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Changes in Precipitation Intensity-Duration-Frequency Curve: A comparison based on CMIP5 and CMIP6

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Abstract

In recent years, India has experienced a considerable loss of lives and properties due to an increase in extreme precipitation events as a potential consequence of global warming. In particular, the short-duration but intense precipitation events have significantly impacted the major Indian cities in the past, and the number of such events is rising. In this context, it is critical to assess the design capacity of urban drainage networks in order to effectively mitigate the potential disasters caused by heavy precipitation in the future. The Intensity-Duration-Frequency (IDF) curve is one such crucial piece of information that plays a major role in infrastructure design and reflects the climate change impact on the precipitation characteristics. In this study, we have utilized hourly observed precipitation data at four metropolitan cities in India, namely Ahmedabad, Kolkata, Mumbai, and Chennai, to analyse the change in the IDF relationships between the past and future. The changes in the future are analysed based on the simulated outputs from multiple Global Circulation Models (GCMs) of Coupled Model Intercomparison Project Phase 5 (CMIP5) and Phase 6 (CMIP6). Two different scenarios for each phase have been considered in this study, i.e., RCP4.5, RCP8.5 from CMIP5, and SSP245, SSP585 from CMIP6. Apart from quantifying the changes in IDF in the future, this study further provides important insight into the comparative assessment between CMIP5 and CMIP6 with respect to the changes in the IDF. Outcomes are beneficial for future planning and designing of various hydraulic infrastructures in the context of changing climate using the updated IDF relationships.

Keywords: Climate change; Precipitation; Intensity; Duration; Frequency; IDF relationship.

1. INTRODUCTION

The intensity-duration-frequency (IDF) curves quantify the relationship of precipitation intensity with its duration and frequency of occurrence and are also essential for designing hydraulic structures like urban drainage networks, small bridges, dams, etc. Traditionally, IDF curves are estimated using historically observed precipitation data. However, the approach has proven inadequate because of the altered spatiotemporal characteristics of extreme precipitation caused by climate change (Asadieh and Krakauer 2015; Sun et al 2021). Therefore, to examine potential changes in IDF curves, outputs from climate models, such as General Circulation Models (GCMs), Regional Climate Models (RCMs), or both, which incorporate different warming and socio-economic scenarios to simulate the future climate in global or regional scale have been used in several studies. The World Climate Research Programme (WCRP) coordinates international climate research groups to provide outputs from various GCMs based on multiple warming and socioeconomic scenarios in various phases such as Climate Model Intercomparison Project Phase Phase 3 (CMIP3), Phase 5 (CMIP5), and the most recent Phase 6 (CMIP6). Multiple studies across the globe indicate changes in IDF curves based on different CMIP. For instance, based on GCMs obtained from CMIP3, Kao and Ganguly (2011) showed a 30% intensification of global averaged extreme precipitation for the worst-case scenario. Based on CMIP5

estimates and scenarios, Chandra et al (2015) and Vu et al (2018) found a 12-53% and 40-45% increase in short-duration rainfall intensity in Bengaluru, India, and Bac Ninh, Vietnam, respectively. Maity and Maity (2022) used CMIP6 outputs to examine the spatio-temporal changes in the IDF relationship using hourly precipitation across India and showed that in the worst-case scenario, an average 40-48% increase in the future is expected. Although CMIP6 is the most recent of the three phases, the future scenarios it uses are modifications of those used in CMIP5. The future simulations in CMIP5 are performed using radiative forcing values from four GHG concentration pathways, known as Representative Concentration Pathways (RCPs), whereas CMIP6 uses Shared Socioeconomic Pathways (SSPs) in combination with RCP scenarios (Eyring et al., 2016; Taylor et al., 2012). SSP narratives are driven by changes in qualitative components in the future, such as demographics, human development, lifestyle, policies and institutions, environment, and natural resources, and quantitative components, such as population, education, urbanization, and economic development. The aforementioned parameters along with RCP forcing scenarios, make the SSPs more robust and meaningful compared to their predecessors (O'Neill et al., 2017).
In this regard, this study examines the differences between the precipitation IDF curves projected by CMIP5 and CMIP6 simulations for the future.

2. STUDY AREA AND DATA USED

In this investigation, we used observed hourly precipitation data from the India Meteorological Department (IMD) for four cities in India: Ahmedabad (23.07ºN, 72.63ºE), Chennai (13.06ºN, 80.23ºE) Kolkata (22.53ºN 88.33ºE), and Mumbai (19.10ºN, 72.85°E). These cities were chosen because they experience a wide range of climate conditions. One Self-Recording Rain Gauge (SRRG) is selected for each city based on the maximum availability of recorded data starting from the year 1969.

The simulated precipitation data for the historical (1969-2005) and future periods (2015-2100) are obtained from the WCRP repository for CMIP5 and CMIP6. For the analysis, the period from 1969 to 2005 (36 years) is chosen as the historical baseline based on observed and simulated data records, and the future period is divided into three epochs, namely, 2015-2040 (immediate future), 2041-2070 (near-future), and 2071-2100. (far-future). Eight GCMs and two scenarios for each CMIP are selected for this study. A brief description of the data is presented in Table 1.

Table 1. Description of the GCMs used in the study

Source	Source Institution	Model Name	Resolution
CMIP5 / CMIP6	Bureau of Meteorology and Commonwealth Scientific and Commonwealth Industrial Research Organisation, Australia	ACCESS1-0, ACCESS1-3 / ACCESS-CM2, ACCESS-ESM1-5	1.25°×1.875°
	Beijing Climate Center, China	BCC-CSM1-1-M / BCC-CSM2-MR	1.12°×1.12°
	Canadian Centre for Climate Modelling and Analysis, Canada	CanESM2 / CanESM5	2.79°×2.81°
	National Center for Atmospheric Research, USA	CESM1-CAM5 / CESM2-WACCM	0.94°×1.25°
	EC-Earth Consortium	Ec-Earth / Ec-Earth3	1.12°×1.12°/ 0.70°×0.70°
	Institut Pierre Simon Laplace, France	IPSL-CM5A-MR / IPSL-CM6A-LR	1.26°×2.50°/
	Max Planck Institute for Meteorology, Hamburg, Germany	MPI-ESM-MR / MPI-ESM1-2-HR	1.86°×1.87°/ 0.93°×0.93°

3. METHODOLOGY

Before proceeding with the analysis, the simulated precipitation data from all the GCMs and scenarios are extracted for the specified latitude and longitude values of all the stations applying the inverse distance weighting interpolation method. The simulated precipitation data are then corrected for bias against the observed daily data using a mixed distribution-based Quantile Mapping (QM) technique (Shin et al., 2019) that uses both Gamma and Gumbel distributions to correct the bias in mean and extreme precipitation (values above the 95th percentile) for all stations considering each scenario. Next, the Annual Maximum Series (AMS) of precipitation intensity is extracted over moving windows of 1, 3, 6, 12, and 24 hours from the observed hourly data for each station. Generalized Extreme Value (GEV) distribution is fitted to the extracted AMS using the method of L-moments (Hosking, 1990). In the same manner, GEV distribution is fitted to the daily AMS extracted from the GCM simulated future data considering all the epochs and scenarios for each GCMs separately. Kolmogorov-Smirnov (K-S) test is used to check the goodness-of-fit. Finally scale-invariance method is used to construct IDF curve at a sub-daily scale from a daily scale (Yeo et al., 2021). Scale invariance implies that extreme precipitation statistics for different durations are proportional to one another and belong to the same distribution family. Mathematically it can be expressed in terms of moments of the distribution as:

$$E[f(t)^q] = \lambda^{-\theta(q)} E[f(\lambda t)^q] \quad (1)$$

here $f(t)$ and $f(\lambda t)$ have same distribution. λ is the scale factor (e.g. if t=24 hr, λt =1 hr, then λ=1/24) and θ is the scaling exponent. Scaling properties of extreme precipitation are shown by the log-linearity between the Non-Central Moments (NCMs) and durations and the existence of simple scaling is shown by the linear relationship between scaling exponent (θ) and order of moments (q). The scaling properties of GEV distribution can be shown as:

$$F(i)=exp\ [-(1+\kappa((i-\alpha)/\beta))^{-1/\kappa}\ ] \quad for\ \kappa \neq 0 \quad (2)$$
$$\kappa(\lambda t) = \kappa(t) \quad (3)$$
$$\beta(\lambda t) = \lambda^{\theta}\, \beta(t) \quad (4)$$
$$\alpha(\lambda t) = \lambda^{\theta}\, \alpha(t) \quad (5)$$
$$I_T(\lambda t) = \lambda^{\theta}\, I_T(t) \quad (6)$$

The location, scale, and shape parameters are expressed by α, β, and κ, respectively. The precipitation intensity of over a T-year return period, denoted by I_T can be expressed as the inverse of the CDF of GEV distribution function, which is written as follows:

$$I_T=\alpha-\beta/\kappa\ (1-[-ln(1-1/T)]^{-\kappa}\ ) \quad (7)$$

The ratio of first-order NCMs of daily and sub-daily duration can be used to estimate the parameter λ^{θ} and it is written as:

$$\lambda^{\theta} = \mu_1\ (\lambda t)/\mu_1\ (t) \quad (8)$$

$\mu_1(\lambda t)$ and $\mu_1(t)$ are the first-order NCMs for sub-daily and daily scale.
Finally, IDF curves are generated for all the cities using three different future epochs and two different scenarios for each GCM from CMIP5 and CMIP6 and compared to the historical IDF.

4. RESULTS AND DISCUSSION

The model simulated precipitation data of historical and future periods are bias corrected using the mixed-distribution based QM approach with sufficient accuracy (Absolute Percentage Bias in Multi-model Ensemble of daily AMS is reduced to the range of 2-39% from 38-71% considering all the cities for baseline period) for the cities of Ahmedabad, Chennai, Kolkata, Mumbai, considering 1969-2005 as the base period. As the entire analysis is based on extreme precipitation events the results of the bias correction are shown in terms of mean bias in daily AMS. The comparison is shown in Table 2.
At 5% significance level, the one sample K-S test does not reject the null hypothesis that the data comes from GEV distribution fitted to all the AMS extracted from observed and bias-corrected simulated data using the method of L-moments. The existence of a scaling relationship between 24-hour and 1-hour extreme precipitation for all the cities are established by high R^2 values of the log-log plot between the NCMs and the duration of precipitation. The strong linearity as shown by high R^2 values between the scaling exponent and order of moments indicates the simple scaling relationship (Ahmedabad: 0.9997,

Chennai: 0.9985, Kolkata: 0.9977). After obtaining sub-daily precipitation intensity, future IDF curves are constructed using the Multi-Model Ensemble (MME) mean approach and compared with historical. The results show that Kolkata, Ahmedabad and Chennai will see more increase in precipitation intensity in an hourly-scale than daily scale in the far future. However, in the case of Mumbai, the increment in hourly intensity is comparatively lower than in other cities. The observations are similar for both CMIP5 and CMIP6 as evident from Figure 1.

Table 2. Bias in terms of mean and standard deviation (Std. dev.) of Daily AMS for the period (1969-2005)

	CMIP5				CMIP6			
City	Bias in Raw Multi-model Ensemble(mm)		Bias in Corrected Multi-model Ensemble (mm)		Bias in Raw Multi-model Ensemble (mm)		Bias in Corrected Multi-model Ensemble (mm)	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Ahmedabad	-89.16	-53.82	18.01	15.01	-88.89	-48.82	6.21	13.13
Chennai	-87.96	-41.88	45.28	22.97	-76.24	-33.94	39.48	14.71
Kolkata	-53.74	-29.07	22.09	4.1870	-46.81	-23.95	15.95	-4.05
Mumbai	-142.01	-42.88	6.86	34.65	-118.05	-31.33	-5.88	12.78

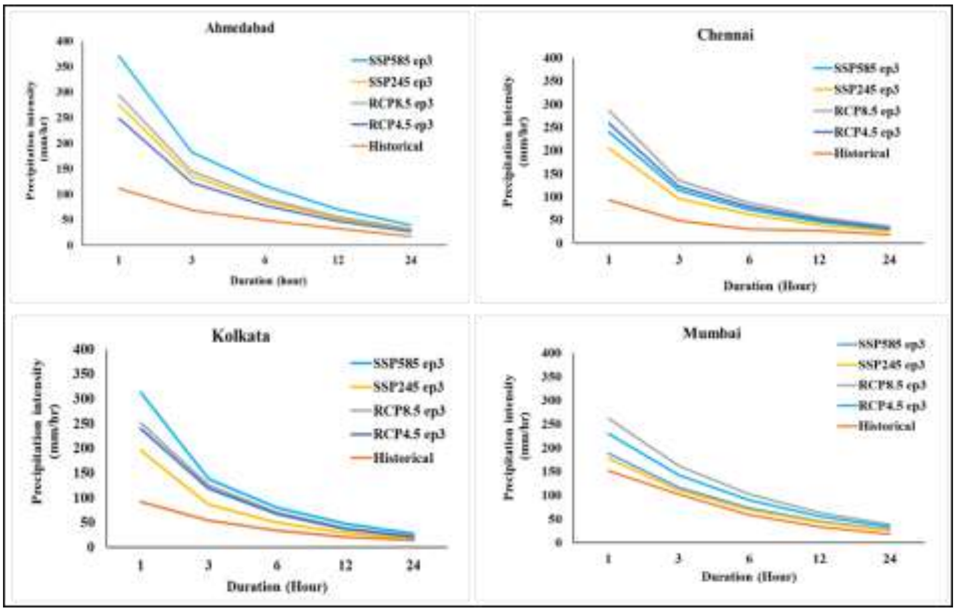

Figure 1. IDF curves for the historical period (1969-2005) and future period (Far-future, ep3: 2071-2100) for four Indian cities considering a 100-year return period.

The changes in precipitation intensity with different durations vary significantly across CMIPs and return periods. Hourly precipitation increases with an increasing return period for Ahmedabad, Chennai, and Kolkata when compared to daily precipitation. However, the hourly precipitation increment in Mumbai decreases with return period, whereas daily precipitation increases. Although both CMIPs show a similar pattern of increase for both scenarios, CMIP6 dominates for Ahmedabad and Kolkata, while CMIP5 dominates for Chennai and Mumbai. These variations could be due to the spatiotemporal variation of the socioeconomic and warming-related assumptions used in the SSP scenarios. Extreme precipitation is expected to increase in the near future (2041-2070) as well. The increase ranges from 60-245% in CMIP5 and CMIP6. In the future (100-year return period), Ahmedabad and Kolkata will have a 195% rise in hourly precipitation, while Chennai will see a 175% increase. In Mumbai, extreme daily precipitation increases by 90%. In conjunction with longer return periods, extreme rainfall with short return periods (e.g. 2-, 5-year) is also rising. Such an increase signifies more frequent flash flood situations and waterlogging in the future. Figure 2 depicts the comparison graphically. Regardless of the differences caused by the different scenarios, the results clearly show that hourly extremes will become more frequent and intense in the future which calls for a sustainable development approach to mitigate the urban flooding arising as an impact of such extreme events.

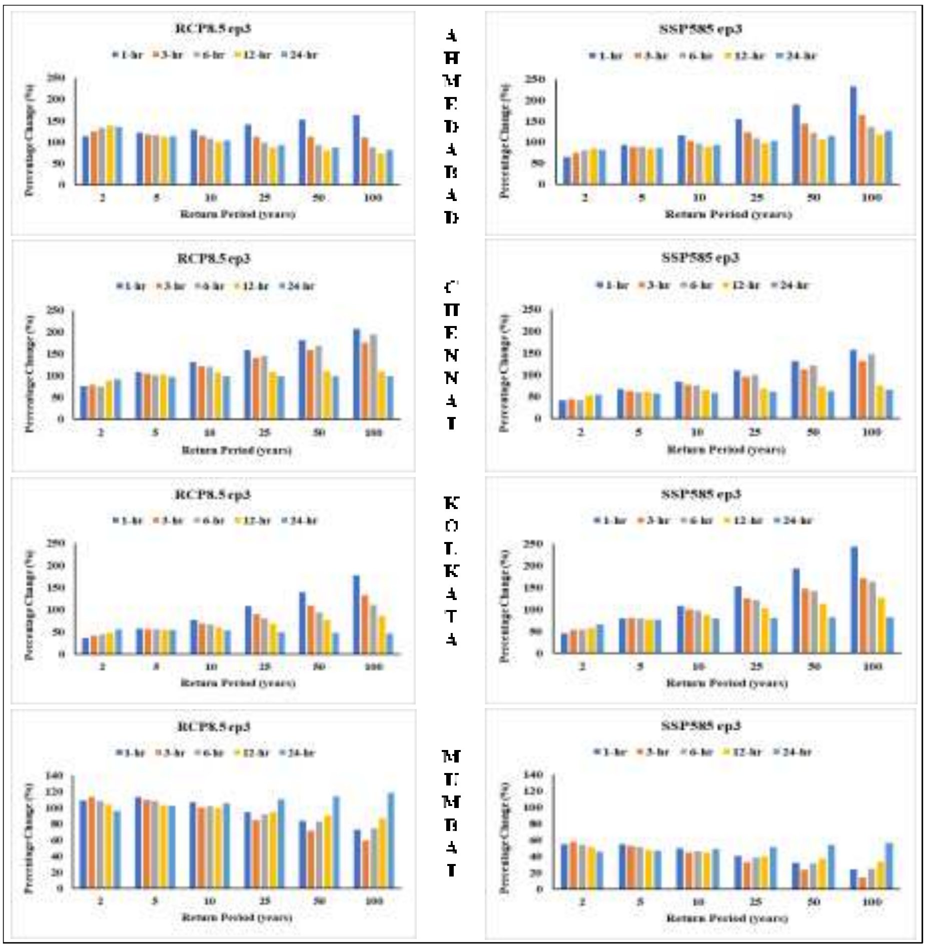

Figure 2. IDF curves for historical period (1969-2005) and future period (Far-future, ep3: 2071-2100) for four Indian cities considering 100-year return period.

Apart from global warming, the changing Land Use Land Cover (LULC) scenario can also lead to rapid accumulation of water in urban areas with a comparatively smaller rainfall intensity (Abdulkareem et al 2018). So, a comprehensive study to identify the effects of both criteria is essential before planning and designing water infrastructures.

5. CONCLUSIONS

The findings of this study indicate a significant increase in extreme precipitation intensity across the selected cities in the near- and far future. The increment range varies between 60-245% across different scenarios of CMIP5 and CMIP6. Considering all scenarios, Ahmedabad and Kolkata will experience almost a 195% increase in hourly precipitation in the future (100-year return period), whereas, for Chennai, it is approximately 175%. However, for Mumbai maximum increase is observed for extreme daily precipitation (≈90%). Irrespective of the variation in the IDF curve, the overall result indicates a need to consider such change in precipitation characteristics to adapt to the adverse effects of increasing extreme precipitation caused by climate change. Different bias-correction methods and multiple station data should be considered to reduce the cost of infrastructure design and execution arising from data uncertainty. Overall, we expect that this analysis will be helpful for future planning and design of various hydraulic infrastructures in the context of climate change.

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