Statistical Downscaling of Precipitation for Mahanadi Basin in India - Prediction of Future Streamflows

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Statistical Downscaling of Precipitation for Mahanadi Basin in India - Prediction of Future Streamflows

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Abstract

Climate change has long-term impacts on precipitation patterns, magnitude, and intensity, affecting regional water resources availability. Besides, understanding the interannual to decadal variations of streamflows in a river basin is paramount for watershed management, primarily extreme events such as floods and droughts. This study investigates impact of climate change in streamflows estimation for four sub-basins of the Mahanadi River, in India. The study includes three major components: (i) Historical trend analysis of hydroclimatic variables, using Mann-Kendall test; (ii) Statistical downscaling of GCM generated precipitation using change factor method and KnnCAD V4 stochastic weather generator; (iii) Dependable flow analysis of future streamflows predicted using Soil Water Assessment Tool (SWAT) model for various future GCM scenarios. It is observed that during the historical period, there is a decrease in number of rainy days and total annual precipitation in all sub-basins. However, the analysis also indicates an increase in flood intensity in two of the sub-basins. The decadal future precipitation has a marginal decrease in precipitation (up to 10%) for future scenarios; however, the precipitation events with high intensities increases. The results indicate that the magnitudes of 5% and 10% dependable flows are higher than the historically observed streamflows, for all future scenarios. This indicates a significant increase in extreme flood events in the basin. Further, only one of the sub-basins has shown an increase in water availability for agriculture and drinking water purposes (75% and 95% dependable flows) in the future. Understanding future flood events in the Mahanadi basin can help decision-makers to implement appropriate mitigation strategies.

Keywords: Statistical downscaling, Climate change, SWAT, Mann Kendall test, KnnCAD, Mahanadi

1. Introduction

Several studies indicate that the increased global temperature is mainly due to the rising carbon dioxide emissions (majorly due to anthropogenic activities), which have intense impacts on the hydrologic cycle (IPCC 2014)—thereby influencing the weather and climate patterns across the globe. Among the extremes, floods have direct impacts on environment and socio-economic development of the region. The planning, operation, and design of flood projection

systems need to be revised or studied under changing climatic. Besides, the quantification of climate extremes changes involves various sources of uncertainty, which requires further investigation. Most of the studies in recent years have focused to study the climate change impacts on the regional water resources, extremes such as floods and droughts, forecasting, hydro-climatological projections, water balance analysis, and water quality modelling (Singh et al. 2017, Sun et al. 2016, Apurv et al. 2015). Downscaling is one of the most widely used methods to identify and evaluate the future extreme flood risks for efficient planning, mitigation, and management. Because of the complexity in the coarse GCMs and the simplifications of the hydrological cycle, the coarse resolution GCM variables cannot be directly employed in the hydrological models. Climate models such as, the Generation Circulation Models (GCMs) estimate the future climate projections at global scale representing the complex processes which involves the coupling of land- atmosphere-ocean circulations. These are the only state-of-the-art models available for deriving the long-term climate change studies especially for the hydroclimatic variables such as temperature, wind, humidity, precipitation. These climate projections are simulated based on the expected future carbon emission scenarios or radiative forcings (IPCC 2014). There is a high degree of consent in the scientific community that GCMs are able to model the varying field types of variables correctly (e.g., surface pressure) and capture the large scale circulation patterns. However, the GCMs are unable to mimic complex processes of variables such as precipitation especially at the regional scales (Hughes and Guttorp 1994). According to IPCC 2014, the sources responsible for climate change includes natural internal processes (such as modulations in solar irradiance, volcanic eruptions, etc.) and external forcings (such as land-use changes, high GHG emissions, etc.). However, anthropogenic factors have caused persistent changes in the compositions of the atmosphere, thus are more attributable to climate change.

To capture the variations in spatial and temporal scale hydroclimatic variables, number of down-scaling methods are developed (Singh et al. 2017, Sun et al. 2016, Humphrey et al. 2016). Trzaska and Schnarr (2014) described "Downscaling is a process that converts large-scale information to finer scale information". In case of coarser spatial resolution (e.g., 500x500 km^2) is converted to finer spatial resolution (e.g., 50 x 50 km^2), it is referred to as Spatial Downscaling. On the other hand, if the downscaling is adopted to con- vert the GCM's coarser temporal scale (e.g., monthly precipitation) to finer temporal scale (e.g., daily precipitation), which is referred to as Temporal Downscaling (Xue et al. 2014). In climate research studies, the downscaling is

mainly distinguished into the following categories: (i) Dynamical downscaling (Xue et al. 2014, Mishra et al. 2014, Shukla et al. 2013); (ii) Statistical/empirical downscaling (Wilby et al. 2014) and (iii) Weather generators. Dynamical downscaling is numerically advantageous to statistical downscaling; however, these models are computationally intensive, require large amounts of datasets and a high level of manpower to generate results (Trzaska and Schnarr 2014). Statistical downscaling methods are computationally inexpensive and efficient. These methods develop a statistical relationship between the observed climate data and baseline GCM data to derive future predictions. They can provide point-scale climate variables for GCM- scale outputs. Weather generator based statistical downscaling generates sub-daily information at multiple sites and variables simultaneously to represent the long-term uncertainty due to climate change and its variations. Each downscaling method has its own limitations and uncertainties. There is no official guideline available in selecting a downscaling method that best suits the users' demands. Therefore, the climate research community is still developing the downscaling methods.

The feedback from various climatic and ecological variables regulates the hydrologic behavior of a catchment. Thereby it is difficult to formulate the relationships between these variables. Whitefield and Cannon (2000) has brought out the importance of the correlations between various hydroclimatic variables using an extensive study across Canada. The changes observed in temperature, precipitation, and streamflow (obtained from climate and hydrology stations) were clustered into different classes and investigated their spatial distribution. It was noted that there is a strong correspondence between the distribution of ecozones and hydroclimatic variables in Canada. Besides, the study highlighted that uncertainty in the variables due to climate have a major impact on the hydrologic systems.

During recent decades, India has experienced multiple destructive climate extremes. According to the Planning Commission (2011), flood disasters have affected nearly 33 million people during year 1953 to 2000. Kumar et al. (2005) reported that on July 26, 2005, the financial capital of India, Mumbai has recorded about 950mm of rainfall, causing havoc and several casualties. Gosain et al. (2006 and 2011) used HadRM2 weather simulations for 12 river basins in India to simulate the changes in future streamflows due to climate change using the SWAT model and GCM. They predicted severe flood conditions in at least three large river basins, namely, Godavari, Brahamani, and Mahanadi. Further, a report by the World Bank (2008) suggested a substantial increase in probability of intense flood frequencies in the Mahanadi basin. Climate

Change Cell (2009) reported that an increase in the extreme events and streamflow volume in the Brahmaputra River Basin (near Bahadurabad), during 1956-2007. Further, it is reported that a 5.7% decrease in forest area showed 4.5% increase in the streamflow near Mundali Outlet of the Mahanadi basin. Mujumdar (2011) used number of GCMs to project the future flow duration curves. They found that in Mahanadi River Basin the performance of the water infrastructure systems for irrigation scheduling and hydropower generation are majorly dependent on the mid-level flows (40–70%). However, the climate projections analysis show that the mid-level flows are decreasing. Similarly, Panda et al. (2013) reported decrease in streamflow trends at Mahanadi River basin (Tikerpara gauging site) in years 1972 to 2007. Some of this reduction is attributed to increased upstream usage. Sudheer (2016) observed that there is a marginal increase in extreme floods at the end of the last quarter of the 21st century for Barmanghat gauging site in Narmada basin. Moreover, Masood et al. (2015) reported rise in streamflows for Ganges-Brahmaputra-Meghna (GBM) basin. Similarly, Mishra and Lilhare (2016) found that under intermediate emission scenario (RCP 4.5) there is a considerable increase in the streamflow volumes in Rivers Ganges, Brahmaputra, and Narmada. However, for river Mahi and Tapi basins it is observed that the streamflows are decreasing. In addition, it is observed that under high emission scenario (RCP8.5) it is reported that there will be a significant increase in streamflows for all the major river basins in India. Das and Simonovic (2012) found that the mean future streamflows in Wainganga River Basin are likely to decrease when compared to the historical period.

The Soil and Water Assessment Tool (SWAT) is an open-source, integrated, and semi-distributed hydrological model developed by the United States Department of Agriculture- Agricultural Research Service (USDA-ARS). Due to its flexibility in watershed modelling, it has been extensively adopted in solving a wide variety of challenges involved in environment, hydrology, and water resources. SWAT model divides the basin based on spatial variations of parameters into multiple sub-basins. [25, 26]. To assess climate change impacts, various studies have adopted SWAT model, especially to understand streamflows variations. Sood et al. (2013) used IPCC A1B scenarios to evaluate effect of climate change on streamflow prediction (years 2021-2050 and 2071–2100) of the Volta River basin, West Africa, when compared to 1983–2012. Sun et al. (2013) found seasonal variations in the future streamflows when compared to the historical flows. It is reported that winter and spring seasons are more affected due to changing climate conditions in future when compared to the other seasons.

Bhatta et al. (2019) assessed SWAT model performance in streamflow predictions for the

Tamor River Basin and quantified uncertainty related to elevation bands, hydrologic response units, and number of sub-basins. Lee et al. (2018) evaluated the impacts of changing precipitation, temperature and Carbon-dioxide on the crop growth. Sharannya et al. (2018) evaluated climate change impacts on precipitation, temperature, and runoff, using SWAT model. For baseline period analysis, the daily weather data generated by CORDEX was used, while the future period analysis was done using RCP4.5 scenario. Shiferaw et al. (2018) developed a SWAT model for Ilala watershed (Ethiopia) for surface runoff generation under changing climate scenarios. The Change Factor Methodology was adopted for statistical downscaling of RCP4.5 and RCP8.5 data. It was observed that there is a significant decrease in runoff in the near future under RCP4.5, while the decrease at the end of the century is minimal for RCP8.5. Shrestha et al. (2018) used SWAT model to identify the impacts of climate change on future streamflows and found a significant decrease in streamflows (19.5% and 24%) and nitrate loadings (11.25% and 15.25%) for RCP4.5 and RCP8.5, respectively. Khalilian and Shahvar (2019) studied the climate change impacts on streamflows and drought characteristics using SWAT and SPI, respectively in Salt Lake sub-basin, Iran. It is observed that under A2 climatic scenario (2027) there is a 2 ^{o}C and 20% decrease in temperature and precipitation, respectively, causing increase in drought severity. The study area also reported 10% reduction in surface water resources, 16% reduction in aquifer recharge, and 20% reduction in renewable water under changing climate.

The study examines climate change impacts on floods in the Mahanadi basin, India. Climate scenarios developed from the GCMs are linked to hydrological models to extract the peak flow values. Trend analysis has been proposed in the study to examine the behavior of rainfall and runoff variables. The large-scale GCM precipitation is downscaled using the delta change method. Further to assess the impacts of climate change, the future streamflows are predicted using SWAT model based on represented concentration pathways (RCPs) as future scenarios.

2. Case Study

The Mahanadi River Basin (Latitude 19°8’-23°32’ N and Longitude 80°28’-86°43’ E) is one of the largest watersheds among the major river systems in India. The majority of the basin (almost 99%) extends over Odisha and Chhattisgarh states, and significantly smaller area of basin is located in Madhya Pradesh, Maharashtra, and Jharkhand states. The Mahanadi river extends over 357 km, after originating from Chhattisgarh (Raipur district) and covers a stretch of 494 km in Odisha, covering total length of 851 km. It separates into multiple streams and finally

discharges to the Bay of Bengal. The basin received the average, maximum, and minimum precipitation of 366.98 cm, 66 cm, and 145.8 cm, respectively, from 1901 to 2008. Among the 14 major tributaries of the Mahanadi river, 12 connect to the Hirakud reservoir upstream, and other two join the reservoir downstream. Odisha state has experienced severe floods, which caused massive destruction to life and property. Hydrological model at a gauge station in Naraj (located Northwest of Jagatsinghpur) projected daily discharges and showed an increase in the probability of flooding under different climate scenarios. The multi-purpose Hirakud dam provides limited flood protection and cannot regulate the flood peaks to a safe flood limit (24,660 cumecs). A study on historic floods in the Mahanadi basin [35] from 1961 to 2011 shows that the causes of major floods in the region are: (i) 69% is due to the downstream uncontrolled catchment (beyond Hirakud reservoir up to Munduli, ahead of Mahanadi delta); (ii) 23% jointly due to Hirakud and downstream catchment up to Munduli, and (iii) remaining 8% were only due to Hirakud releases. The investigation concluded that the hydrologic response under climate change over the uncontrolled catchment beyond Hirakud has to be studied. Figure.1 shows the study area details, including the gauge and discharge sites for Ong, Ib and Tel tributaries flowing downstream of Hirakud dam (middle of Mahanadi basin). The daily discharge data at the gauging sites obtained from Central Water Commission (CWC) is provided in Table.1. 1^ox1^o average gridded precipitation data from 1901 to 2004 purchased from Indian Meteorological Department (IMD), Pune is used for climate change investigation.

3. Methodology

3.1. Statistical Trend Analysis

The Mann-Kendall (M-K) is adopted in this study to identify the linear trends in time series of precipitation and discharge. Several studies have extensively used the M-K test to determine whether a time series of climatic variables, particularly the rainfall characteristics has a monotonic upward or downward trend in relation to climate change (Taylor and Loftis 1989, Burn 1994, Burn et al. 2004). Before applying M-K test it is necessary to recognize the serial correlation present in the data. For the Mahanadi River Basin data, various blocks are tested to identify serial correlation. For the detailed steps involved in the M-K test, readers are referred to (Salas 1993, Storch and Navarra 1995, Partal and Kahya 2006).

3.2. Statistical Downscaling

The Global Circulation Models (GCMs) provide the climate information at global or continental scale. Downscaling is adopted to build a relationship between GCM outputs and regional or local climate variable (coarser to finer spatial resolution). Downscaling is classified as dynamical and statistical downscaling approaches. The first approach deals with the regional scale derivation of GCM outputs, using the boundary conditions of GCMs and local physiographic information. The models obtained are called regional climate models (RCMs). The latter one is preferred to spatially downscale GCM outputs to local scale. The dynamic downscaling process demands ample amount of data and is computationally extensive. Also, the uncertainty in the GCMs significantly affects the outcomes of the dynamically downscaled results [42, 43]. on the contrary, statistical downscaling is a less computationally demanding approach. It is based on the principle of inter-dependency among the climate data and regional data having physiographic characteristics (IPCC 2014).

Weather generators are generally used to replicate statistical characteristics of local climate data to generate long simulations of climatic variables. they have also adopted for temporal downscaling of monthly or annual average data to obtain multiple daily time series of weather variables. The method requires large amount of data and post-processing of the outputs. On the other hand, the Change Factor (CFM) or Delta change Method is being extensively used in statistical downscaling due to its easy and computationally straight forward application. changes projected by future climate models can be incorporated in the historically observed climate variables using Change Factors (CFs). Different change factor methodologies are comprehensively explained in Anandhi et al. (2011). There are two types of CFs, namely additive and multiplicative CFs as given in equations 1 and 2.

$$CF_{add} = \overline{GCM_f} - \overline{GCM_b} \tag{1}$$

$$CF_{mult} = \overline{GCM_f} \,/\, \overline{GCM_b} \tag{2}$$

Where, $\overline{GCM_b}$ and $\overline{GCM_f}$ are average of modelled climate values over baseline and future period respectively. These CF_{add} and CF_{mult} are then added and multiplied respectively to the observed local climate variables to obtain the future modelled values.

3.3. KnnCAD Version 4 Algorithm

In this study KnnCAD V4 based stochastic weather generator (King et al 2015) is used to simulate multi- variable hydroclimatic data for future time-periods. The two major components of

the KnnCAD V4 model are: (i) preservation of spatial characteristics using identification of 'k' nearest neighbors, covariance matrix of potential neighbors and PCA; and (ii) preservation of temporal characteristics using Mahalanobis distance and block bootstrapping. In addition, the method uses perturbation to generate the extremes. The nearest-neighbor models are easily applicable for several sites unlike the parametric weather generators which is restricted by the statistical assumptions. For the detailed steps involved in KnnCAD V4 algorithm, the readers are referred to (King et al. 2015).

3.4. SWAT Model Description

SWAT model encompasses several components of watershed management such as hydroclimatic variables, soil characteristics, sediment yield, crop yield, pesticides and nutrients, and alter- native management scenarios for effective management of water resources. For brevity the readers can refer to (Saleh et al. 2009) for the detailed description on the SWAT data structure and inputs. The SWAT model involves two major components: (i) Hydrological component- Prediction of soil water con- tent using water balance equation; and (ii) Surface Runoff Estimation - Using Soil Conservation Service-curve number method (SCS-CN). Curve number can be estimated by considering the evapotranspiration. The SWAT theoretical documentation (Neitsch et al. 2005) provides a detail explanation on the SWAT components, equations, curve numbers and their adjustments for various soil and moisture conditions.

The SWAT model performance is evaluated using Nash-Sutcliffe efficiency N_{SE}. The details about model performance measures is presented as follows:

$$NSE = 1 - \frac{\sum_{t=1}^{T} \left(Q_0^t - Q_m^t\right)^2}{\sum_{t=1}^{T} \left(Q_0^t - \overline{Q}_o\right)^2} \tag{3}$$

Where, Q_0^t *and* Q_m^t are observed and modelled discharges at time t, respectively. $\overline{Q}_o$ is average observed discharge. NSE value of 1 implies an exact fit between the model simulated and observed values.

3.5. Spatial Interpolation of Gridded Observed Data and GCM Data

The Inverse Distance weighting (IDW) method is adopted to determine the unknown value of any ungauged location. In this method, the nearest grid points to the ungauged station are weighted by an inverse distance function from the station to the grid points. Thus, the closest grid points

are weighted more than the grid points further away from the station.

The mathematical expression for IDW method is given as:

$$w_i = \frac{1/d_i^2}{\sum_{i=1}^{k} 1/d_i^2} \tag{4}$$

Where, d_i is a distance from the ungauged station to the ith grid point. k is number of nearest grid points. Spatially interpolated precipitation for the ungauged station using the above weights can be calculated using formula given by:

$$P = \sum_{i=1}^{k} P_i w_i \quad (5)$$

4. Results and Discussions

4.1. Trend Analysis for Precipitation and Discharge Data

The precipitation and discharge trends are identified using the Mann-Kendall test. The discharge data series is tested for serial correlation, and it is observed that a significant correlation is obtained at 95% confidence level. Thus, the pre-whitened data series is used further for the M-K test. Table 2 implies that Kantamal and Kesinga gauging sites on Tel tributary are experiencing an increasing trend. In contrast, Salebhatah gauging site on Ong tributary is experiencing a decreasing trend. A similar analysis is carried out for precipitation at four gauging sites obtained from spatially interpolated IMD gridded climate data. The M-K test results for monthly precipitation are tabulated in Table 3, which shows that the precipitation series does not experience a significant statistical trend during monsoon months. Despite that the seasonal precipitation shows a decreasing trend at all gauging stations in both the seasons (Table 4). However, decreasing trend in the non-monsoon season is not significant. In addition, a monthly variation of precipitation from 1961 to 2003) is presented in the Figure 2. It is observed that Sundergarh and Kantamal sub-basins of the Mahanadi river are receiving maximum rainfall during monsoon season.

Further analysis is carried out to verify the precipitation pattern using total number of rainy days (Figure 3). For all sub-basins, the plots indicate a decreasing number of rainy days over the years for all four sub-basins, with the highest decrease in precipitation events observed for Kesinga sub-basin. The precipitation events with 50 mm, 75 mm, and 100 mm intensities for four sub-basins are plotted and presented in Figures 4 and 5. It is observed that the precipitation events are increasing for all sub-basins. However, the Sundergarh sub-basin has a marginal decrease in number of rainy days for all precipitation intensities. This has resulted in the increased dry spells within the catchment. It is also evident from the analysis that although the Tel river basin has experienced fewer precipitation events, their intensities have increased. It is also evident from the increasing discharge trends observed for Kantamal and Kesinga gauging sites.

4.2. Statistically Downscaled GCM Data for Mahanadi Basin

In this analysis, an integrated approach combining change factor methodology (CFM) and KnnCAD weather generator is used to predict future climate variables (2006-2100). CanESM2 model data (grid size: 256 x 192 km) with realisations R1 to R5 is downloaded from (Climate Model Data). The data consists of historical (1950-2005) and future precipitation projections (2006-2100) based on three emission scenarios: low (RCP2.6), intermediate (RCP4.5), and high (RCP8.5) level. The CFM is adopted for downscaling precipitation data from future time scales based on combinations of 75 GCM outputs for four sub-basins of Mahanadi river.

The analysis shows that no significant variations have been observed for daily, monthly and annual precipitation during the future projection period in all 75 GCM combinations. For brevity, the results are presented only for R1 realisation of CanESM2 model. The decadal variation of precipitation for future projection period (2006-2050) for each RCP is shown in Figure 6. It can be noted that during the mid-century period, all sub-basins have a marginal decrease in precipitation (Salebhata: 6.7-8%, Sundergarh: 7.6-10%, Kantamal: 3 to 4%, Kesinga: 1.5-2.5%). The results also indicate that the precipitation decreases from RCP2.6 to RCP4.5, whereas from RCP4.5 to RCP8.5, it rises. Among the sub-basins, Kantamal and Kesinga sub-basins have shown a minimum precipitation changes in the future.

Further, to verify the future precipitation patterns, an analysis is carried out similar to historical precipitation events for all GCM combinations. For brevity, the results are shown for R1 realisation of CanESM2 model in figures 7-10, which indicate the variation in number of rainy days with in- tensities 50mm, 75mm, and 100mm for each sub-basin for 2007 to 2050. It is observed that for all intensities precipitation events are increasing with increase in climate projection scenarios (RCP2.6 to RCP8.5) for all sub-basins. From Figures 7 and 8, it is evident that in Salebhata and Sundergarh sub-basins, the number of high-intensity precipitation events (more than 100 mm) is significantly less compared to Kesinga and Kantamal sub-basins in future periods. Salebhata sub-basin shows no trend for low-intensity precipitations and a marginal increase for high-intensity precipitation. At the same time, the Sundergarh sub-basin has a marginal decreasing trend for all precipitation intensities. This may cause a rise in high-intensity rainfall events in Salebhata sub-basin and dry spells in Sundergarh sub-basin in future periods. The Kesinga and Kantamal sub-basins have increased precipitation events in the future periods, with the maximum increase observed in the Kesinga sub- basin (Figures 9 and 10). This indicates

the Tel river basin can experience more precipitation events with higher intensities.

4.2.1. SWAT model Application to Mahanadi Basin

The major inputs used in SWAT model for Mahanadi basin includes: (i) DEM (Shuttle Radar Topography Mission (SRTM); (ii) Land use ; (iii) Soil type (soil maps of scale 1:250,000 from Nation Bureau of Soil Survey and Land Use Planning); and (iii) Climatic datasets: Precipitation and temperature from IMD ($1^o \times 1^o$) (Rajeevan et al. 2006). The maps showing SWAT model setup along with the drainage networks for Kantamal, Kesinga, Sundergarh, and Salebhata sub-basins are shown in Figure 11, respectively. In this analysis, 5 years of warm-up period is considered. Based on the availability of the gauging sites data, different calibration periods are adopted for each site, such as Salebhata (1978-2000), Sundergarh (1983-2000), Kesinga (1983-2000), and Kantamal (1978- 2000). The remaining data record of 9 years (2001 to 2009) is used for validation at all the sites.

The efficacy of the SWAT model performance is carried out using Nash-Sutcliffe Efficiency (NSE). It is observed that the models have been well calibrated and have shown reasonably good NSE values. The efficiencies for Kantamal, Kesinga, Sundergarh, and Salebhata sub-basins are reported as 78%, 82%, 76%, and 68% respectively. Table 5 represents the calibrated parameters and efficiency for different gauging sites during calibration. Figure 12 represents the observed and SWAT simulated flows during the calibration period. It is observed that the characteristics of the historical streamflows are well preserved, however the extremes are not well preserved. One-at-a-time (OAT) technique-based sensitivity analysis is performed and following parameters are observed to be sensitive: *CN_2*, *SOL_AWC*, *SOL_K*, *ALPHA_BF*, *ESCO*, *GWQMN* and *GW_DELAY*. After calibration, the models have been validated with the independent dataset for the period 2001-2009). To assess the climate change impacts, this validated SWAT model is further used for analysis of future water resources.

4.3. Future Water Resources Scenario in Mahanadi Basin

The future projected precipitation at four gauging sites is adopted in for calibration and validation of SWAT model. It is simulated for different combinations of GCMs, i.e., from low to high (RCP2.6 to RCP8.5) emission scenarios with different realisations and for the three selected time horizons (2006-40, 2041-70, and 2071-99). These alternate climate scenarios are further analysed for simulating outflows: (i) to identify changes in availability of water and (ii) the extreme events.

An empirical distribution is fitted to perform the dependable flow analysis (Weibull 1951). Dependable flow represents a relationship between volume of water available for utilization and the period of time for which its available during a year. In this study, the dependable flow is estimated at five exceedance probability which includes: (i) extreme flood events (5% and 10% dependability), (ii) moderate flood events (20% dependability), (iii) median flows (50% dependability), (iv) water availability for agriculture (75% dependability), and (v) water availability for domestic drinking demand (95% dependability). The annual dependable flows at four gauging sites for different GCM emission scenarios are compared and represented in Figure 13-16. It is observed that for all future scenarios in Mahanadi River Basin there is a considerable increase in 5% and 10% dependability flows. This indicates an increase in extreme to moderate future flood events for few sub-basins. The depend- able flows in each sub-basin are compared with the historical observed flows and the results are as follows:

1. Salebhata sub-basin
   (a) The 5% dependability flows have decreased in the future, which indicates decrease in extreme future flood events.
   (b) The 10% and 20% dependability flows have increased considerably, indicating increase in moderate flood events.
   (c) Also, there is availability of median flow (50% dependability) during the future periods.
   (d) The 75% and 95% dependability flows are not observed in the future periods.

2. Sundergarh sub-basin
   (a) R1, R2, and R5 realisations of RCP8.5 scenario show a significant increase in 5% and 10% dependability flows compared to the other two scenarios and realisations. This can increase the occurrences of the extreme floods in future period.
   (b) The 20% dependability flows have increased, indicating increase in moderate floods in the future period.
   (c) The median flows have also increased for all scenarios in future period.
   (d) The 75% and 95% dependability flows are not observed in the future periods.

3. Kesinga sub-basin

   (a) There is a significant increase in 5% and 10% dependability flows indicating increase in extreme flood events in the future.

   (b) The 20% dependability flows have increased in the future period, which indicates in-crease in moderate flood events.

   (c) The median flows are also increased in the future period.

   (d) There is no availability of 75% and 95% dependability flows.

4. Kantamal sub-basin

   (a) There no change in 5% dependability flows. This indicates similar future extreme flood events as the historical period.

   (b) The 10% and 20% dependability flows have moderately increased in the future period, which indicates increase in the moderate flood events.

   (c) The median flows are significantly increased in future period.

   (d) There is significant increase in 75% and 95% dependability flows, indicating availability of water in future period for agriculture and domestic drinking requirement.

5. Summary and Conclusions

In the present study, a Mann-Kendall trend analysis is carried out for historical rainfall and discharge series for the Mahanadi river basin of Odisha. After finding a significant correlation in discharge data, the pre-whitened discharge series is provided for M-K test. Daily discharge trends are analysed for various gauging sites, and it is observed that the Tel tributary is experiencing an increasing trend, whereas the Ong tributary is experiencing decreasing trend. Daily, monthly and seasonal precipitation trends are analysed for the period between 1961 and 2004. No trend is found for daily and monthly precipitation data. It is to be noted that during the monsoon period, rainfall decreases significantly for two sub-basins (Salebhata and Sundergarh) using the M-K test. During the non-monsoon season, a decreasing trend is observed for all stations, but these are not

significant. The historical (1961 to 2004) precipitation variation points out a reduction in number of rainy days and total annual precipitation for all sub-basins. Kesinga sub-basin has observed the highest decrease in precipitation events in the Mahanadi basin. However, the precipitation events with high intensities (more than 100mm precipitation) have increased over the Kesinga and Kantamal sub- basins, indicating an increase in the Tel tributary discharge.

The precipitation data obtained from CanESM2 GCM has been downscaled using the change factor method in combination with KnnCAD to extract future climate projections (2006-2100). It is observed that the KnnCAD approach can capture the statistical relationship between the observed and GCM simulated data. The decadal analysis of projected precipitation shows a slight decrease in precipitation (1.5 to 10%) for all RCP scenarios. However, the number of precipitation events with high intensities are increasing in the Tel tributary. All the RCP scenarios indicate an increase in future precipitation intensities. It is observed that the RCP2.6 and RCP4.5 show a moderate increase in the precipitation intensities, whereas RCP8.5 shows a significant increase. The SWAT model has been developed for four sub-basins to generate future discharge scenarios using down-scaled data. The SWAT model simulations show that an increase in the extreme rainfall events will get translated into floods in the Mahanadi basin. The dependable flow analysis using the future model simulations indicated that the magnitude of flood events is expected to increase substantially compared to observed historic floods.

6. Limitations and extensions

1. The study includes change factor methodology for statistical downscaling of precipitation; however various regression-based techniques can be adopted to improve the performance.
2. The study is restricted to only precipitation as a predictor for its downscaling; however other hydroclimatic variables such as temperature, humidity, pressure, geopotential height, etc. can be included in the analysis for better prediction of precipitation.
3. In this study, only CanESM2 model data has been adopted to obtain climate change projections; however various GCM ensembles with their realisations can be included in the analysis.

Declaration

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Conflicts of interest/Competing interests: Authors declare that they have no conflict of interest.

Availability of data and material : Some data pertaining to the rainfall, river flow which is classified data used in the study were provided by a third party (Water Resources Department, Govt. of Odisha and Central Water Commission, Bhubaneswar, India). Direct request for these materials may be made to the provider.

Code availability: The codes are available in public domain

Authors' contributions: Conceptualization: [Nayak P. C.]; Methodology: [Nayak P. C., Roshan Srivastav]; Formal analysis and investigation: [Nayak P. C., Poonam Wagh, Venkatesh B., Thomas T., Satyaji Rao Y.R.S.]; Writing - original draft preparation: [Nayak P. C., Poonam Wagh]; Supervision: [Nayak P. C., Roshan Srivastav].

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S.No.	Gauging site	Tributry	Period	Years	Catchment area (sq.km)
1	Salebhata	Ong river	1971-2009	39	4650
2	Sundergarh	Ib river	1978-2009	32	5870
3	Kesinga	Tel river	1978-2009	32	11,960
4	Kantamal	Tel river	1972-2009	38	19,600

Table 2: M-K sign test result for discharge data

S.No.	Gauging site	Tributry	H	p	alpha	Z	Inference
1	Salebhata	Ong river	1	6.63E-06	0.05	-3.989	Decreasing trend in the Pre-whitened series
2	Sundergarh	Ib river	0	0.8121	0.05	0.2377	NO trend in the Pre-whitened series
3	Kesinga	Tel river	1	0	0.05	35.79	Increasing trend in the Pre-whitened series
4	Kantamal	Tel river	1	0	0.05	30.11	Increasing trend in the Pre-whitened series

Table 3: M-K sign test result for monthly precipitation data

S.No.	Gauging site	H	alpha	Z	Inference
1	Salebhata	0	0.05	-0.65791	NO trend
2	Sundergarh	0	0.05	-0.61984	NO trend
3	Kesinga	0	0.05	-0.69411	NO trend
4	Kantamal	0	0.05	-0.43594	NO trend

Table 4: M-K sign test result for seasonal precipitation data

S.No.	Gauging site	H	alpha	Z	Inference
1	Salebhata	0	0.05	-1.34522 (M) -0.25117 (NM)	Decreasing trend
2	Sundergarh	0	0.05	-1.83071 (M) -0.83725 (NM)	Decreasing trend
3	Kesinga	0	0.05	-0.83950 (M) -0.69073 (NM)	Decreasing trend
4	Kantamal	0	0.05	-0.77881(M) -0.35583 (NM)	Decreasing trend

Table 5: Calibrated parameters and efficiency for each sub-basin

Parameter	Kantamal		Kesinga		Sundargarh		Salebhata	
	Calibrated values	Rank	Calibrated values	Rank	Calibrated values	Rank	Calibrated values	Rank
ALPHA_BF	0.95	6	6.84E-0.1	6	0.18	5	0.03	7
CN2	76.40	1	81.70	1	76.10	2	85.10	1
EPCO	0.42	9	0.82	9	0.61	1	0.00	10
ESCO	0.04	4	0.77	4	0.65	4	0.12	4
GW_DELAY	3.00	10	7.38	10	5.33	6	0.00	9
GWQMN	402.00	3	820.00	3	745.00	7	0.27	3
RCHRG_DP	0.76	2	0.16	2	0.70	10	0.66	2
SOL_AWC	12.00	5	21.50	5	20.50	3	0.10	5
SOL_K	16.6	7	19.90	7	19.80	9	0.04	6
SURLAG	0.92	8	0.00	8	0.25	8	0.02	8
NSE	0.78		0.82		0.76		0.68	

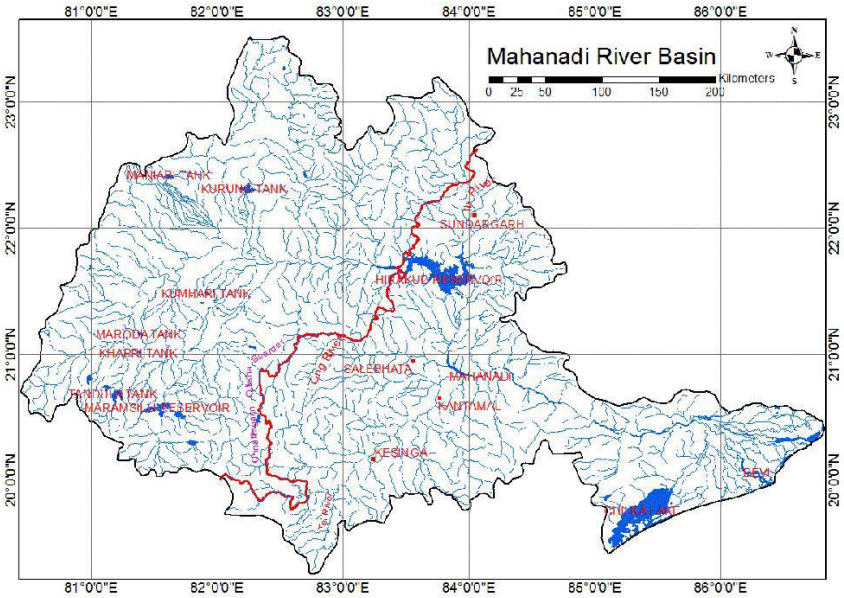
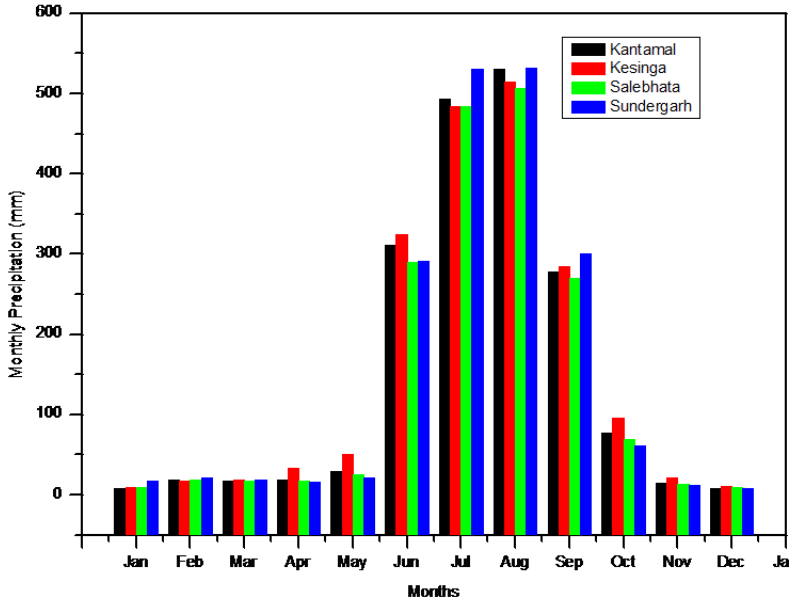


Figure 1: Map showing gauging sites for the Mahanadi basin



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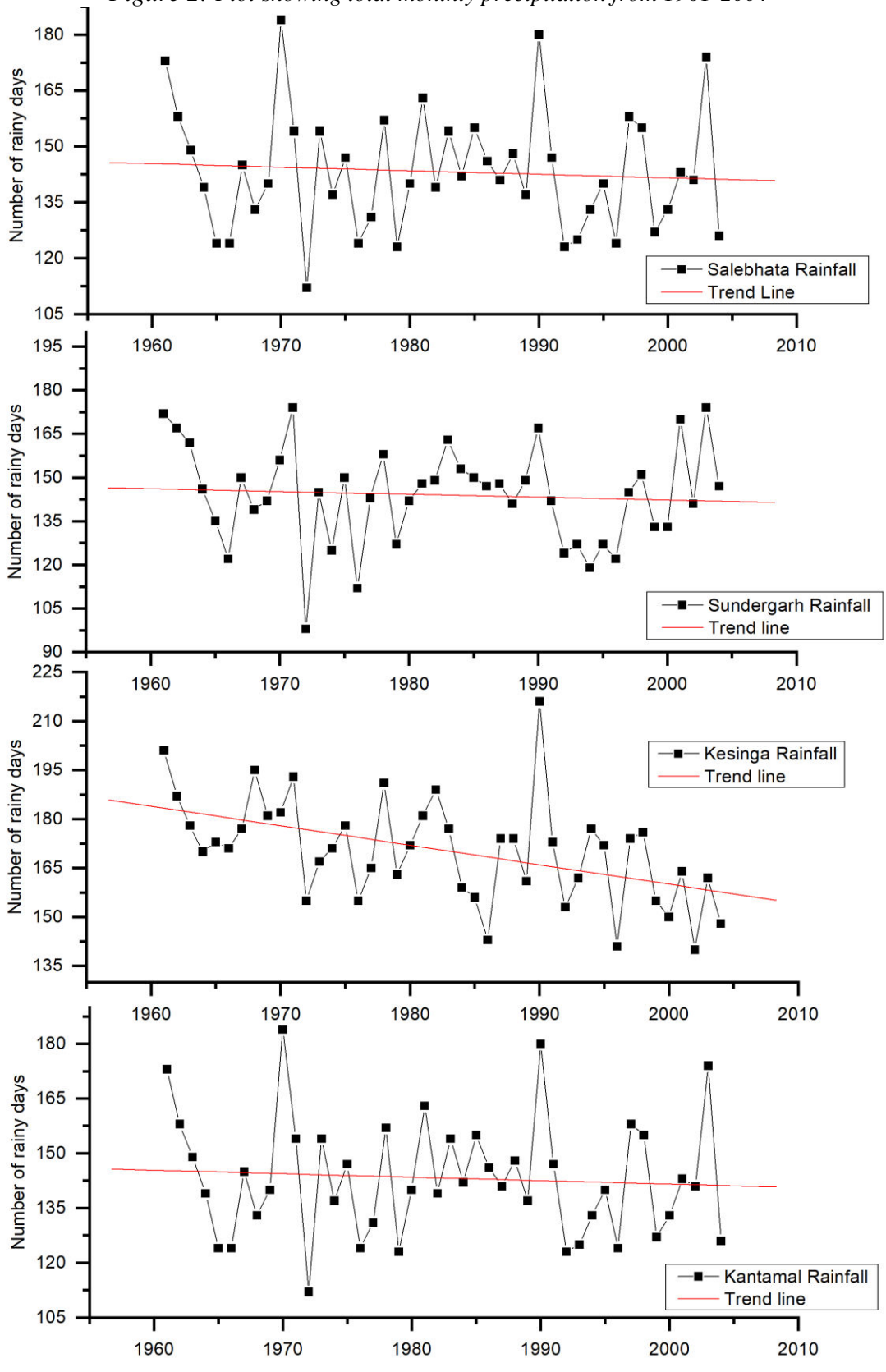

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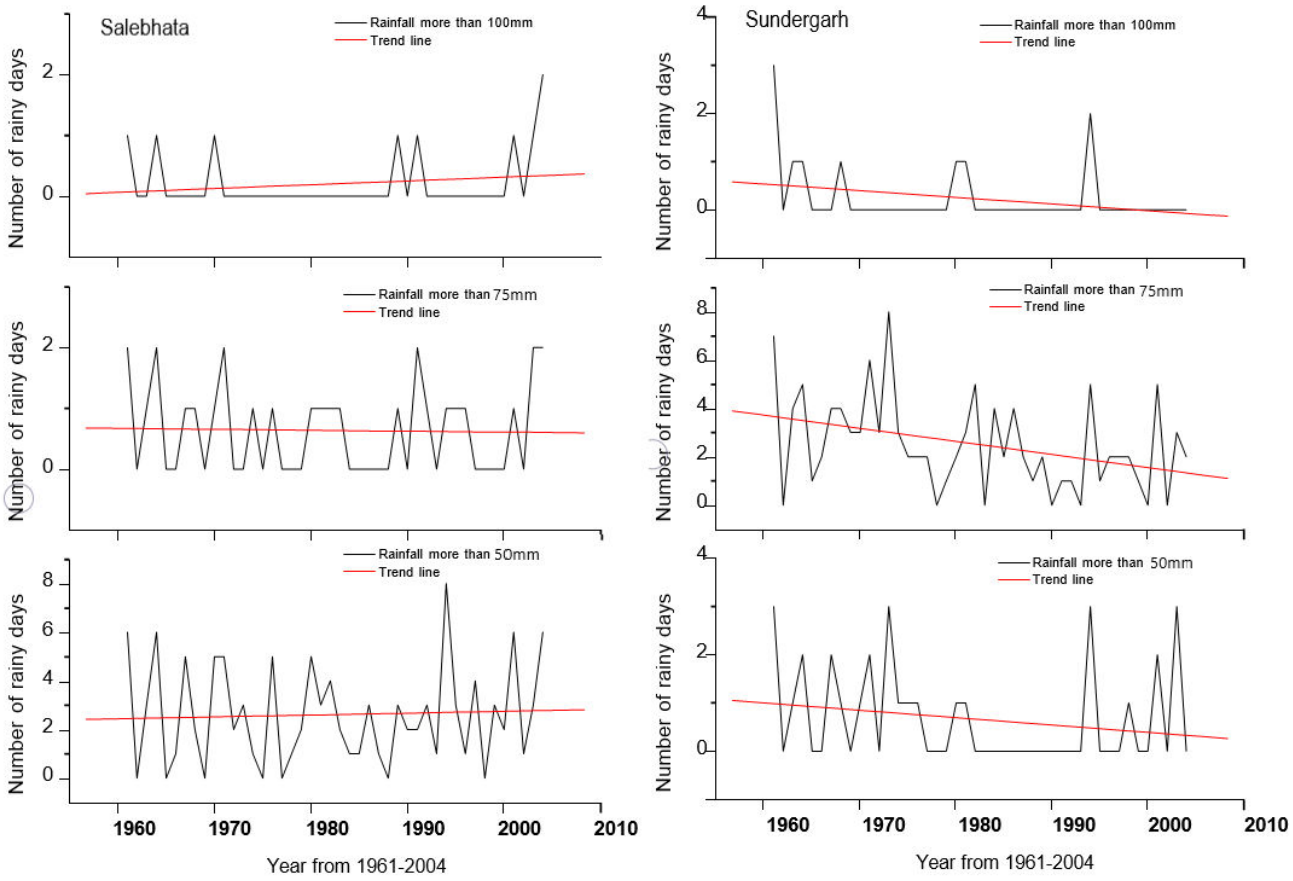
Figure 3: Number of rainy days for different sub-basins in Mahanadi river for years 1961 to 2004



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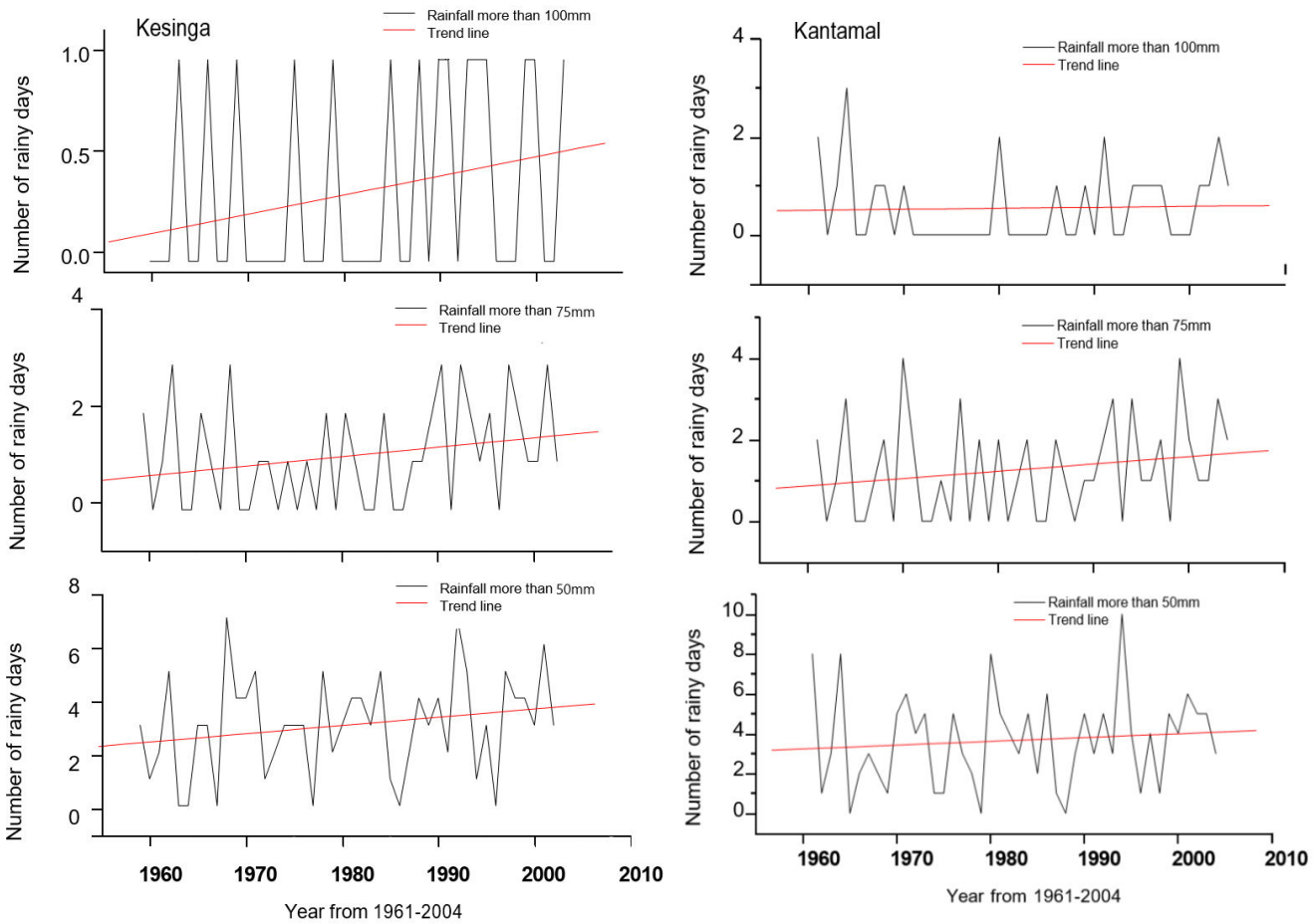

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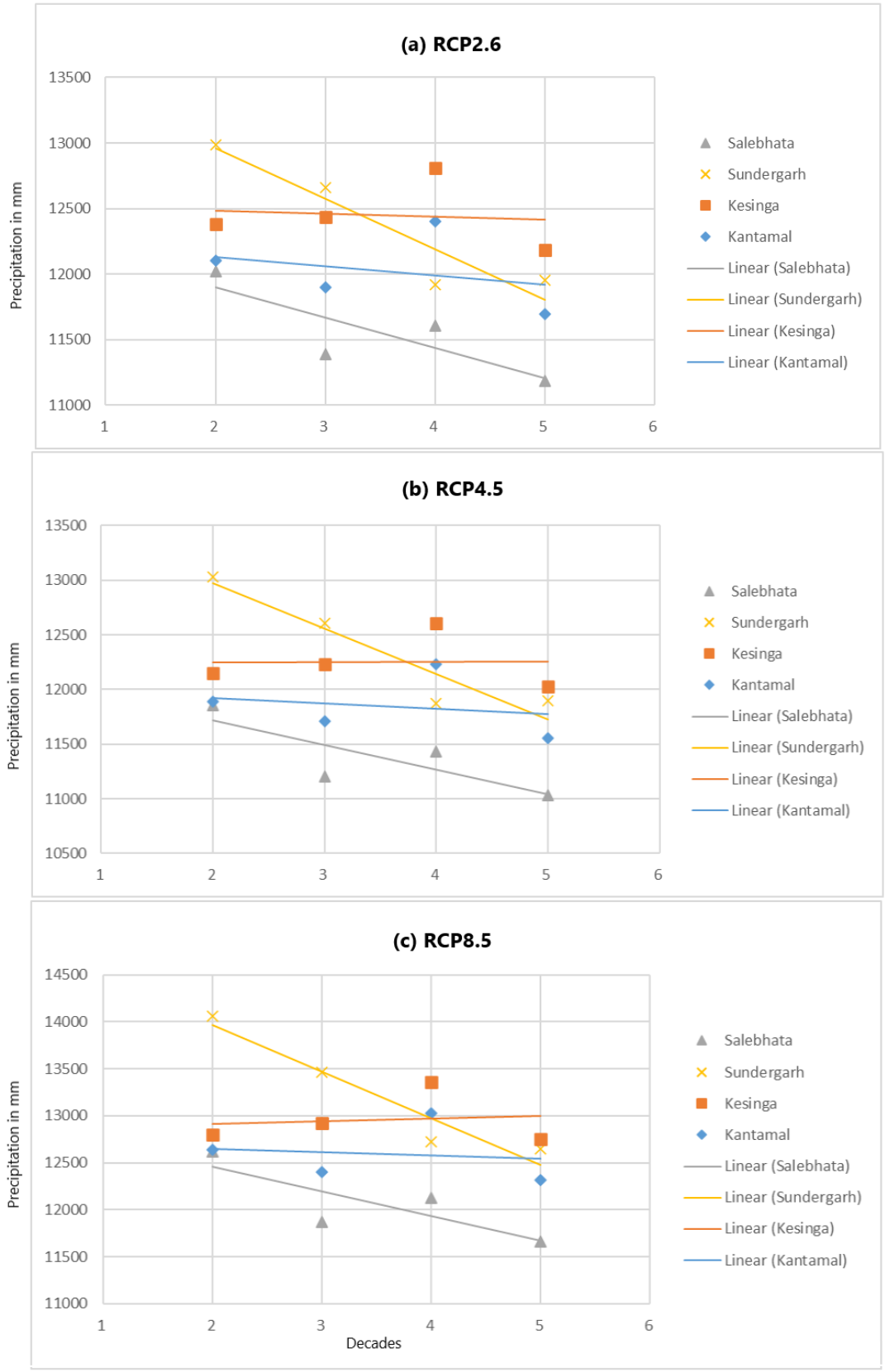

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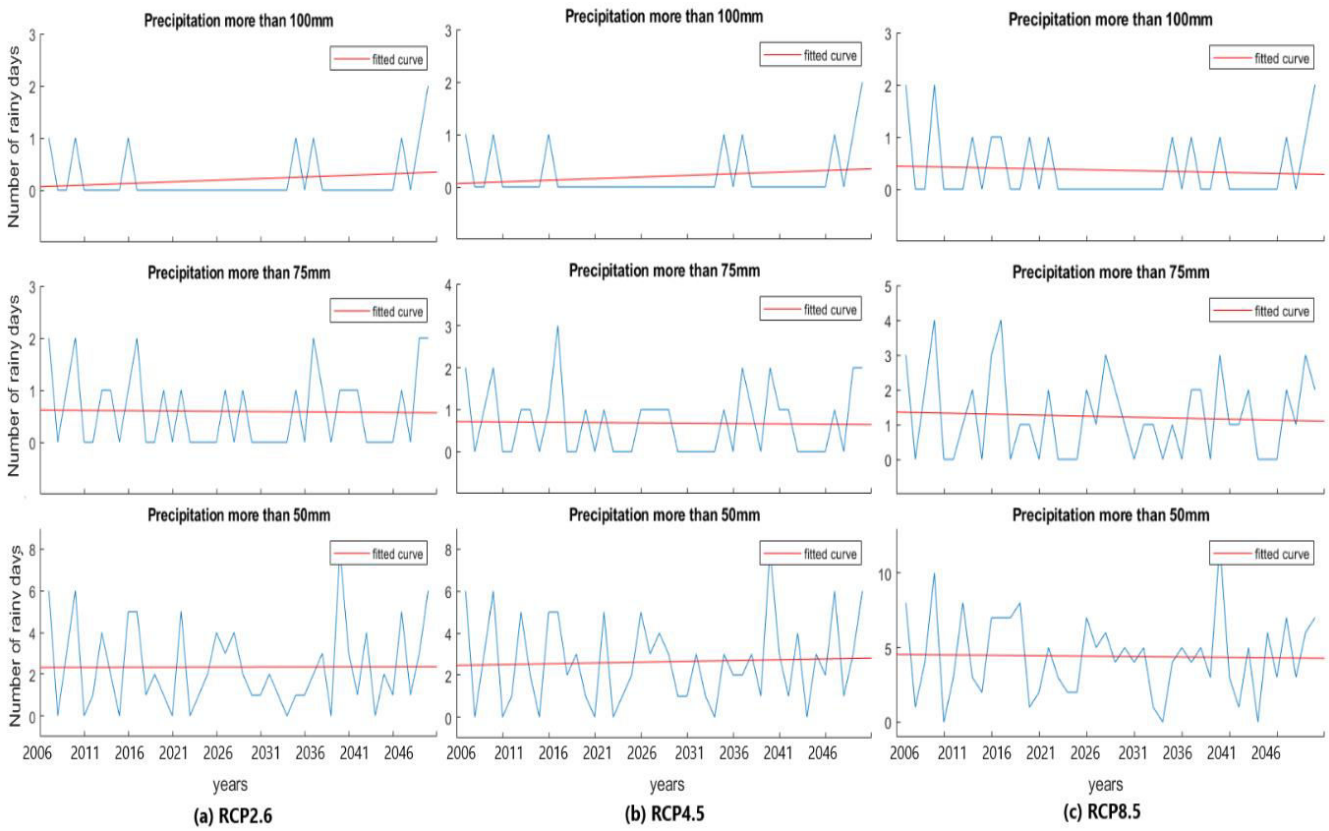

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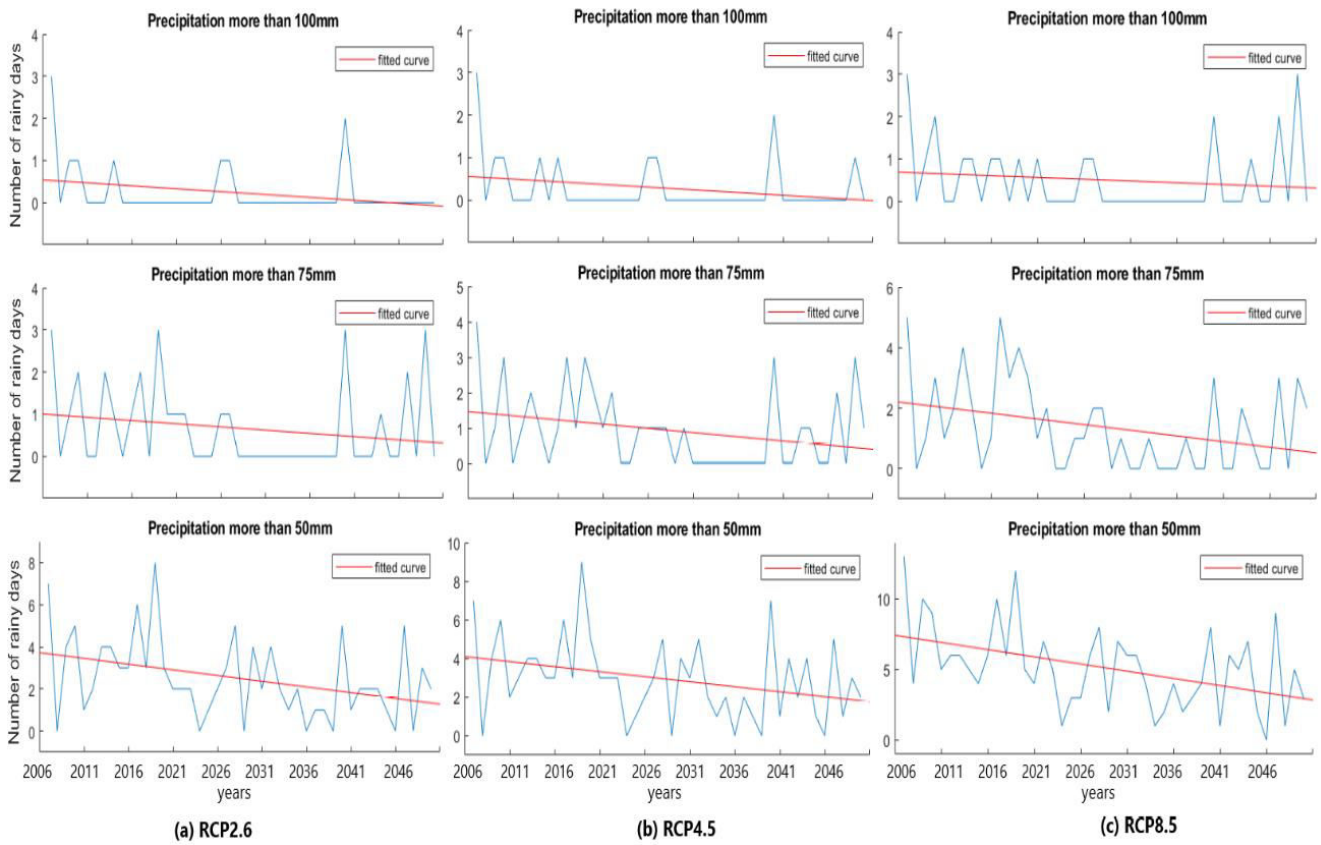

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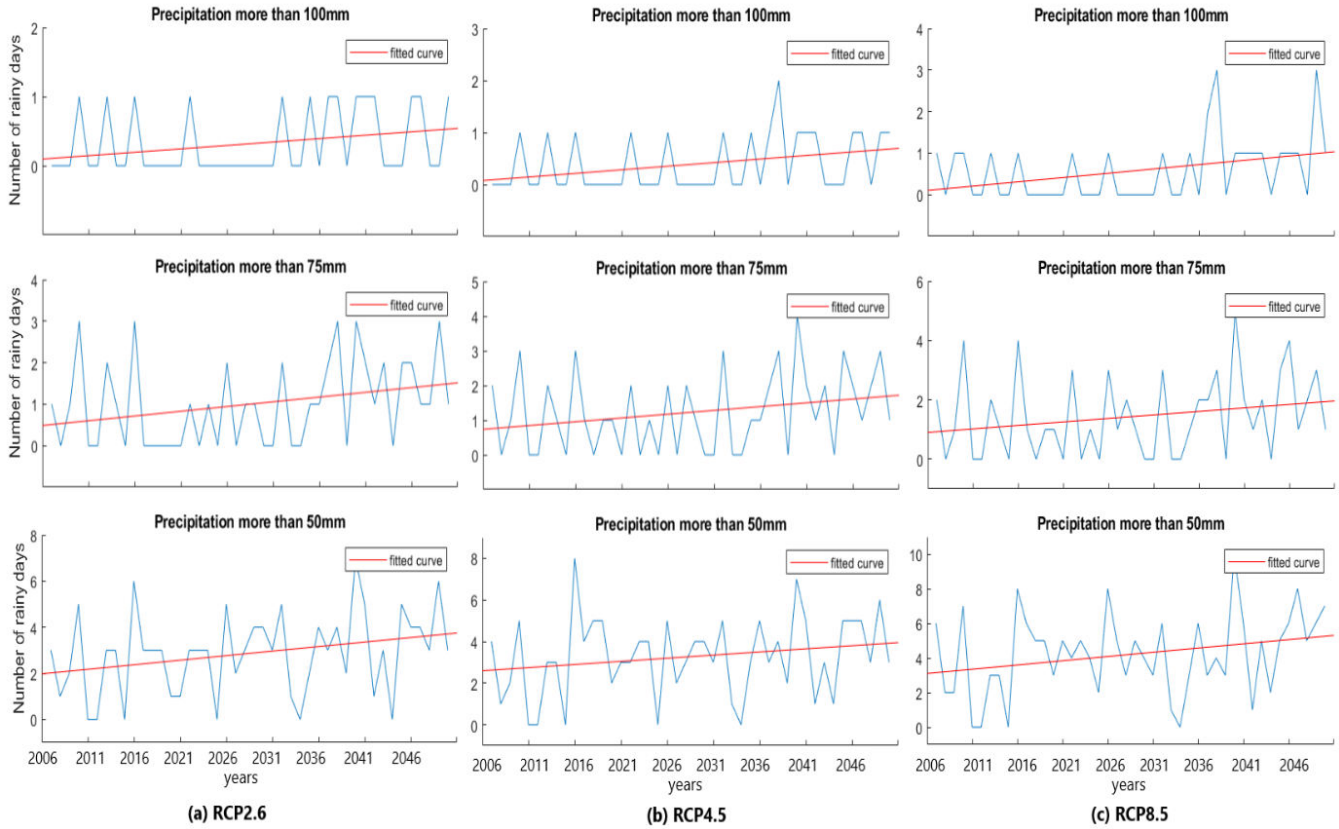

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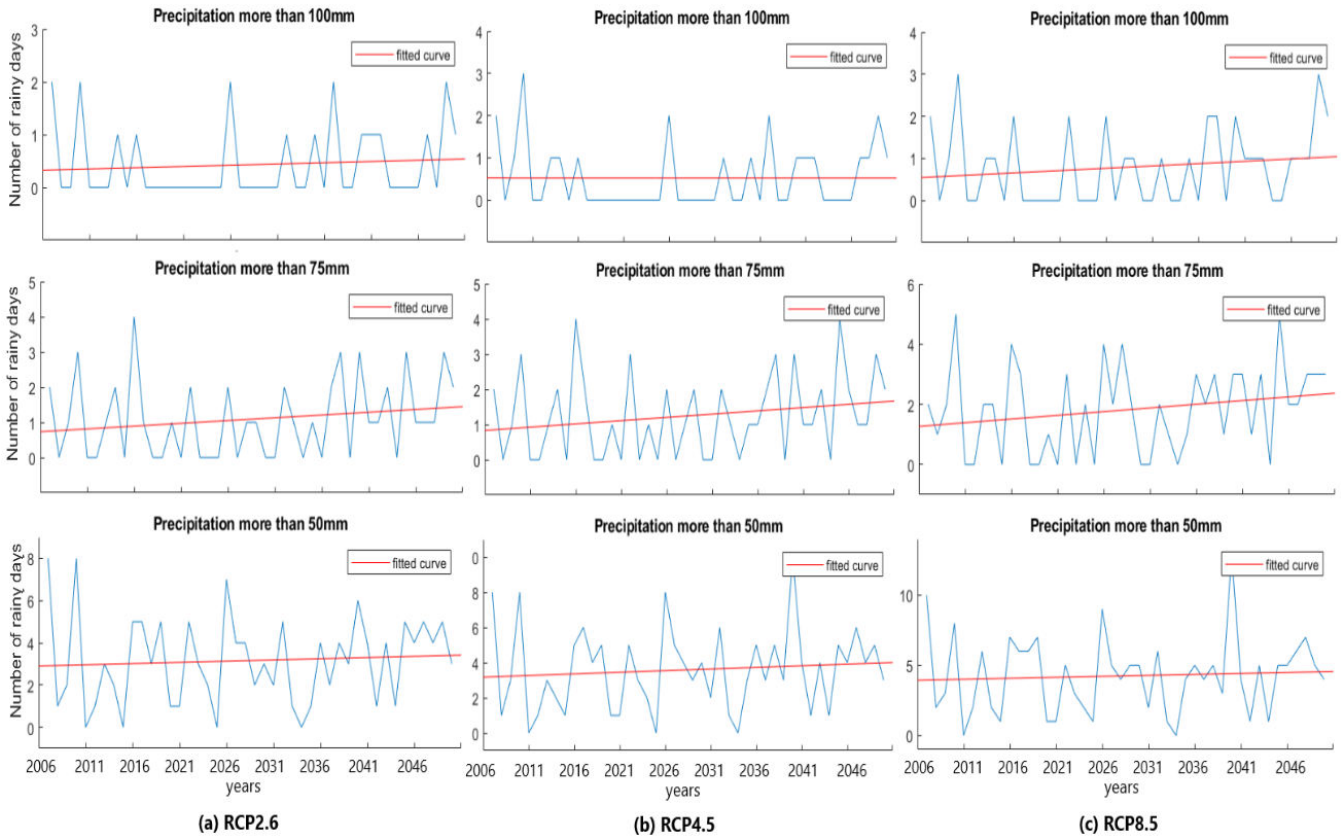

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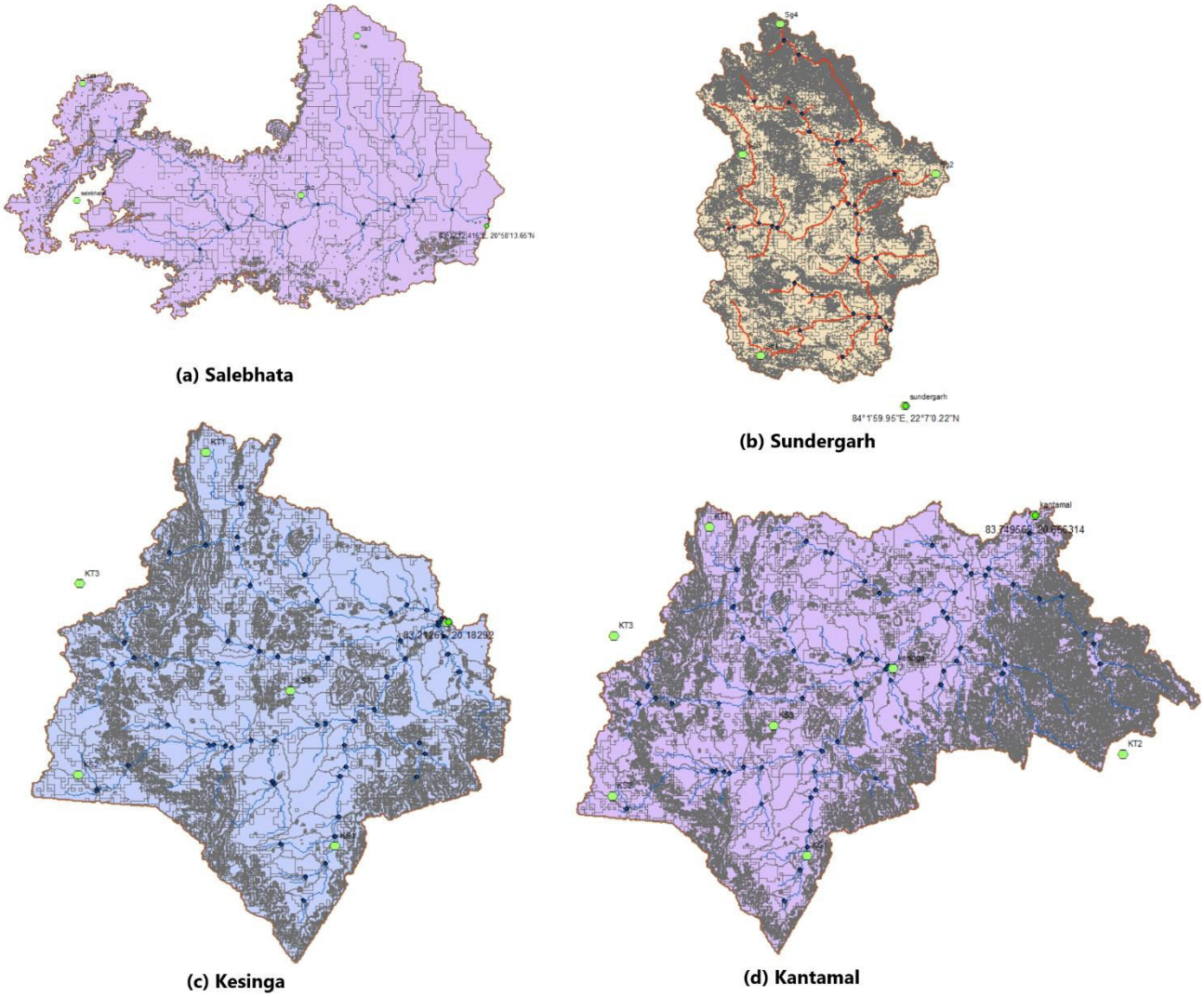

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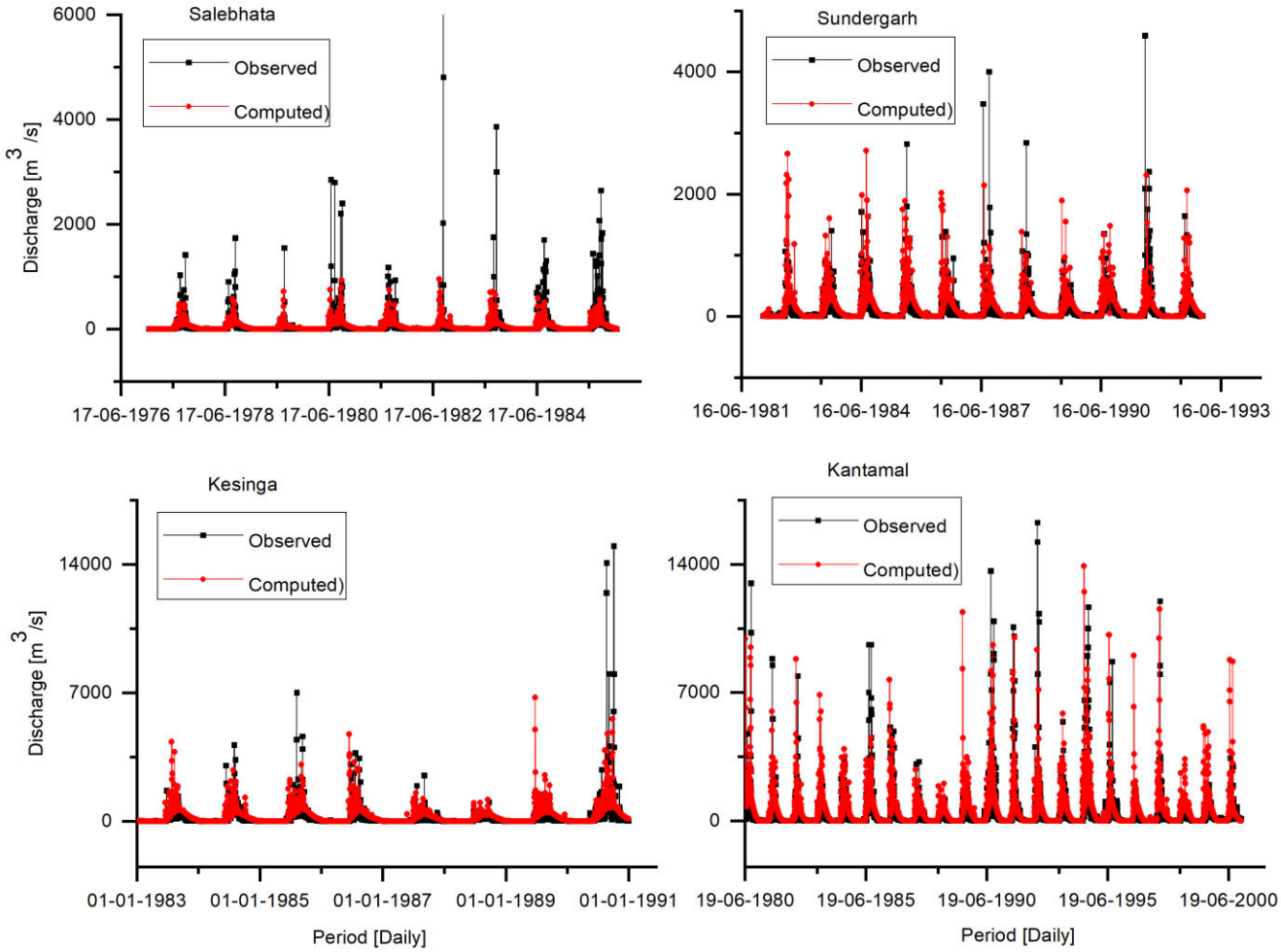

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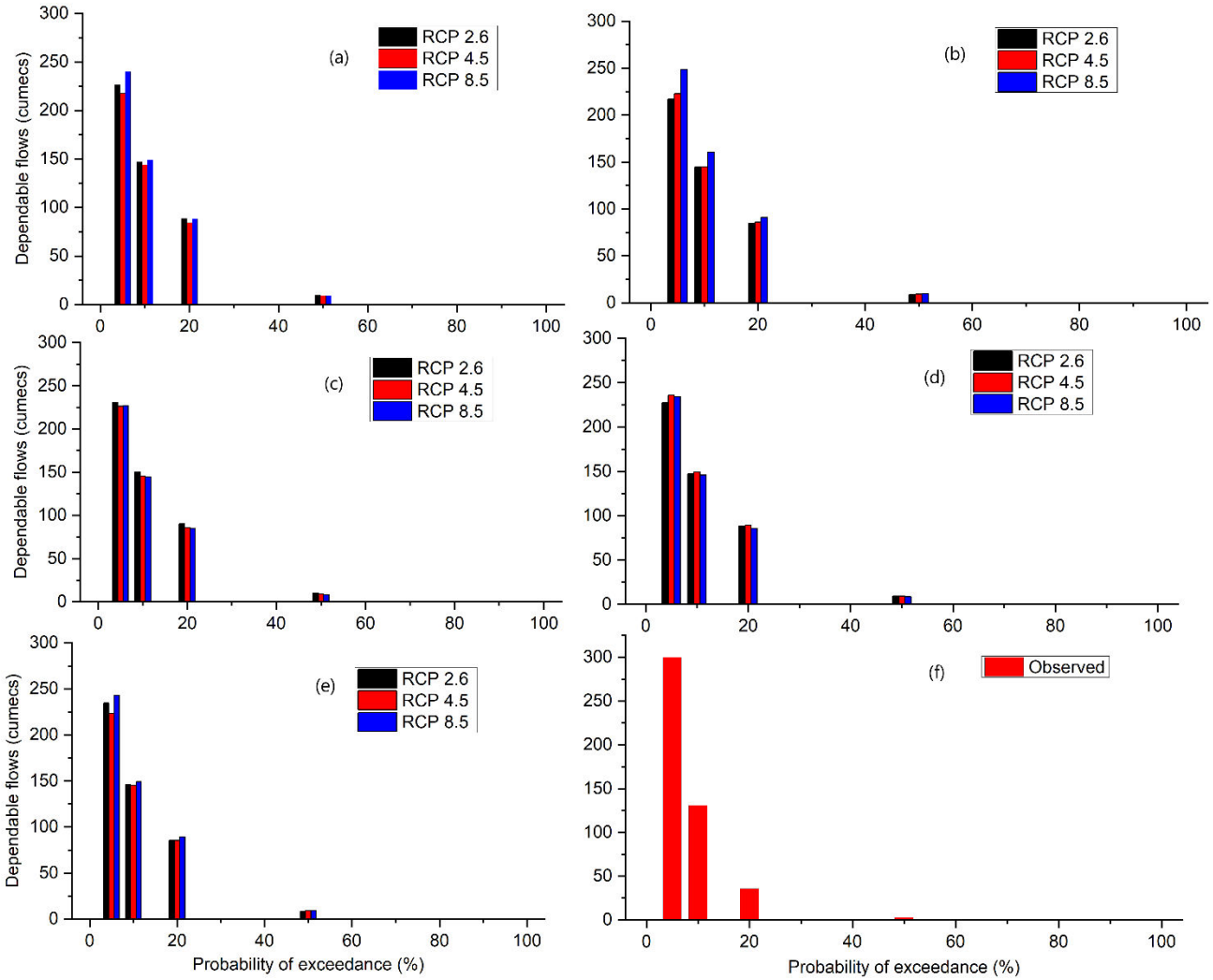

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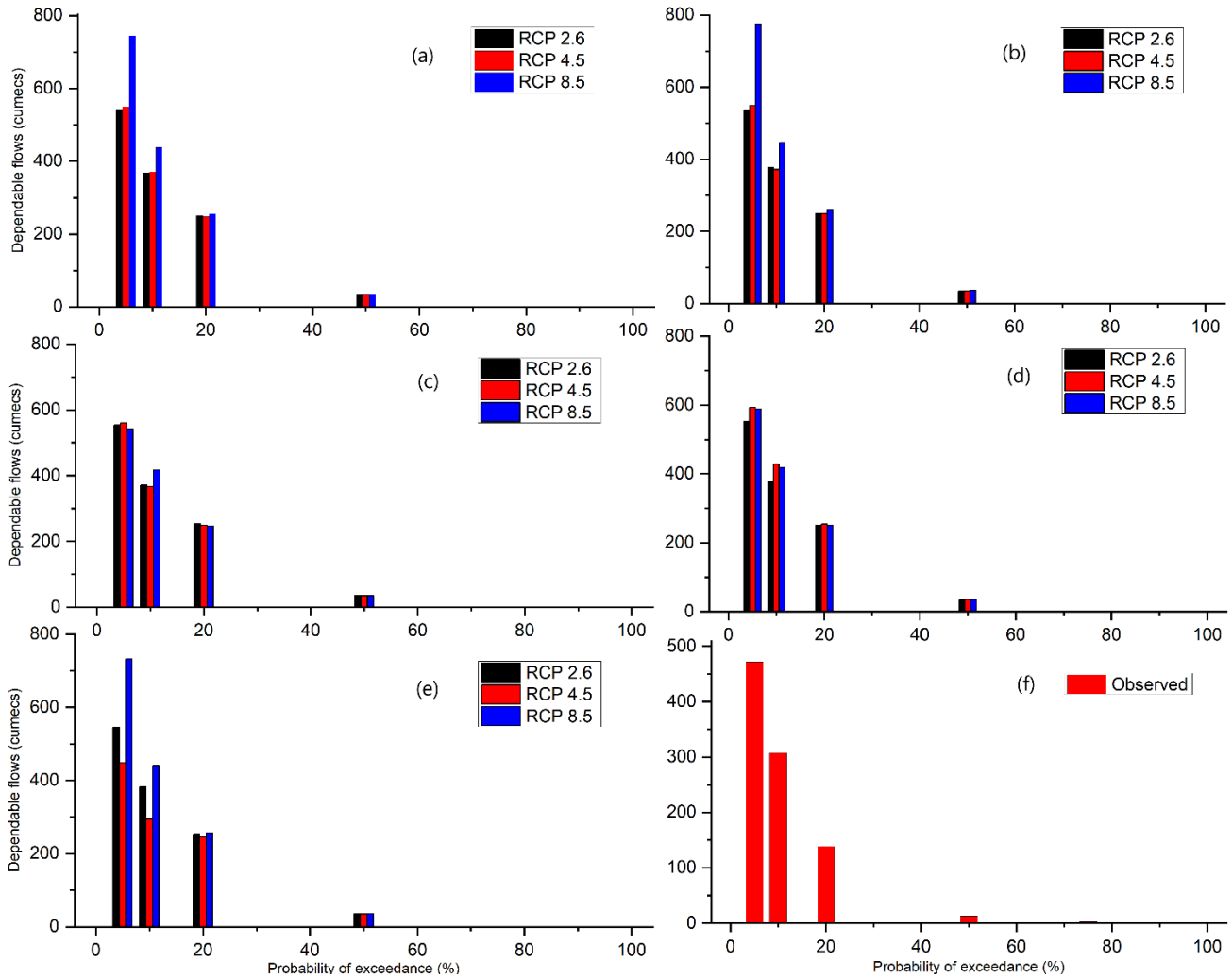

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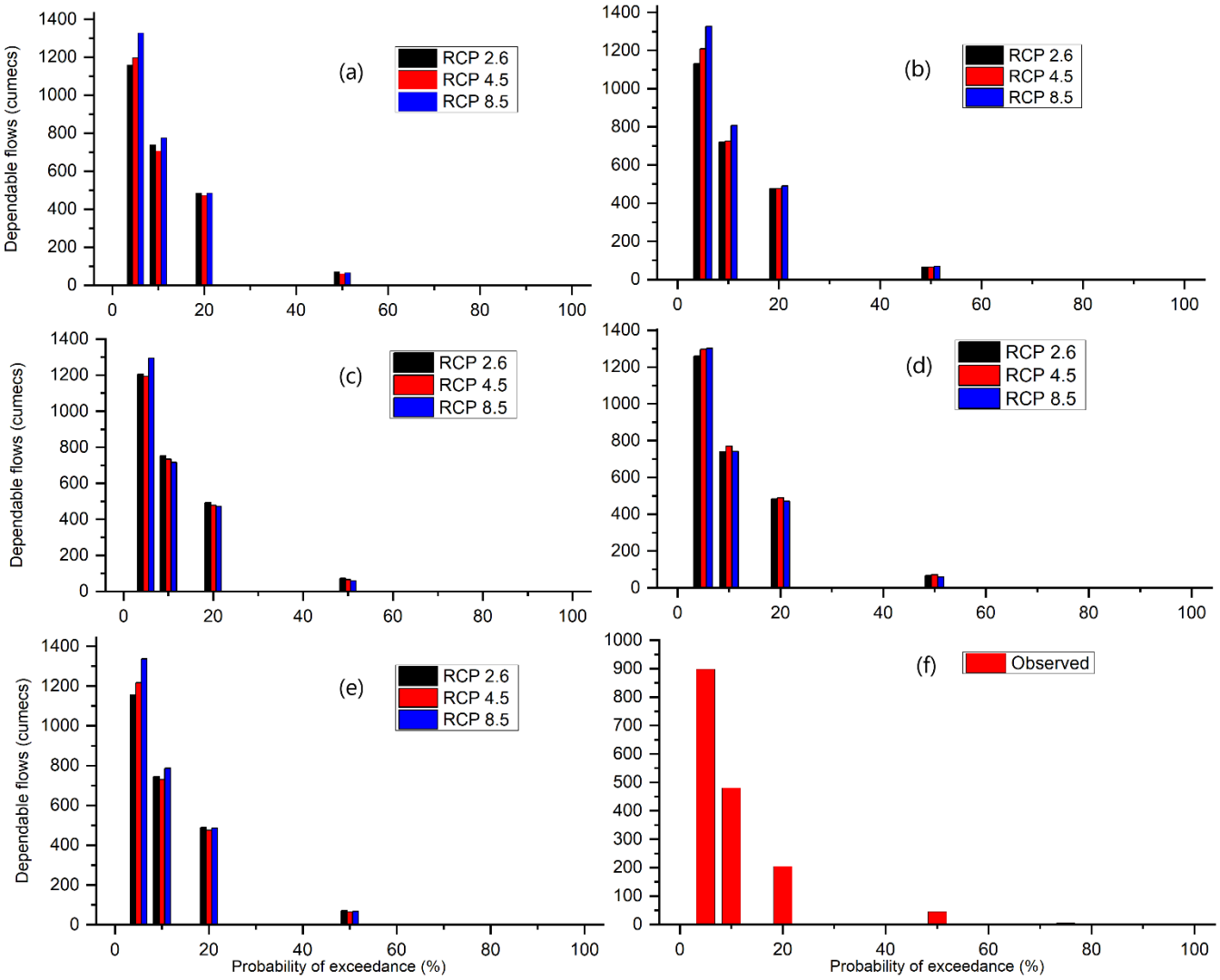

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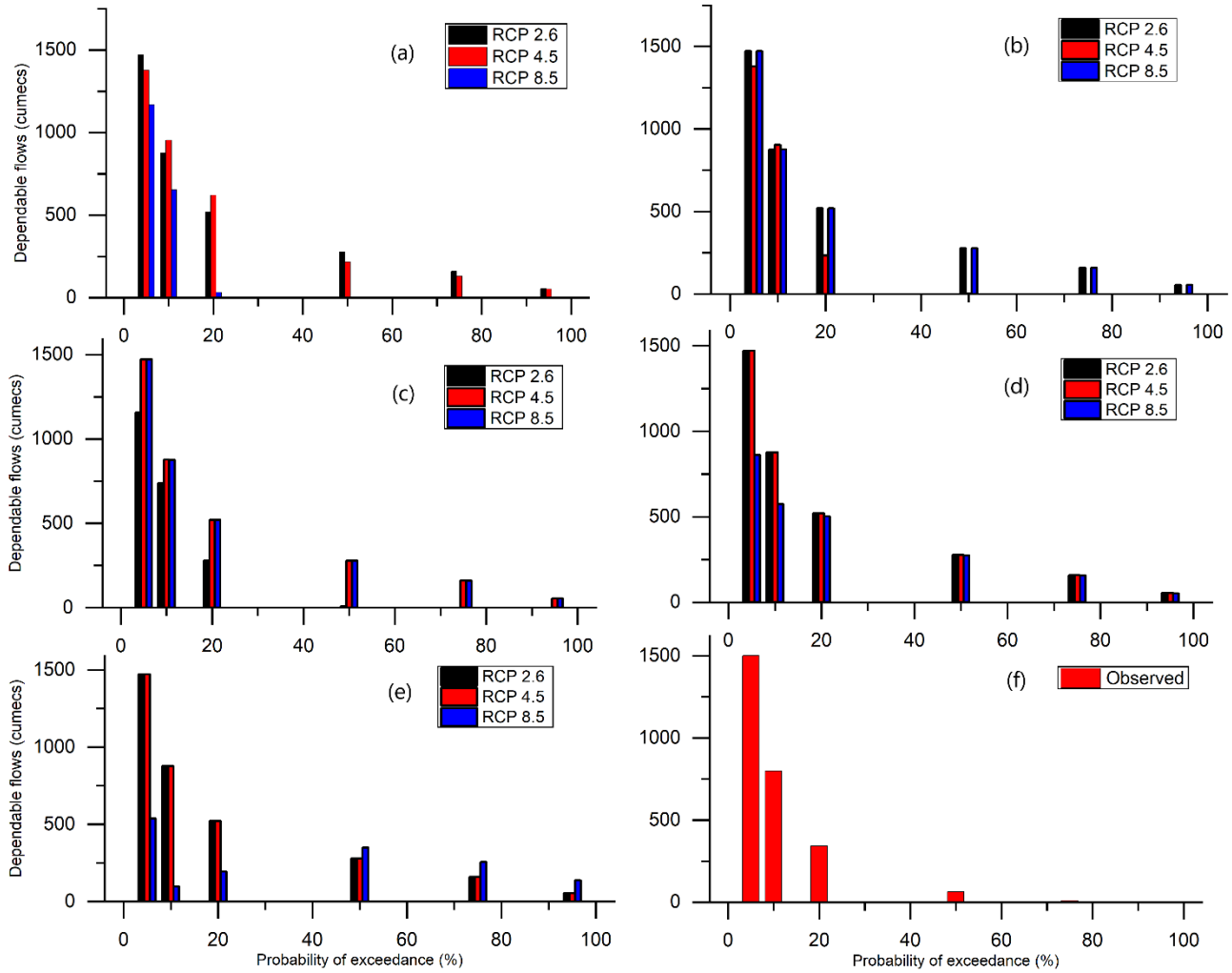

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