Lower RMSE values indicate better model performance. It is calculated using Equation 2.

$$RMSE = \left(\frac{\sum (y_i - \hat{y}_i)^2}{n} \right)^{1/2} \quad (2)$$

Where,

y_i : observed rainfall;
 $\hat{y}_i$: model rainfall; and
 n : Number of observations

b) Mean Bias Error (MBE)

The Mean Bias Error (MBE) measures the average systematic error of a model (Equation 3). An ideal value is zero (0.0), which indicates no systematic bias in the predictions. It is calculated using Equation 3.

$$MBE = \frac{1}{n} \sum (\hat{y}_i - y_i) \quad (3)$$

Where,

y_i : observed rainfall;
 $\hat{y}_i$: model rainfall; and
 n : Number of observations

c) Pearson Correlation Coefficient (r)

This metric measures the strength of the linear relationship between observed and model data. A correlation close to 1 indicates a strong agreement between the two datasets. It is calculated using Equation 4.

$$r = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum(x_i - \bar{x})^2 \sum(y_i - \bar{y})^2}} \tag{4}$$

Where,

- x_i, y_i : Observed and modeled values, respectively; and
- $\bar{x}, \bar{y}$: Means of the respective datasets.

d) Contingency Table Metrics

To assess the model's ability to detect rainfall events, a 2×2 contingency table is constructed using hit (H), miss (M), false alarm (FA), and correct negative (CN) values (Table 2).

Table 2. Contingency table for rainfall events

	Observed: Rain	Observed: No Rain
Model: Rain	Hit (H)	False Alarm (FA)
Model: No Rain	Miss (M)	Correct Negative (CN)

From Table 2, two key indicators are derived:

- Probability of detection (POD)

This metric indicates how effectively the model captures actual rainfall events. It is calculated using Equation 5.

$$POD = \frac{Hit}{Hit+Miss} \tag{5}$$

- False alarm ratio (FAR)

This metric reflects the rate of over-predicted rainfall events. Lower FAR values indicate better model reliability. It is calculated using Equation 6.

$$FAR = \frac{False\ Alarm}{Hit+False\ Alarm} \tag{6}$$

e) Nash-Sutcliffe Efficiency (NSE)

The Nash-Sutcliffe Efficiency (NSE) is a normalized statistic that determines the relative magnitude of the residual variance compared to the observed data variance (see equation 7). NSE values typically range from ∞ to 1. A value of 1 indicates a perfect fit between the observed and simulated data. A value of 0 indicates that the model predictions are no better than the mean of the observed data. A value less than 0 suggests that the mean of the observations is a better predictor than the model itself. It is calculated using Equation 7.

$$NSE = 1 - \frac{\sum (y_i - \hat{y}_i)^2}{\sum (y_i - \bar{y}_i)^2} \quad (7)$$

Where,

- y_i : observed rainfall;
- $\hat{y}_i$: model rainfall;
- $\bar{y}_i$: mean of the observed value *and*
- n : Number of observations

f) Kling-Gupta Efficiency (KGE)

The Kling-Gupta Efficiency (KGE) is a performance metric that offers a more comprehensive diagnostic evaluation than NSE by decomposing the model error into three key components: correlation, bias, and variability (ratio of standard deviations). It measures the Euclidean distance from the ideal point (where all components equal 1) (Equation 8).

KGE values typically range from ∞ to 1. A value of 1 indicates a perfect simulation fit, similar to NSE. It is calculated using Equation 8.

$$KGE = 1 - \sqrt{(r - 1)^2 + (\alpha - 1)^2 + (\beta - 1)^2} \quad (8)$$

Where,

- r : linear correlation coefficient between simulations and observations;
- α : the variability ratio (standard deviation of simulations divided by standard deviation of observations) and
- β : the bias ratio (mean of simulations divided by mean of observations)

2.2.3 Rainfall Duration-frequency-intensity Analysis

To evaluate potential changes in extreme rainfall characteristics under future climate scenarios, this study performs a detailed analysis of rainfall intensity based on varying durations and return periods. The analysis includes two main steps: estimation of rainfall returns periods using statistical frequency analysis (1), and calculation of rainfall intensity for different durations using the Mononobe equation (2).

a) Frequency Analysis for Return Periods

Estimating extreme rainfall magnitudes for different return periods is a fundamental step in hydrological risk assessment. In this study, frequency analysis is conducted using either the Normal distribution or the Gumbel distribution, depending on the results of the Kolmogorov–Smirnov (K–S) goodness-of-fit test. If the test shows that the data do not conform to a normal distribution, then the Gumbel distribution is adopted, which is commonly used for modelling extreme hydrological events. Once the appropriate distribution is selected, rainfall depth for specific return periods (e.g., 5, 10, 25 years) is computed using the following equations (Equations 9, 10, and 11):

- For the normal distribution:

$$X_T = \underline{x} + K_T s \quad (9)$$

- For the Gumbel distribution (used when data are not normally distributed)

$$X_T = b + \frac{1}{a} \cdot Y_t \quad (10)$$

$$b = \underline{x} - \frac{Y_n s}{\sigma n} \rightarrow \frac{1}{a} = \frac{s}{\sigma n} \quad (11)$$

Where,

X_T : Rainfall depth for return period T (mm)

K_T, Y_t : Frequency factors based on distribution

S : Standard deviation

$\underline{x}$: Mean of annual maximum rainfall (mm)

$Y_n, \sigma n$: Gumbel distribution constants

These computations are applied to both historical and projected rainfall datasets to identify trends in rainfall extremes over time.

b) Estimating Rainfall Intensity

After calculating rainfall depths for selected return periods, rainfall intensity for various durations is derived using the Mononobe formula. Since the available dataset consists of daily rainfall (24-hour), the intensity for shorter durations (e.g., 1, 2, 3, 6, 12 hours) is estimated using Equation 12.

$$I = \frac{R_{24}}{24} \left(\frac{24}{t} \right)^{2/3} \quad (12)$$

Where,

- I : Rainfall intensity (mm/hour);
- t : Rainfall duration (hours);
- R_{24} : Maximum daily rainfall (mm) for a specific return period.

This equation transforms daily rainfall estimates into sub-daily intensities, enabling the construction of Intensity–Duration–Frequency (IDF) curves. The calculated intensities for each duration (1, 2, 3, 6, 12, 24 hours) are then plotted against their respective durations for various return periods to visualize and compare rainfall patterns across both historical and future scenarios. It should be noted that the application of the Mononobe equation assumes a generalized temporal distribution of rainfall derived from daily observations. This approach may not fully capture short-duration convective rainfall characteristics, particularly in tropical regions where rainfall intensity can vary significantly at sub-daily scales. Consequently, the derived sub-daily rainfall intensities (e.g., 1–12 hours) are subject to uncertainty.

By analyzing changes in rainfall intensity across different durations and return periods, the study provides insights into how extreme rainfall events may evolve under climate change. This information is essential for designing resilient urban drainage systems, flood mitigation infrastructure, and early warning strategies, especially in topographically diverse and climate-sensitive regions such as Lampung Province

3. Results and Discussion

3.1 Trend Analysis of Projected Rainfall under SSP Scenario

Understanding long-term trends in rainfall projections is essential for anticipating climate-related hydrological risks and for formulating resilient water resource management strategies. This section presents a refined analysis of projected rainfall trends from the ACCESS-ESM1-5 global climate model under the NEX-GDDP-CMIP6 framework, focusing on four distinct Shared Socioeconomic Pathway (SSP) scenarios (Table 3).

Linear regression results show that most slopes are negative, indicating declining rainfall trends, with statistical significance ($p < 0.05$) in high-emission scenarios. In contrast, SSP1-2.6 and SSP2-4.5 exhibit p-values greater than 0.05 at monthly and annual scales, suggesting no statistically significant relationship between current and future rainfall. The strongest declines occur under SSP3-7.0 (−12.3 mm/year) and SSP5-8.5 (−12.77 mm/year) at the annual scale, with monthly trends ranging from −0.08 to −0.09 mm/month/year. These results highlight the amplifying influence of anthropogenic greenhouse gas emissions on long-term precipitation deficits, consistent with tropical climate projections where higher temperatures alter atmospheric moisture capacity and disrupt monsoonal systems (The Intergovernmental Panel on Climate Change (IPCC), 2021).

Table 3. Regression coefficients of rainfall projection trends for different time scales under SSP Scenarios (2015–2060)

Time Scale	SSP1-2.6	SSP2-4.5	SSP3-7.0	SSP5-8.5
Daily	−0.000019x +	−0.000024x + 6.8	−0.0000097x +	−0.000101x +
	6.66		6.9	7.19
	P-value : 0,02		P-value : 0,00	P-value : 0,00
Monthly	−0.01x + 202.6 *	−0.02x + 207.9 *	−0.08x + 211.9	−0.09x +
	P-value: 0,52	P-value : 0,42	P-value : 0,0009	218.81
				P-value : 0,0004
Annual	−1.89x + 2417 *	−2.4x + 2478 *	−12.3x + 2524	−12.77x +
	P-value: 0,67	P-value: 0,62	P-value : 0,015	2603
				P-value : 0,007

Rainfall changes vary by temporal resolution. Daily slopes are minimal (−0.000019 to −0.000101), suggesting that individual rainfall events remain relatively stable, while monthly and annual scales show more pronounced reductions in accumulated rainfall. This indicates that although event intensity

may remain similar, overall frequency and water contribution decrease, affecting water supply, agriculture, and flood management. The steepening of slopes with longer timescales reinforces that long-term hydrological trends are more reliable indicators of climate change impacts than short-term variability, which can still be influenced by natural oscillations such as ENSO.

The interaction between emission pathways and temporal resolution reveals critical insights. While all SSPs show minor decline at the daily scale, the rate of reduction becomes significantly more divergent at larger scales, particularly under high-emission scenarios. For example, SSP3-7.0 and SSP5-8.5 show similar behavior at the daily scale (-0.0000097 and -0.000101 , respectively) but diverge dramatically at the annual scale (-12.3 mm/year vs. -12.77 mm/year). This divergence indicates that accumulated rainfall is disproportionately affected in scenarios with higher greenhouse gas concentrations, and that such impacts accumulate more visibly over longer periods.

The absence of statistically significant trends under SSP1-2.6 and SSP2-4.5 at the monthly and annual scales suggests that strong mitigation pathways may effectively dampen long-term changes in accumulated rainfall. Similar findings have been reported in previous CMIP-based studies, where low-emission scenarios exhibit weaker or statistically insignificant hydrological responses due to reduced radiative forcing and the continued influence of natural climate variability (Martel *et al.*, 2021). This result reinforces the role of emission pathways in shaping future hydroclimatic risks and highlights the potential benefits of global mitigation efforts for regional water security.

Importantly, this study represents a key advancement over previous rainfall trend analyses in Indonesia, which mostly rely on stationary assumptions or historical observations alone. By integrating bias-corrected CMIP6 projections across multiple SSP scenarios, it provides one of the first forward-looking assessments of rainfall trends for Lampung Province. The clear divergence between low- and high-emission scenarios underscores the necessity of climate-informed approaches in hydrological planning, particularly in regions with high climate sensitivity such as the Maritime Continent. In doing so, the study directly addresses the research gap noted in the Introduction regarding the lack of CMIP6-based, scenario-dependent rainfall trend analyses at the regional scale.

3.2 Model Verification Results

Climate models, by nature, are mathematical representations of complex atmospheric systems, and therefore inevitably exhibit discrepancies when compared to observed data. To assess the accuracy of the ACCESS-ESM1-5 model in replicating actual rainfall conditions, a verification was conducted using observed daily rainfall data from four rainfall stations under BBWS Mesuji–Sekampung for the period 2012–2014. This verification evaluated model outputs both before and after statistical downscaling using quantile mapping, a bias correction technique commonly employed to align modelled distributions with observed climatology.

Table 4. Mean bias error (MBE) of daily rainfall before and after bias correction (2012–2014)

No	Station	Bias Before	Bias After	$\Delta Bias$
1.	Kebon Tebu	0,86	0,6	-0,26
2.	Bukit Kemuning	2,79	0,08	-2,71
3.	Natar	0,46	0,21	-0,25
4.	Way Jepara	0,09	0,00	-0,09
		Average		-0,217

Table 4 summarizes the Mean Bias Error (MBE) values for each observation station to evaluate the accuracy of daily rainfall data before and after bias correction. The MBE serves as an indicator of the model's tendency to either overestimate or underestimate precipitation relative to observed data. Prior to the application of bias correction, MBE values ranged from 0.09 to 2.79, indicating a general tendency of the model to overestimate rainfall compared to actual field conditions. Following the implementation of bias correction, all stations exhibited a significant reduction in MBE values, with an average improvement ($\Delta Bias$) of -0.217.

The most substantial improvement was observed at the Bukit Kemuning station, where the bias was significantly reduced from 2.79 to 0.08 ($\Delta Bias = -2.71$). The Kebon Tebu and Natar stations also showed decreases of -0.26 and -0.25, respectively. The most optimal result was achieved at the Way Jepara station, which yielded a final bias value of 0.00, signifying that the model estimates have become fully aligned with the observed mean.

Table 5 summarizes the Root Mean Square Error (RMSE) values for each station. The RMSE serves as a quantitative measure of the difference between modelled and observed rainfall values. Before bias correction, RMSE values

ranged from 8.49 mm/day to 15.15 mm/day, indicating considerable deviation. After applying quantile mapping, most stations exhibited a reduction in RMSE, with an average improvement of -1.95 mm/day. The most significant improvement occurred at Kebon Tebu station, with a reduction of -4.56 mm/day, followed by Bukit Kemuning (-3.46 mm/day) and Way Jepara (-1.35 mm/day). These results suggest that quantile mapping effectively improved the model's ability to represent observed rainfall magnitudes at these locations. However, Natar station exhibited a counterintuitive increase in RMSE ($+1.57$ mm/day), implying that the correction process was less effective there and may require further investigation or alternative bias correction approaches.

Table 5. Root mean square error (RMSE) of daily rainfall before and after bias correction (2012–2014)

No	Station	RMSE (mm)	Before	RMSE (mm)	After	Δ RMSE (mm)
1.	Kebon Tebu	15,13		10,57		-4,56
2.	Bukit Kemuning	15,15		11,69		-3,46
3.	Natar	9,22		10,79		+1,57
4.	Way Jepara	8,49		7,14		-1,35
		Average				-1,95

To assess the strength of the linear relationship between model outputs and observations, Pearson correlation coefficients were computed. Prior to correction, correlation values were low, ranging from 0.04 to 0.1, indicating weak correspondence. After quantile mapping, however, correlations dramatically increased to between 0.94 and 0.99, with an average improvement of $+0.86$ (Table 6). This substantial enhancement confirms that quantile mapping significantly improves the temporal alignment of rainfall events between the model and observations.

Table 6. Pearson Correlation Coefficient (r) of Daily Rainfall Before and After Bias Correction (2012–2014)

No	Station	r Before	r After	Δ r
1.	Kebon Tebu	0,04	0,94	+0,9
2.	Bukit Kemuning	0,09	0,98	+0,81
3.	Natar	0,1	0,96	+0,88
4.	Way Jepara	0,1	0,99	+0,89
		Average		+0,86

These findings align with previous studies, such as Kurnia *et al.* (2020), which demonstrated that quantile mapping can effectively enhance the correlation

between ECMWF rainfall model data and ground-based observations in Sulawesi. The success of this method reinforces its suitability for correcting systematic biases in CMIP6 GCM outputs before applying them to local hydrological or climatological applications.

The Probability of Detection (POD) was analyzed to determine the model’s ability to correctly predict rainfall events that occurred in the observed data. Before correction, POD values ranged from 0.84 to 0.90, suggesting that some rainfall events were not captured by the raw model outputs. Post-correction, all four stations achieved a perfect detection rate of $POD = 1$, as shown in Table 7. This implies that after quantile mapping, all observed rainfall events were successfully captured by the model, significantly enhancing its predictive reliability. The perfect detection rate ($POD = 1.00$) should be interpreted with caution. This result is likely influenced by the persistence of drizzle bias in GCM outputs and the absence of a dry-day correction step in the quantile mapping procedure, which may lead to an overestimation of rainfall occurrence.

Table 7. Probability of Detection (POD) of Daily Rainfall Before and After Bias Correction (2012–2014)

No	Station	POD Before	POD After	ΔPOD
1.	Kebon Tebu	0,88	1	+0,12
2.	Bukit Kemuning	0,87	1	+0,13
3.	Natar	0,9	1	+0,1
4.	Way Jepara	0,84	1	+0,16
Average				+0,12

The highest increase in POD occurred at Way Jepara (+0.16), followed by Bukit Kemuning (+0.13), Kebon Tebu (+0.12), and Natar (+0.10). The average POD improvement across all stations was +0.12, highlighting the efficacy of quantile mapping in improving event detection capabilities across varying topographies and microclimates.

While POD reflects improved detection, it must be interpreted in conjunction with the False Alarm Ratio (FAR), which quantifies the frequency at which rainfall was predicted by the model but did not occur in observations. Before correction, FAR values varied from 0.46 to 0.79. After applying quantile mapping, FAR values exhibited mixed results (Table 8). Kebon Tebu and Natar showed slight increases in FAR by +0.02, and Way Jepara increased by +0.03. In contrast, Bukit Kemuning showed a slight improvement, with a decrease of -0.01 . This mixed trend suggests that while the model improves

at detecting actual rain events, it also tends to overpredict rainfall, potentially due to temporal misalignment or the smoothing effect introduced by statistical correction. The average change in FAR was +0.01, indicating a marginal decline in specificity.

Table 8. False Alarm Ratio (FAR) of daily rainfall before and after bias correction (2012–2014)

No	Station	FAR Before	FAR After	Δ FAR
1.	Kebon Tebu	0,46	0,48	+0,02
2.	Bukit Kemuning	0,61	0,6	-0,01
3.	Natar	0,79	0,81	+0,02
4.	Way Jepara	0,67	0,7	+0,03
Average				+0,01

Table 9 illustrates a significant enhancement in model performance following bias correction, with Nash-Sutcliffe Efficiency (NSE) values shifting from negative ranges (−0.87 to −0.96) to a high-efficiency spectrum of 0.87 to 0.97. This average improvement of +1.84 indicates a transition from unreliable estimates to highly accurate replications of observed daily rainfall patterns. Way Jepara achieved the highest efficiency (0.97), followed by Bukit Kemuning (0.96) and Kebon Tebu (0.94), confirming the effectiveness of the bias correction method in validating rainfall projection data.

Table 9. Nash-Sutcliffe efficiency of daily rainfall before and after bias correction (2012–2014)

No	Station	NSE Before	NSE After	Δ NSE
1.	Kebon Tebu	-0,87	0,94	+1,81
2.	Bukit Kemuning	-0,87	0,96	+1,83
3.	Natar	-0,95	0,87	+1,82
4.	Way Jepara	-0,96	0,97	+1,93
Average				+1,84

Table 10 presents the Kling-Gupta Efficiency (KGE) values, which provide a more comprehensive evaluation of model performance by integrating three key statistical components: correlation (r), bias ratio (β), and variability ratio (α). Before bias correction, the KGE values were extremely low, ranging from −0.02 to 0.05, indicating that the raw model struggled to capture the overall dynamics and distribution of daily rainfall.

Table 10. Kling-Gupta Efficiency (KGE) of daily rainfall before and after bias correction (2012–2014)

No	Station	KGE Before	KGE After	ΔKGE
1.	Kebon Tebu	0,003	0,93	+0,92
2.	Bukit Kemuning	0,05	0,97	+0,92
3.	Natar	-0,02	0,93	+0,95
4.	Way Jepara	0,005	0,98	+0,97
Average				+0,94

Following the application of bias correction, there was a remarkable improvement across all stations, with an average increase ΔKGE of +0.94. The post-correction KGE values reached an excellent range of 0.93 to 0.98. Specifically, Way Jepara achieved the highest score of 0.98 ($\Delta KGE = +0.97$), followed by Bukit Kemuning at 0.97. This significant enhancement across all components, mean, variance, and correlation, demonstrates that the bias correction method effectively synchronized the modeled rainfall with the observed seasonal and daily characteristics

The comprehensive evaluation of the model performance confirms that the statistical downscaling approach using quantile mapping substantially improved the model’s alignment with observed data. Statistical metrics across all stations demonstrate a significant reduction in systematic errors, as evidenced by the decline in Mean Bias Error (MBE) and Root Mean Square Error (RMSE). The model’s predictive skill also saw a remarkable transition, with Nash-Sutcliffe Efficiency (NSE) values shifting from negative ranges to high-efficiency scores between 0.87 and 0.97. This enhancement is further validated by the Kling-Gupta Efficiency (KGE) results, which increased to an average of 0.943, indicating that the correction effectively synchronized the model’s correlation, bias ratio, and variability with actual field conditions.

Moreover, the model’s capacity to detect actual rainfall events (POD) was significantly enhanced. However, the slight increase in FAR values across several stations suggests that the model may still produce false positives, emphasizing the need for complementary or alternative bias correction strategies. Therefore, while quantile mapping proves to be a powerful tool for enhancing model realism by optimizing both magnitude and linear correlation, it should be carefully calibrated to balance the trade-off between detection sensitivity and false alarm rates in long-term rainfall projections.

The substantial improvement in NSE and KGE values after bias correction demonstrates not only enhanced mean and variance representation but also

improved skill in reproducing rainfall variability relevant to extreme-event analysis. Previous studies have emphasized that performance metrics such as NSE and KGE are particularly suitable for hydrological applications, as they jointly account for correlation, bias, and variability (Gupta *et al.*, 2009). The strong post-correction performance across all stations supports the suitability of the bias-corrected CMIP6 projections for subsequent IDF curve development and extreme rainfall assessment.

3.3 Projected in Rainfall Intensity-Duration-Frequency (IDF) Curve

Building on the verified and bias-corrected rainfall projections, the following analysis focuses on projected changes in rainfall extremes as expressed through Intensity–Duration–Frequency (IDF) curves. Unlike traditional IDF analyses derived from stationary historical records, the climate-informed IDF curves presented here explicitly account for future climate conditions under multiple SSP scenarios. This approach enables a more realistic representation of design rainfall under climate change, particularly for regions with complex topography such as Lampung Province.

Specifically, this section examines the projected changes in rainfall extremes in Lampung Province by analyzing IDF curves under multiple Shared Socioeconomic Pathways (SSPs), specifically SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5. The IDF curves were derived using the Mononobe method for three return periods (5, 10, and 25 years) and rainfall durations across four elevation zones: high hills, hills, low hills, and lowlands. These projections were then compared to the historical baseline period (1985–2014) to assess the magnitude and spatial distribution of future extreme rainfall intensification.

As shown in Figure 2, the historical 1-hour rainfall intensity for a 5-year return period ranged from 70 mm/hour in the high hills to 19 mm/hour in the lowlands. In all future climate scenarios, these values increase significantly. For example, under SSP3-7.0, the high hills are projected to receive 166 mm/hour, while under SSP5-8.5, the low hills could experience about 183 mm/hour. This represents a near tenfold increase in the most vulnerable topography, posing serious flash flood risks in low-lying regions. The 24-hour rainfall intensity changes are more restrained but still noteworthy. In the high hills, historical values around 22 mm/hour rise to 25 mm/hour under SSP3-7.0, indicating that longer-duration events may be less sensitive to climate forcing. Nevertheless, the steady increase across SSPs and elevations suggests

that prolonged rainfall events will become more common and intense, stressing river basins and catchment areas.

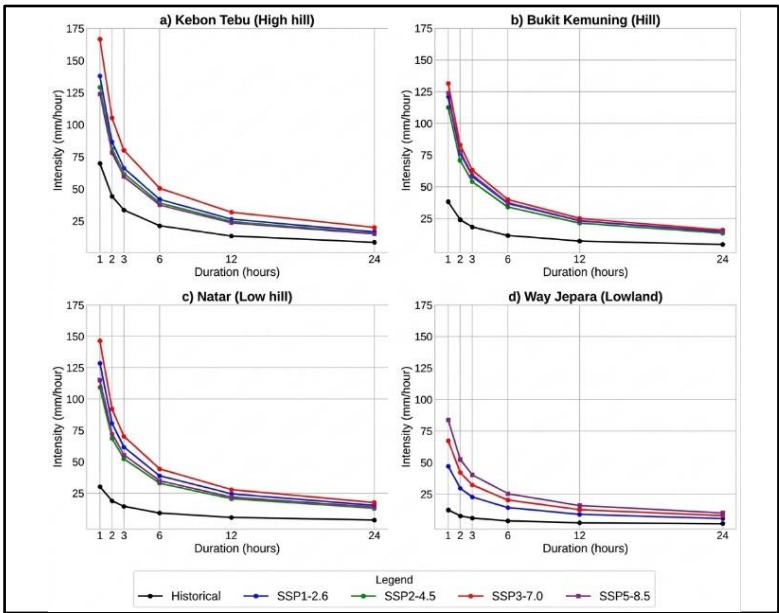


Figure 2. Historical and projected rainfall intensities for a 5-year return period across elevation zones in Lampung Province

The 10-year return period analysis (Figure 3) reveals heightened spatial contrasts and further evidence of intensification. Historically, the high hills have experienced rainfall intensities of around 125 mm/hour over a 1-hour period. Under SSP3-7.0, this increases to 186 mm/hour. Interestingly, the same elevation under SSP5-8.5 shows a lower projection (37 mm/hour), which may be attributed to statistical variability or model ensemble uncertainty. In lowland zones, 1-hour intensities increase to 95 mm/hour under SSP2-4.5 and 87 mm/hour under SSP3-7.0, representing a significant rise from the historical average of 19 mm/hour. These changes suggest that even moderate return periods can result in damaging rainfall events in flat, urbanized, and poorly drained areas. For 24-hour durations (Figure 3), the trends are consistent and more stable, reinforcing the importance of integrating climate projections into long-term hydrological planning.

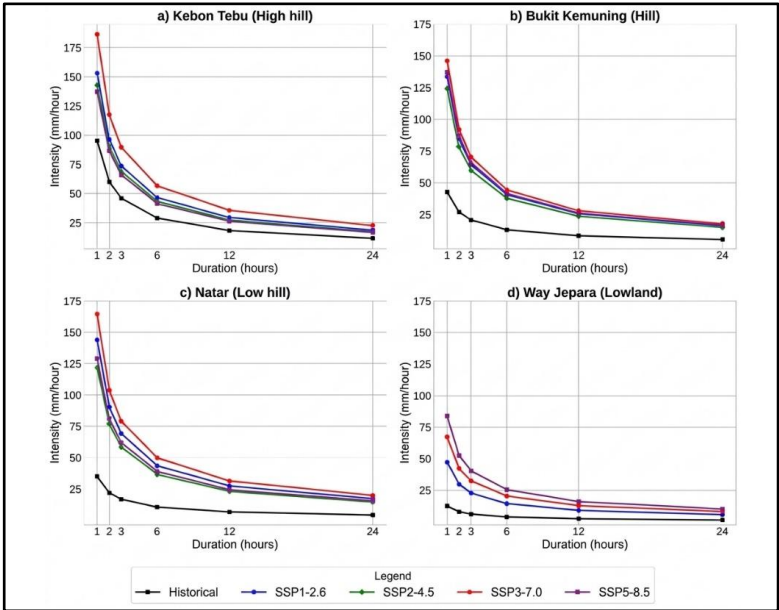


Figure 3. Historical and projected rainfall intensities for a 10-year return period across elevation zones in Lampung Province

At the 25-year return period, the projected changes have critical implications for infrastructure resilience and design thresholds. Figure 4 shows a significant increase in 1-hour rainfall intensities, particularly in the high hills, where values rise from 125 mm/hour to 210 mm/hour under SSP3-7.0, a 68% increase. Such intensities exceed typical design capacities of urban stormwater systems and demand urgent reevaluation of construction codes and drainage infrastructure. For the low hill, the historical 1-hour value of 25 mm/hour increases to over 100 mm/hour under SSP2-4.5 and SSP5-8.5. Though absolute values remain lower than in upland regions, the percentage growth is extraordinary. This presents high risks to communities, businesses, and infrastructure situated in flood-prone lowland areas, particularly where stormwater management systems are outdated or undersized.

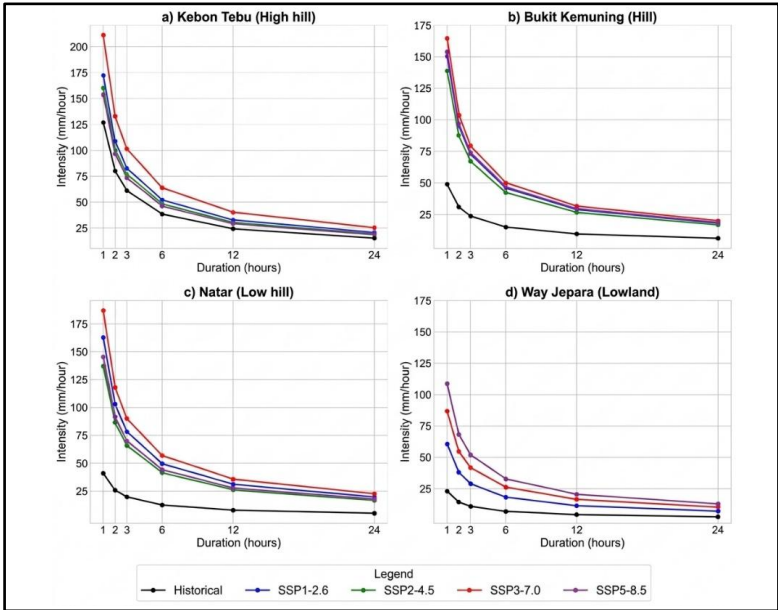


Figure 4. Historical and projected rainfall intensities for a 25-year return period across elevation zones in Lampung Province

The results consistently highlight the role of elevation in shaping rainfall intensity patterns. High-elevation regions are more prone to intense rainfall due to orographic uplifts and microclimatic conditions. However, the sensitivity to climate scenarios varies considerably. SSP3-7.0, which represents a fragmented world with minimal climate action, shows the highest increases in all metrics. SSP5-8.5, characterized by fossil-fueled development, also predicts substantial increases, though more variable in some zones. SSP1-2.6, the most sustainable pathway, shows the least change, reinforcing the benefits of global mitigation efforts. Furthermore, the variation across SSPs suggests that policy decisions and emission trajectories will strongly influence future rainfall extremes. The difference in intensities between SSP1-2.6 and SSP5-8.5 underlines the urgency of adopting low-emission development strategies. These results are critical for guiding urban planning, water resource management, and climate adaptation strategies. As short-duration, high-intensity rainfall becomes more frequent, especially in the lowlands, cities must invest in adaptive infrastructure. Drainage channels, retention ponds, and green infrastructure will need to be redesigned with rainfall projections in mind. In rural upland areas, which may face even higher absolute intensities, strategies should include soil stabilization, early warning systems, and

sustainable land use to mitigate landslides and runoff. For low-return-period events, policy must recognize the increased baseline risk and expand the scope of flood zoning and emergency response mechanisms. Figure 2-4 also shows a consistent and concerning trend: climate change is projected to intensify extreme rainfall events in Lampung Province across all return periods and durations. The increases are most dramatic in short-duration, low-return-period events that are often underrepresented in planning documents.

Overall, the projected IDF results consistently indicate a significant intensification of short-duration extreme rainfall across all elevation zones in Lampung Province, with the strongest increases occurring under high-emission scenarios. These findings demonstrate that climate change is likely to alter not only the magnitude but also the spatial distribution of design rainfall, challenging the validity of stationary IDF curves currently used in infrastructure planning. The elevation-dependent response further emphasizes the need for localized design standards rather than uniform regional thresholds. Incorporating climate-informed IDF curves into drainage design, flood control, and land-use planning is therefore essential to enhance long-term climate resilience and reduce future hydrological risks in the region.

In addition to the differences across SSP scenarios, it is important to acknowledge several sources of uncertainty associated with this study. First, the analysis is based on a single GCM (ACCESS-ESM1-5), which limits the ability to quantify inter-model (ensemble) uncertainty. Different climate models may produce varying precipitation responses due to differences in physical parameterizations and representations of atmospheric processes. Therefore, the results presented here should be interpreted as model-specific projections rather than a comprehensive multi-model consensus. Second, uncertainty may arise from the bias correction process, as quantile mapping assumes that the statistical relationship between observed and modeled rainfall remains stationary under future climate conditions. Third, the use of the Mononobe equation to derive sub-daily rainfall intensities from daily data introduces additional uncertainty, particularly in representing short-duration convective extremes. Fourth, the relatively short observational record used for calibration may limit the representation of interannual variability and extreme rainfall tails. Finally, the choice of statistical distributions for frequency analysis (e.g., Gumbel or Normal) introduces further uncertainty in estimating design rainfall. These uncertainties should be considered when applying the projected IDF curves for engineering and climate adaptation purposes.

4. Conclusions and Recommendations

This study presents one of the first elevation-based projections of rainfall Intensity–Duration–Frequency (IDF) curves for Lampung Province using bias-corrected CMIP6 data. Applying quantile mapping substantially improved model accuracy, particularly in capturing temporal patterns and extreme events. The results reveal a consistent intensification of short-duration rainfall extremes across all SSP scenarios, with the largest increases under SSP3-7.0 and SSP5-8.5. Lowland areas experience the highest relative increase in 1-hour rainfall intensity, up to tenfold, while high-elevation regions show the greatest absolute intensities due to elevation-driven enhancement. In contrast, 24-hour rainfall intensities show more moderate growth, highlighting the particular sensitivity of short-duration extremes to climate change.

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