Author/s:
Bhattacharyya, S;Sreekesh, S;King, A

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Characteristics of extreme rainfall in different gridded datasets over India during 1983-2015

Suman Bhattacharyya[1], S. Sreekesh[1]* and Andrew King[2]

[1]Centre for the Study of Regional Development, Jawaharlal Nehru University, New Delhi, India.

[2]School of Earth Sciences and ARC Centre of Excellence for Climate Extremes, The University of Melbourne, Melbourne, Australia.

* Corresponding author
Email: sreekesh@mail.jnu.ac.in

Abstract

Understanding the spatial and temporal occurrences of extreme rainfall events and their changes is crucial for reducing the risk associated with extreme events, especially under anthropogenic warming. This study presents a comparative analysis of twelve gridded rainfall datasets in representing the spatial and temporal variation of extreme rainfall events and trends in the recent past (1983 -2015) over India. The selected datasets fall into four categories: gauge-based (APHRODITE, CPC, GPCC, REGEN), satellite-derived (CHIRPS, PERSIANN-CDR), reanalysis (ERA-5, MERRA2, PGF, and JRA-55), and products merged from these three types (WFDEI and MSWEP). For comparison, a gauge-based, high resolution (0.25° × 0.25°) daily gridded rainfall dataset, prepared by the India Meteorological Department (IMD) is used as a reference dataset. Eleven extreme climate indices, defined by the World Meteorological Organization's Expert Team on Climate Change Detection and Indices (ETCCDI) and the IMD are used to represent the magnitude, frequency, and duration of extreme rainfall events in India. The relative performance of these datasets in capturing extreme rainfall events is evaluated by computing model evaluation matrices i.e. correlation-coefficient (CC) and Percentage Bias (PBIAS). Trends in extreme rainfall indices and their magnitudes are calculated using Mann-Kendell and Sen's slope methods respectively, to compare with the IMD dataset. Our study finds large uncertainties in representing extreme rainfall events where in most cases the datasets underestimate higher extreme events compared to the IMD data. GPCC and MSWEP better capture the magnitude, duration, and frequency of extreme rainfall events in India and are comparable to the pattern of the IMD dataset. CHIRPS and ERA-5 perform better than other satellite and reanalysis rainfall datasets. All of these selected datasets consistently underestimate extreme rainfall events over the northern Himalayan region. The gridded datasets are unable to capture the spatial pattern of observed trends in extreme rainfall indices in India when compared t the IMD dataset.

Keywords: Extreme rainfall; Gridded rainfall dataset; ETCCDI extreme precipitation indices; Reanalysis dataset; Merged dataset; Trend analysis.

1. Introduction

The nature of extreme climatic events, such as extreme rainfall, drought, and heat waves, is changing as a consequence to recent human-induced warming (Fischer and Knutti et al., 2015; Matthews et al., 2019; Perkins-Kirkpatrick and Lewis 2020;). Rainfall extremes have socio-economic impacts as they often translate into devastating floods and droughts, which hinder agricultural production and result in human casualties. Accurate measurements of rainfall over the globe are crucial to understand rainfall processes, extremes, and their changes associated with climate change. Point-based measurements of rainfall are highly accurate, but are limited over the globe owing to the sparse distribution of gauge networks (Kidd et al., 2017) and can suffer from data quality issues (Viney and Bates 2004). These problems can be partly addressed by developing gridded rainfall datasets through the interpolation of gauge-based rainfall data over regular grid surface. Various gridded rainfall datasets are now available with global or near-global coverage but the relative performance of these datasets varies in space and time (Sun et al., 2018). Despite several limitations, gridded datasets are widely used in climate science for studying global/regional rainfall characteristics (Masunaga et al., 2020; Satgé et al., 2020), in climate change detection and attribution studies (Paik et al., 2020), event attribution studies (e.g. Wiel et al., 2017), and they are commonly used for climate model evaluation. The satellite rainfall datasets, that have undergone gauge-based correction, can represent rainfall climatology and be used for robust estimation of trends in extreme rainfall (Alexander et al., 2020). An ensemble of these corrected satellite products is useful for studying extremes, especially annual maximum rainfall, and thus can be applicable to data sparse regions (Bador et al., 2020; Nguyen et al., 2020). Another popular choice is to use reanalysis rainfall datasets as they provide a dynamically consistent record of rainfall at finer temporal scale across the Globe.. Reanalyses assimilate irregular observations into a forecast model to simulate temporally continuous estimates of several atmospheric variables over spatially homogenous grids (Sun et al., 2018). Products from these above three categories can also be 'merged' together and used for studying rainfall characteristics under various climate regimes (Beck et al., 2017). Merged products, produced by combining rainfall records from gauge-based, satellite and reanalysis datasets, provide reliable estimates of rainfall extremes at Global and regional scale (Rajulapati et al., 2020; Chen et al., 2020). Therefore, it is increasingly important to evaluate these datasets for studying extreme rainfall

behavior at regional scale (Fischer and Knutti et al., 2015) and here we perform such an analysis for India.

At present various gridded rainfall datasets are available including those from the Frequent Rainfall Observations on Grids (FROGS) database (Roca et al., 2019). Global gauge-based gridded datasets lack good station coverage in the South Asian domain and in India (Nguyen et al., 2020). Regional gridded datasets such as the Asian Precipitation Highly Resolved Observational Data Integration Towards Evaluation of Water Resources (APHRODITE) provide good estimates of large scale monsoon rainfall when compared to the IMD regional gridded dataset (Rajeevan and Bhate, 2009). However, the APHRODITE lacks good station coverage (Nguyen et al., 2020) in East Coast, North central plain, North West and North-Eastern parts of India (Rana et al., 2015). A comparison of the APHRODITE with IMD gridded data found poor correlation for these areas (Rajeevan and Bhate, 2009). They also noted that rainfall in the Western Ghats and NE parts of India is underestimated (bias >3mm/day) in APHRODITE and the maximum rainfall is also underrepresented by this dataset. The high resolution IMD gridded data, which is an improvement over previous generation IMD grid-datasets is found to better resolve the rainfall climatology in India especially in the Western Ghats (Fig. 1) and the core monsoon region (For more details on development of this data see Pai et al., 2014). Pai et al., (2014) compared APHRODITE along with other coarser resolution IMD datasets and observed that rainfall features including heavy rainfall areas in the mountainous belts of the West coast and NE India, and low rainfall in the lee ward side of the Western Ghats are more realistic and better presented in the IMD dataset due to its higher spatial resolution and to the higher density of stations compared to other regional datasets. Therefore, for analyzing regional rainfall patterns, extremes and comparing other gridded rainfall products this high resolution IMD (Pai et al., 2014) data has become a popular choice to climatologist.

Recent studies suggest that extreme rainfall over some areas of India has increased in the last few decades. Roxy et al., (2017) reported that central India has experienced a threefold rise in extreme rainfall events due to increasing moisture variability from the Arabian Sea. Significant increase in extreme rainfall events over the southern parts of India and decrease in the northern parts since 1970s is noted by Bisht et al., (2018), which is subsequently corroborated by Dash and Maity (2019). Mukherjee et al., (2018) attributed

these changes to anthropogenic forcing using a suite of CMIP5 experiments with and without human GHG emissions. In these circumstances, it is essential to understand how gridded rainfall datasets from various sources can capture these recent observable trends in extreme rainfall events, which have become more prominent in the last few decades over some areas of India.

Previous gridded data inter-comparison studies mainly focused on the mean state of climate while assessing their reliability for climatological application (Rana et al., 2015; Fallah et al., 2019). Gridded datasets have also been compared for drought characterization (Zhan et al., 2016; Golian et al., 2019; Chen et al., 2019) and hydrological modelling (Bhattacharyya and Sanyal 2019; Kolluru et al., 2020) in different parts of the world. Since extreme rainfall events are particularly important in triggering natural hazards and determining rate of erosion, it is imperative to focus on extreme rainfall while comparing gridded datasets from different sources. Some recent analyses have assessed the reliability of these gridded datasets in capturing extreme precipitation characteristics on global (Alexander et al., 2020; Bador et al., 2020) and regional scale (Kim et al., 2019; Timmermans et al., 2019; Cavalcante et al., 2020). However, these studies are limited to the analysis of a small subset of available gridded datasets or given lesser emphasis to extreme rainfall characteristics especially in data-sparse country like India (Bharti et al. 2016; Mondal et al., 2018; Singh et al., 2019; Prakash, 2019; Gupta et al., 2019).

Nguyen et al., (2020) showed that the magnitude of annual maximum daily rainfall in different sub-regions of monsoon Asia exhibits substantial differences especially in regions that are poorly sampled (e.g. India). . Their results revealed that gauge-based and satellite datasets with correction have stronger similarity than un-corrected products especially in regions with higher station densities (e.g. Japan) in line with other studies (Alexander et al., 2020; Bador et al., 2020). While in data-sparse regions such as India, higher inconsistencies are noted among the datasets and the differences are large for higher extremes. However, Nguyen et al., (2020) only assessed the inter-product differences focusing on annual one-day maximum rainfall. On the other hand, the analysis of magnitude, frequency, and duration of rainfall extremes is limited in India.. Therefore, there are still many gaps in our understanding of the behavior and representation of extreme rainfall in different gridded datasets in India in comparison with high-resolution

regional gauge based datasets, like IMD gridded data. Owing to the variability of Indian summer monsoon rainfall and recurring occurrences of climatic extremes, it is important to evaluate the ability of gridded rainfall datasets in reproducing extreme rainfall characteristics.

Therefore, the objectives of this study are (1) to compare twelve gauge-based, satellite-derived, reanalysis, and merged rainfall datasets for their suitability to study magnitude, frequency, and duration of extreme rainfall events over different regions of India (2) to assess their performance in reproducing the spatial pattern of observed trends in frequency, duration, and magnitude based indices of extreme rainfall and (3) identify the better performing gridded datasets among the selected ones for extreme rainfall studies. In order to compare these rainfall products, a high resolution (0.25° × 0.25°) and purely gauge-based gridded rainfall dataset, obtained from IMD, is used. The main reason for selecting IMD gridded data as the reference dataset is that it is developed from higher number gauge observations in India than other gauge-based datasets (Fig. 1) and it better represents the orographic rainfall than other gauge-based products (Pai et al., 2014; Bharti et al., 2015).

2. Materials and methods

2.1 Study area

To analyze extreme rainfall events in India, smaller homogenous regions are identified based on physiographic divisions and spatial rainfall patterns (Fig. 1A). These regions are Thar Dessert (TD), Northern-Himalaya (NH), Ganga plain (GP), North-East (NE), Central India (CI), Eastern Peninsula (EP), Southern Peninsula (SP), Western Ghats (WG), West Coast (WC), and East coast (EC). Annual average rainfall over India increases from <200mm (in TD) to >6000mm (NE India) following the west to east rainfall gradient. Monthly rainfall in most of these regions reaches its peak during June-September with the arrival of South-West monsoon. An exception to this is observed in parts of southern EC and SP region, where rainfall mostly occurs during post-monsoon (SON) months with the reversal of the monsoon system.

2.2 Datasets

At present different global and regional gridded-rainfall datasets are available at daily temporal scale from various sources, which are categorized as gauge-based, satellite, reanalysis, and merged/blended products. This study make use of twelve of these products having a grid resolution finer than 1 degree with continuous daily records of at least 30 years since 1983 (Table 1). Thus, five gauge-based (IMD, APHRODITE, CPC, GPCC, and REGEN); two satellite derived (PERSIANN-CDR and CHIRPS); four reanalysis (ERA5, MERRA2, PGF, and JRA-55); and two blended (WFDEI and MSWEP – described later) rainfall products are considered in this study.

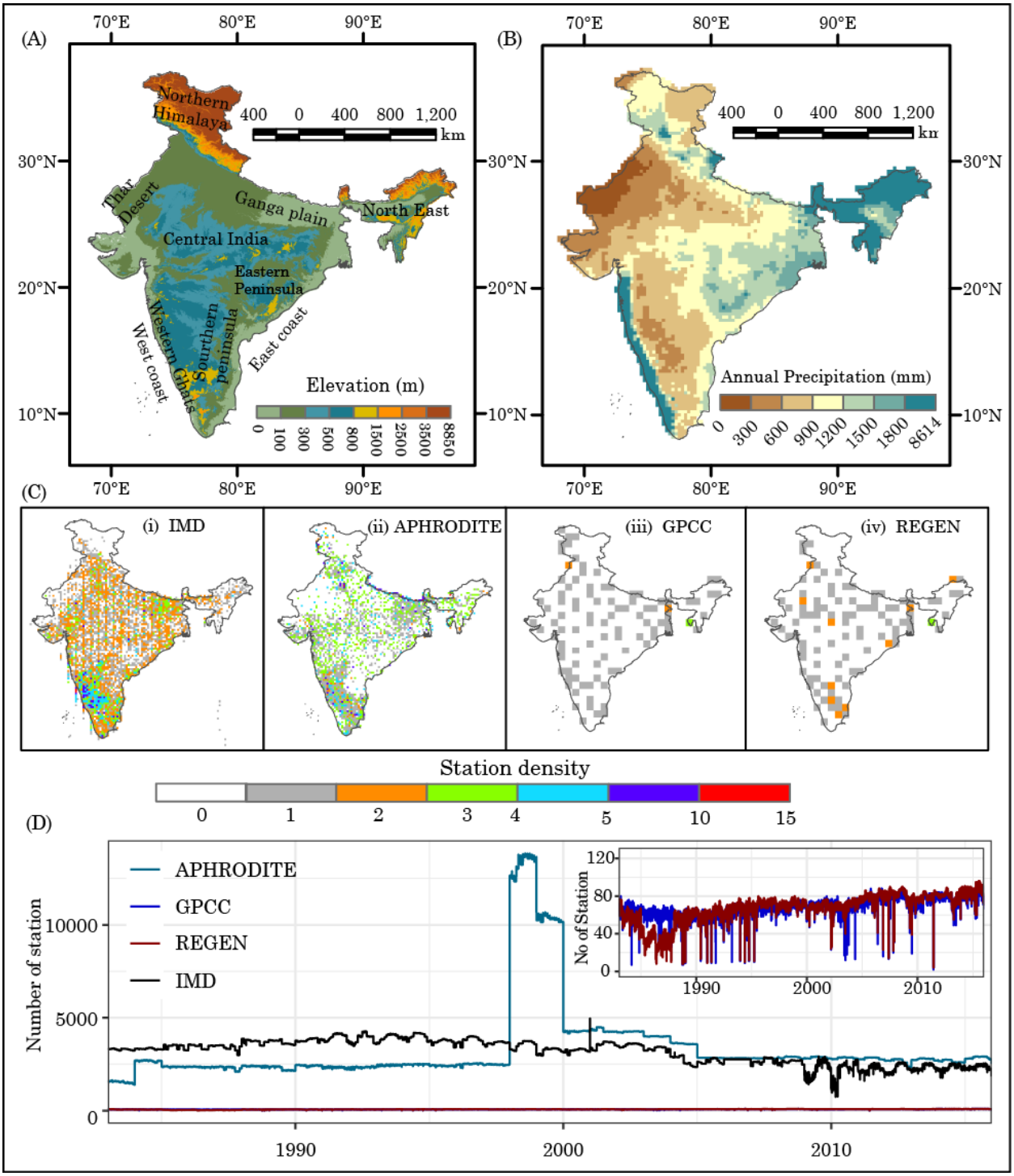


Fig. 1 (**A**) Elevation distribution along with major physiographic regions in India and (**B**) the distribution of annual average precipitation in India (derived from the IMD gridded dataset) during the study period (1983 – 2015). (C) Average station density in IMD (i), APHRODITE (ii), GPCC (iii), and REGEN (iv) gridded datasets in India at their native resolution; note that the white areas represent no station while light gray represents very

sparse station. (D) Temporal variation in daily gauge information used in APHDROFITE, GPCC, REGEN, and IMD datasets in India during the period of 1983 – 2015; in the inset, temporal variation plotted for GPCC and REGEN since number of stations ranged between 0-100.

The APHRODITE is a high-resolution continental-scale gauge-based dataset developed using the Spheremap interpolation (Willmott et al., 1985) by combining data shared via Global Telecommunication System (GTS) and other data compiled under the APHRODITE project. Unified Climate Prediction Centre (CPC) dataset combines gauge data from national and international agencies using optimal interpolation algorithm (Chen et al., 2008). The Global Precipitation Climatology Center (GPCC) Full Data Daily V2018 (V2) uses ordinary block kriging method to interpolate in-situ observations shared via Global Telecommunication System (GTS) over the Global land surface. The Rainfall Estimates on a Gridded Network (REGEN) is a newly developed gauge-based dataset that combines station observations from multiple sources i.e. Global Historical Climatology Network – Daily (GHCN-Daily) and GPCC using ordinary block kriging method (Contractor et al., 2020). The REGEN dataset with 'All Station' version is used in this study.

The Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks–Climate Data Record (PERSIANN-CDR) is quasi-global satellite data, developed using the Gridsat-B1 satellite data and adjusted using monthly dataset of Global Precipitation Climatology Project (Ashouri et al. 2015). Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS v.2) provides blended satellite-gauge information at quasi-global coverage (Funk et al., 2015). MSWEP v2.0 combines satellite data (CMORPH, GridSat, GSMaP-MVK, SM2RAIN-ASCA and TMPA 3B42RT) and the ERA-Interim and JRA-55 reanalyses as well as gauge based products (GPCC, CPC) (Beck et al., 2017). The WATCH Forcing Data-ERA-Interim (WFDEI) combines ERA-interim reanalysis with gauge based datasets using sequential elevation correction (Weedon et al., 2014). The dataset better represent annual daily maximum rainfall over the globe than other datasets (PERSIANN-CDR, MSWEP, ERA-Interim, and NCEP2) when compared to GPCC (Chen et al., 2020) and also outperform other reanalysis in simulating river discharge (Essou et al., 2016).

Table 1 Description of gridded rainfall dataset used in this study.

Dataset	Period	Resolution	Data source	References
IMD	1901-Present	0.25° × 0.25°	Gauge-based	Pai et al. (2014)
APHRODITE	1951 – 2015	0.25° × 0.25°	Gauge-based	Yatagai et al. (2012)
CPC	1979 - Present	0.5° × 0.5°	Gauge-based	Xie et al. (2007)
GPCC	1982 - 2016	1° × 1°	Gauge-based	Schamm et al. (2014)
REGEN	1950 - 2016	1° × 1°	Gauge-based	Contractor et al., 2020
CHIRPS	1981 - Present	0.25° × 0.25°	Satellite	Funk et al. (2015)
PERSIANN-CDR	1983 - Present	0.25°× 0.25°	Satellite	Ashouri et al. (2015)
PGF	1948 - 2016	0.25° × 0.25°	Reanalysis	Sheffield et al. (2006)
ERA-5	1979–present	0.25°× 0.25°	Reanalysis	Hersbach et al., (2020)
MERRA-2	1980 - Present	0.5° × 0.67°	Reanalysis	Gelaro et al. (2017)
JRA-55	1958-Present	0.5625° × 0.5625°	Reanalysis	Kobayashi et al. (2015)
MSWEP	1979 - 2016	0.1° × 0.1°	Merged	Beck et al., 2019
WFDEI	1979 - 2016	0.5° × 0.5°	Merged	Weedon et al., (2014)

The Princeton Global Forcing (PGF) daily dataset is produced by using global observation-based datasets with the NCEP/NCAR reanalysis at 0.25° resolution (Sheffield et. al, 2006) ERA5 is the fifth generation reanalysis from the European Centre for Medium-Range Weather Forecast (ECMWF) with several improvements in model parameterization and higher spatial and temporal resolution than ERA-Interim (Hersbach et al., 2020). The Modern-Era Retrospective Analysis for Research and Applications, version 2 (MERRA- 2), atmospheric reanalysis is the newest reanalysis product by NASA‘s Global Modeling and Assimilation Office (GMAO) replacing the previous generation MERRA product. It uses the new version of the GEOS-5 atmospheric model and includes more observational data, recent satellite observations, and an improved assimilation model (Molod et al. 2015). The Japanese 55-year Reanalysis (JRA-55) is the second reanalysis product from the Japan Meteorological Agency (JMA) which is an improved version of the previous JRA-25 and uses

a 4D-VAR approach for data assimilation and variational bias correction technique (Kobayashi et al. 2015).

The gridded rainfall data, obtained from the IMD is used as the reference dataset as it has been produced using the largest number of observational stations (N = 6955) in India, compared to other gauge-based gridded data that is available to date. We acknowledge that even fine-resolution gridded products based on large number of gauge data exhibit biases and are known to underestimate rainfall extremes (King et al. 2013; Gervais et al. 2014). The IMD dataset has a spatial resolution of 0.25° with daily rainfall records from 1901 – 2015 and it has been adjusted for orographic and other controlling factors of rainfall distribution over India (Pai et al., 2014; Pai et al., 2015; Bharti et al., 2015). Over Indian subcontinent, global datasets (i.e. GPCC, CPC, and REGEN) have poor station coverage. As noted in Nguyen et al. (2020), in the 2000s the station number in APHRODITE in India decreases although it is relatively higher than the IMD dataset. Moreover, the IMD dataset has higher number of station than APHRODITE for pre-1998 period and has better spatial coverage than other datasets. Regional rainfall distribution is also better represented by this high-resolution IMD gridded dataset (see Pai et al., 2014; Pai et al 2015 for more details) and also used in in detecting cloud-burst events over NH (Jena et al., 2020). Therefore, the results from the selected gridded datasets are compared with the IMD dataset.

2.3 Methods

Study of extreme rainfall is carried out in two ways, either by fitting parametric extreme value distribution to assess rare events or by using non-parametric methods of calculating indices for extreme rainfall events, solely based on empirical data analysis. Here we used the non-parametric approach by calculating eleven extreme rainfall indices (Table 2) to encompass a wider range of the extreme rainfall climatology in India, based on absolute and percentile based rainfall thresholds, to evaluate gridded rainfall datasets. Out of these eleven indices, eight indices are selected from ETCCDI (for more details see http://etccdi.pacificclimate.org/indices_def.shtml) and have been widely used for detection, attribution and climate change projection studies around the world (Cavalcante et al., 2020; Dash and Maity, 2019; Kim et al., 2020; Schoof and Robeson, 2016; Srivastava et al., 2020). The other three indices are selected from the IMD rainfall intensity classes (IMD, 2015).

We considered only the last three IMD rainfall intensity classes with rounding of the intensity values namely: heavy rainfall (HR) (65 to 115 mm), very heavy rainfall (VHR) (115 to 205 mm) and extremely heavy rainfall (EHR) (≥ 205 mm).

Extreme indices, characterizing different magnitude (RX1day, RX5day, R95p and R99p), frequency (R10mm, R20mm, HR, VHR, EHR) and duration (CDD, CWD) of annual extreme rainfall in India are calculated from daily wet day rainfall, over each grid-cell, resulting in one value per year for each gridded rainfall product. In this study, a wet day is defined as a day with rainfall ≥1 mm (Chaudhary et al., 2017).

The spatial resolution of selected gridded rainfall datasets varies widely from 0.25° to 1° (Table 1) thus hindering direct comparison with the reference (IMD) dataset. Re-gridding from higher to lower resolution affects localized extreme rainfall values as higher extreme values get reduced through the process of averaging. 'The order of operation' in calculating extreme rainfall indices and interpolating to the target grid for comparison has substantial effects on the representation extreme rainfall values (Herold et al., 2017). Previous studies shown that the effects of first re-gridding to coarser grid and then calculating extreme indices can be eliminated by changing the order of operation (Avila et al., 2015; Herold et al., 2017). Therefore, in this study, the extreme rainfall indices are first calculated at the native resolution of the datasets and then interpolated to a common 1° grid for a fair comparison among the datasets.

Differences between IMD and other gridded datasets are expressed in terms of percentage BIAS (PBIAS) and calculated following Eq.1.

$$PBIAS = \frac{\sum_{i=1}^{n}(R_{si} - R_{oi})}{\sum_{i=1}^{n}(R_{oi})} \times 100 \qquad \text{Eq. 1}$$

Where R_{oi} is the i^{th} observation from IMD gridded data, R_{si} is the corresponding i^{th} estimated rainfall from other gridded datasets.

Table 2 Extreme rainfall indices recommended by ETCCDI and IMD (highlighted in bold) considered in this study.

Category	Index	Index Name	Description	Unit
	RX1day	Maximum 1-day rainfall	Annual 1-day maximum rainfall	mm

Magnitude	RX5day	Maximum 5-day rainfall	Annual 5-day maximum rainfall	mm
	R95p	Very wet days	Annual rainfall above long-term 95th percentile	mm
	R99p	Extremely wet days	Annual rainfall above long-term 99th percentile	mm
Frequency	R10mm	Number of 10mm or more rainfall days	Annual count of days when daily rainfall ≥10mm	days
	R20mm	Number of 20mm or more rainfall days	Annual count of days when daily rainfall ≥20mm	days
	R65mm	**Heavy Rain (HR)**	Number of days with daily rainfall (R) 65 mm ≤ R < 115 mm	days
	R115mm	**Very Heavy Rain(VHR)**	Number of days with daily rainfall (R) 115 mm ≤ R < 205 mm	days
	R205mm	**Extremely Heavy Rain (EHR)**	Number of days with daily rainfall ≥ 205 mm	days
Duration	CDD	Maximum length of consecutive dry days	Maximum number of consecutive days with daily rainfall <1mm	days
	CWD	Maximum length of consecutive wet days	Maximum number of consecutive days with daily rainfall ≥1mm	days

In addition, the probability density functions (PDFs) of average extreme rainfall from twelve other datasets are compared to the PDF from IMD to explore how well these datasets resemble the average spatial distribution of different rainfall indices in India. For this, long-term average values of extreme rainfall indices from all the grid cells in India are considered. Here, the PDFs are estimated using a nonparametric smoothing technique, the Kernel Density Estimator (KDEs) to reduce the sampling error associated with the choice of distribution functions. A Gaussian kernel is used to develop the KDE (Teegavarapu et al., 2013). The temporal variations in average extreme rainfall values in India in different datasets are compared using line graphs.

The direction (increasing/decreasing) and magnitude of the trend in extreme rainfall indices over each grid-cell are calculated using the non-parametric Mann-Kendall test (Mann, 1945; Kendall, 1948) and Sen's slope estimator (Sen, 1968) for the study period of 1983 - 2015. The trend analysis is performed to assess whether the gridded datasets can reproduce

the observed trends in extreme rainfall in India or not. The calculation of PBIAS, PDFs and trends are done after re-gridding the extreme indices to a common 1° grid.

3. Results

In order to compare the datasets, we calculated eleven rainfall indices (Table 2). However, considering the limited length of the manuscript, two magnitude-based (RX5day and R95p), three frequency-based (R20mm, HR, VHR) and two duration-based indices (CDD and CWD) are presented in the manuscript, where other indices are presented in the supplementary information (RX1day, R99p, R10mm and EHR).

3.1 Magnitude of extreme rainfall

In the orographic rainfall zones of WG, NH, NE (Meghalaya plateau) and parts of CI, EP, and GP regions average RX5day rainfall is high (>250 mm). In the dry parts of SP and TD, it is below 150 mm whereas in remaining areas of India it is between 150 mm and 250 mm. Compared to the IMD data, other gridded datasets mostly underestimate (dry bias) RX5day rainfall in India (Fig. 2). Relatively greater underestimation (above 60%) is noted in the orographic belts of NH in all datasets. It tells datasets are unable to capture the orgraphic influence on rainfall distribution. It should be noted that the gauge density in this region is very sparse especially in the eastern parts of NH and that may explain the higher bias in representing extreme rainfall, especially in the higher elevation zones. Among the gauge-based products, GPCC has better agreement with IMD with a lower bias (Fig. 2d) and also better represents temporal variability of RX5day rainfall (Fig. 3c) than APHRODITE, CPC, and REGEN. Except MERRA2, most of the datasets show overestimation of RX5day rainfall in parts of NE India. Similar overestimation (bias >30%) is found in the SP region in PERSIANN-CDR, MSWEP, and PGF. The JRA-55 overestimates RX5day rainfall over GP and NW India. Overall, APHRODITE, WFDEI, and MERRA2 show higher amount of dry bias while the GPCC, WFDEI, and ERA5 exhibit relatively lower bias in most parts of India. Similar spatial pattern of dry and wet bias is noted for RX1day rainfall (Fig. S1). However, the amount of dry bias is relatively higher for stronger extreme events (RX1day) and comparatively milder extremes (RX5day) rainfall.

Comparison of PDFs (Fig. 3a) suggests that except for GPCC, MSWEP, and ERA5 all other datasets overestimate the area of India with RX5day rainfall below ~200 mm and

underestimate the area with rainfall above 200 mm (Fig. 3a). This further indicates that the higher extreme rainfall amounts are underestimated by the gridded datasets whereas the tendency of overestimating relatively lower values of extreme rainfall is common, especially over the mountainous belts and dry parts of India. PGF reanalysis is unable to capture RX5day and R95p above 200 mm (Fig. 3a& 3b) whereas the recent generation ERA-5 reanalysis gives more comparable estimates of extreme rainfall to the IMD dataset. Compared to absolute values of higher rainfall indices i.e. RX5day and RX1day, the spread of PDFs is lower for percentile based indices i.e. R95p and R99p. This may due to the independent structure of rainfall distribution and percentiles among these products rather than higher specific amounts that are relatively hard to capture especially by the satellite and reanalysis products. Temporal variations of RX5day and R95p are better represented by GPCC, MSWEP, and ERA5 among their respective groups. In contrasts, WFDEI and PGF underestimate the temporal variability of RX5day and R95p and also have lower CC among the selection of merged and reanalysis products. Similar differences are noted for RX1day and R99p rainfall (Fig. S2) in India

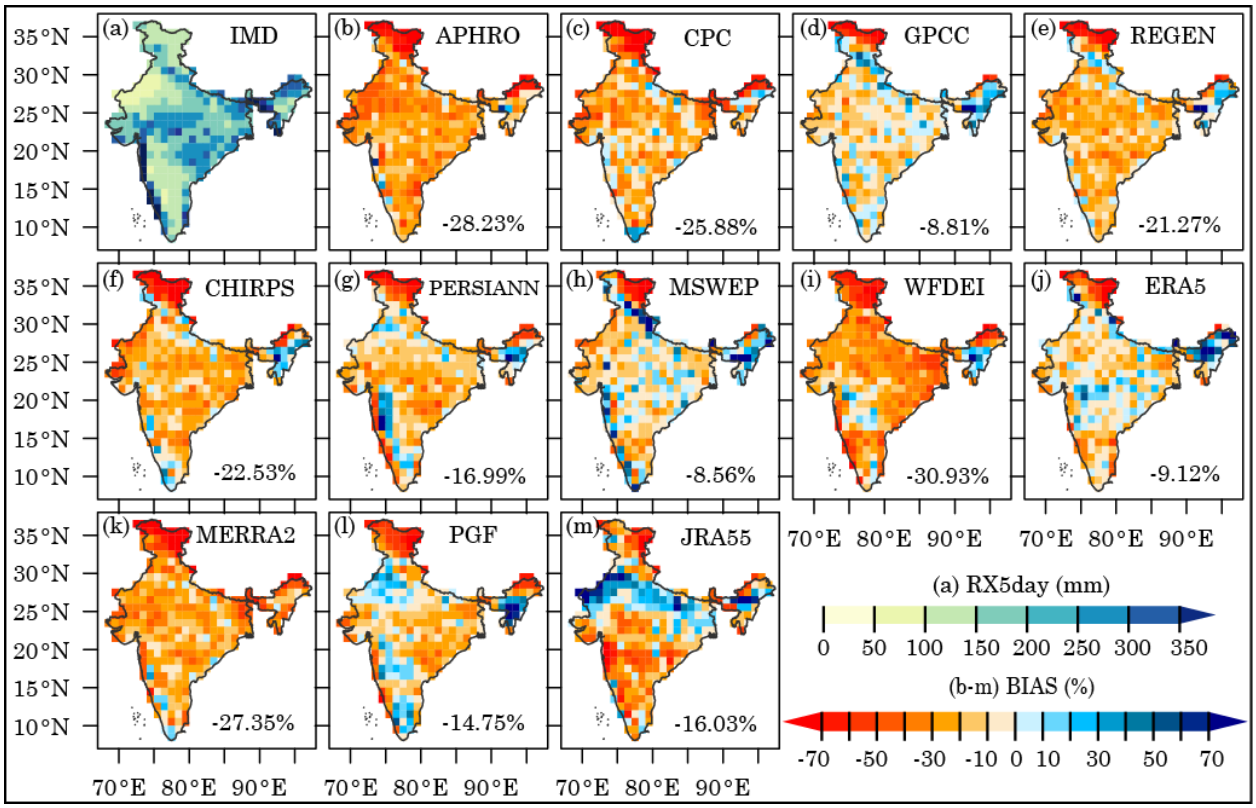


Fig. 2. Climatological value of RX5day (over the period of 1983 to 2015) in the IMD dataset (a) and Percentage BIAS in RX5day from IMD dataset in other rainfall datasets (**b-m**). The number inserted in each panel is the median PBIAS in India for respective datasets.

Gauge-based datasets have higher spatial correlation with the IMD dataset than other types of products in representing magnitude RX5day and R95tp in India (Fig. 3e&3f). This is not surprising given the assimilation of direct rainfall records in these datasets. Among the gauge-based products, CPC has relatively poor spatial correlation. CHIRPS, MSWEP, and ERA5 have relatively higher spatial correlation among the satellite, merged and reanalysis products. PGF reanalysis performed worst among all other products as it greatly underestimated the spatial and temporal occurrences of magnitude of extreme rainfall in India. However, the spatial correlation coefficients of these datasets decrease for higher extreme i.e. RX1day and R99p (Fig. S2).

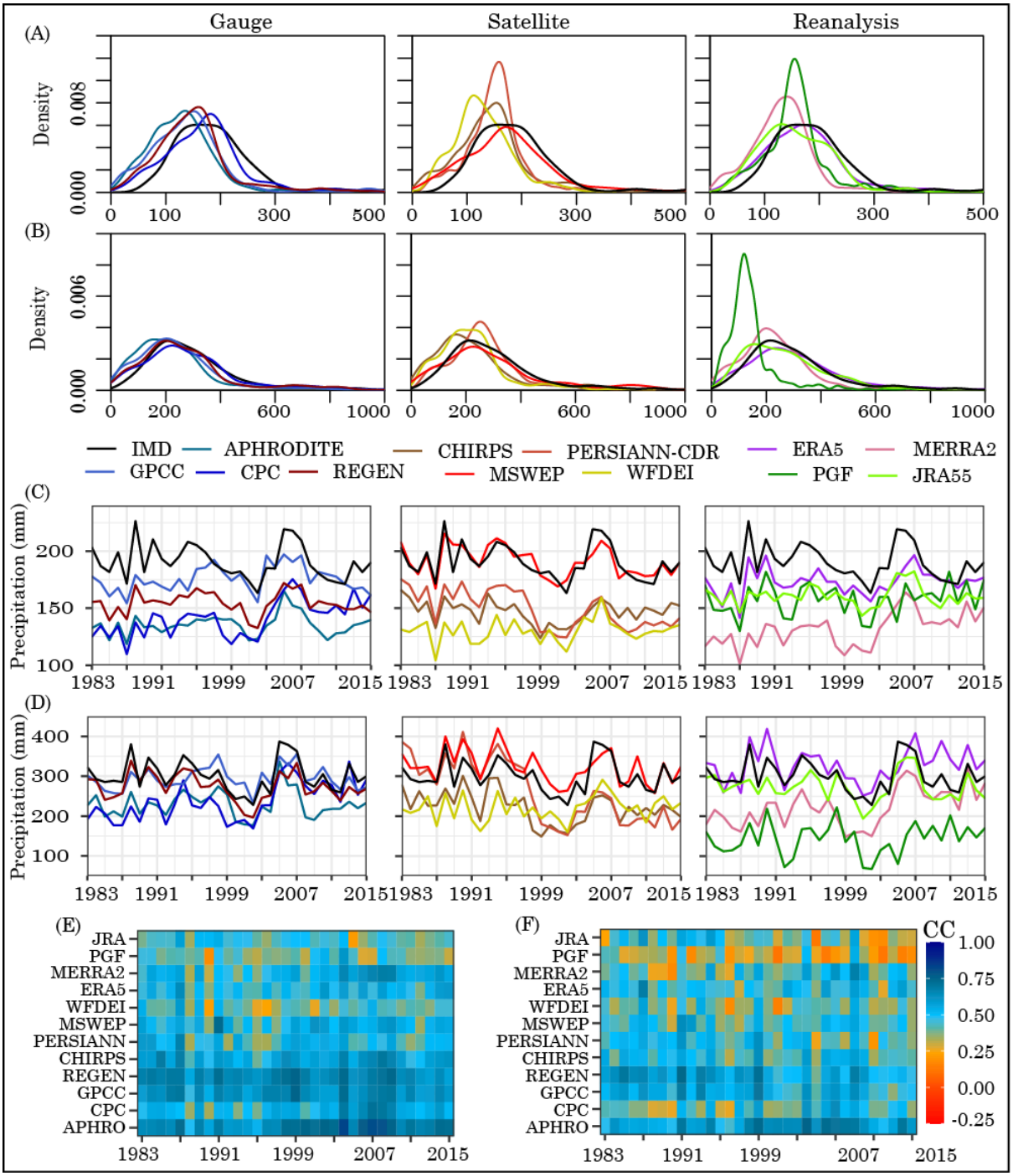


Fig. 3 Probability Density Functions represents climatological values RX5day (A) and R95p (B) in India during 1983 – 2015. Temporal variation of area averaged RX5day (C) and R95p rainfall (D) in different in gauge-based (left), satellite & merged (middle) and reanalysis (right) datasets. Spatial correlation coefficients between IMD and other gridded dataset in representing RX5day (E) and R95p rainfall (F) in India.

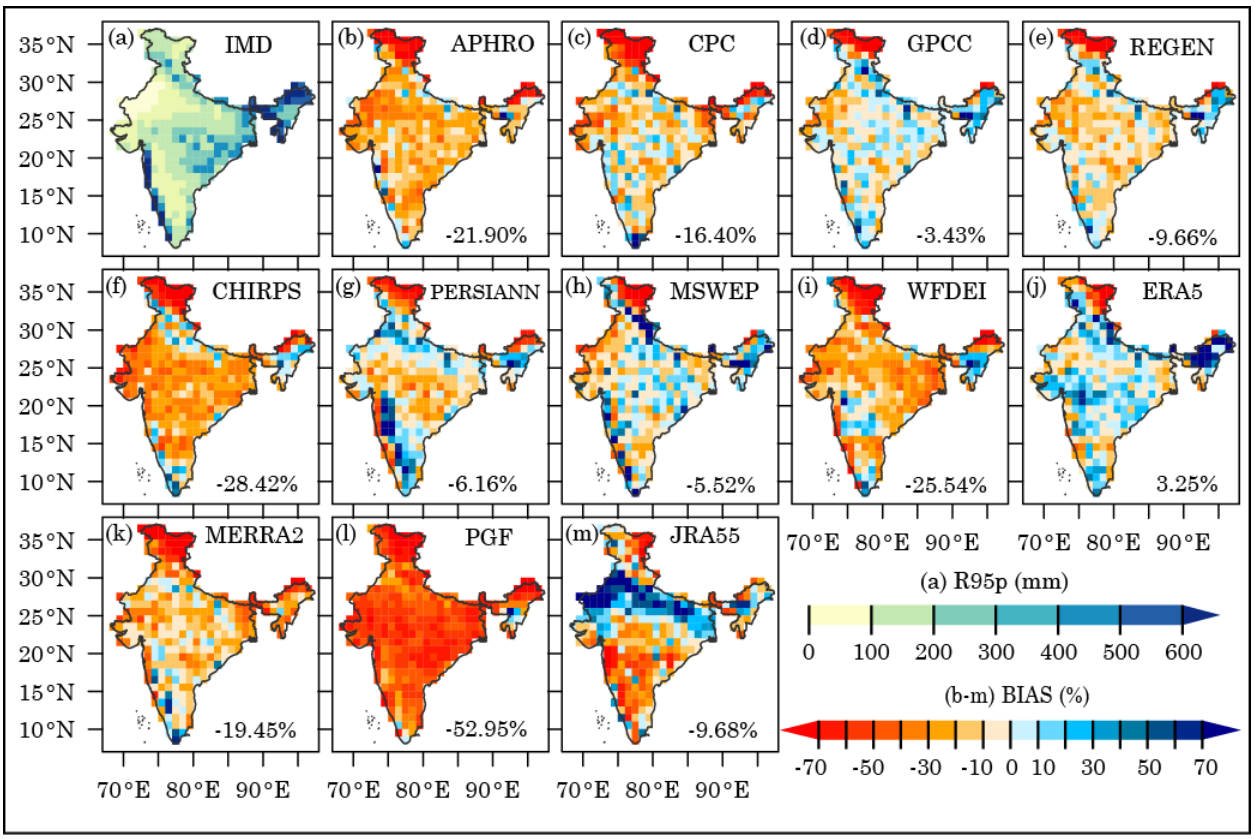


Fig. 4. Same as Fig. 2 but for R95p.

The spatial pattern of R95p is similar to that for RX5day i.e. areas with higher extreme rainfall (R95p>500) mm are found over the eastern side of WG and parts of NE India (Fig. 4). In the CI and EP, R95p is between 300-500mm. Similarly, GPCC performs better than other gauge-based products whereas PERSIANN-CDR, MSWEP, and ERA5 have better performance than other satellite, merged, and reanalysis products respectively. However, over the WG region, CHIRPS, PERSIANN-CDR, and MSWEP overestimate R95p (Fig. 4) and R99p (Fig. S3). This may be due to the overestimation of orographic rainfall over complex topography by the satellite rainfall datasets which is also noted by Gupta et al., 2019). Although ERA-5 exhibits lower bias for magnitude based indices than other reanalysis datasets, it overestimates magnitude of rainfall indices over the NE parts (Fig. 4).

3.1 Frequency of extreme rainfall

Distribution of R20mm closely follows the spatial distribution of annual rainfall in India where relatively higher frequency of R20mm (>30 days/year) can be found in areas where the annual average rainfall is above 1800 mm (Fig. 1b), especially over WG, NE, and in parts of NH (Fig. 5a). In the EP, GP, and parts of NH and CI the R20mm is between 15-30 days/year whereas in other areas of India it is below 15 days/year. APHRODITE, CPC, WFDEI, ERA5, and MERRA2 in general show dry bias in India in representing frequency of R20mm. In contrast, CHIRPS, PERSIANN-CDR, PGF, and JRA-55 mostly exhibit wet bias, especially over SP, CI, GP, and NW India. The magnitude of wet bias in these datasets increases for lower rainfall thresholds (R20mm and R10mm) and a mixed pattern of wet and dry bias is noted, compared to the substantial dry bias for higher extreme indices. Lower rainfall i.e. R10mm is more common, especially during the monsoon season. These low rainfall days are generally overestimated in the satellite and reanalysis rainfall datasets. Overestimation of R20mm is highest in PGF over most parts of India, except NH and parts of NE and WG region. This dataset underestimates frequency of R20mm below 20 days and overestimates it between 20-40 days (Fig. 6a) which is in contrast to the large dry bias that is found for higher extreme rainfall indices.

Similar to magnitude based indices, greater dry bias (>60%) is found in the NH. The PDFs suggest that the gauge-based, satellite, and merged products (except APHRODITE and WFDEI) overestimate R20mm below 10 days but better represent R20mm above 20 days (Fig. 6a). These datasets (gauge-based, satellite and merged) are also better in representing the spatial and temporal variation in R20mm than the reanalysis (Fig. 6b) and can be considered as a useful resource for analyzing lower extremes (e.g. R20mm). In contrast, the APHRODITE, WEDEI, and MERRA2 overestimate R20mm below 10 days and underestimate R20mm above 10days which also explain the underrepresentation of temporal variations by these datasets. Reanalysis datasets have higher inter-product spread than other type of datasets, thus the temporal variations are less consistent among the reanalyses. Similar inconsistencies between reanalyses are also noted globally (Alexander et al., 2020) as well as for Asia and India (Nguyen et al. 2020). . Spatial correlation of R20mm (Fig. 6c) and R10mm (Fig. S5) is higher than the magnitude-based indices. GPCC and REGEN have correlation above 0.8 for most years. This indicates that there is more agreement between IMD and other datasets for lower rainfall thresholds.

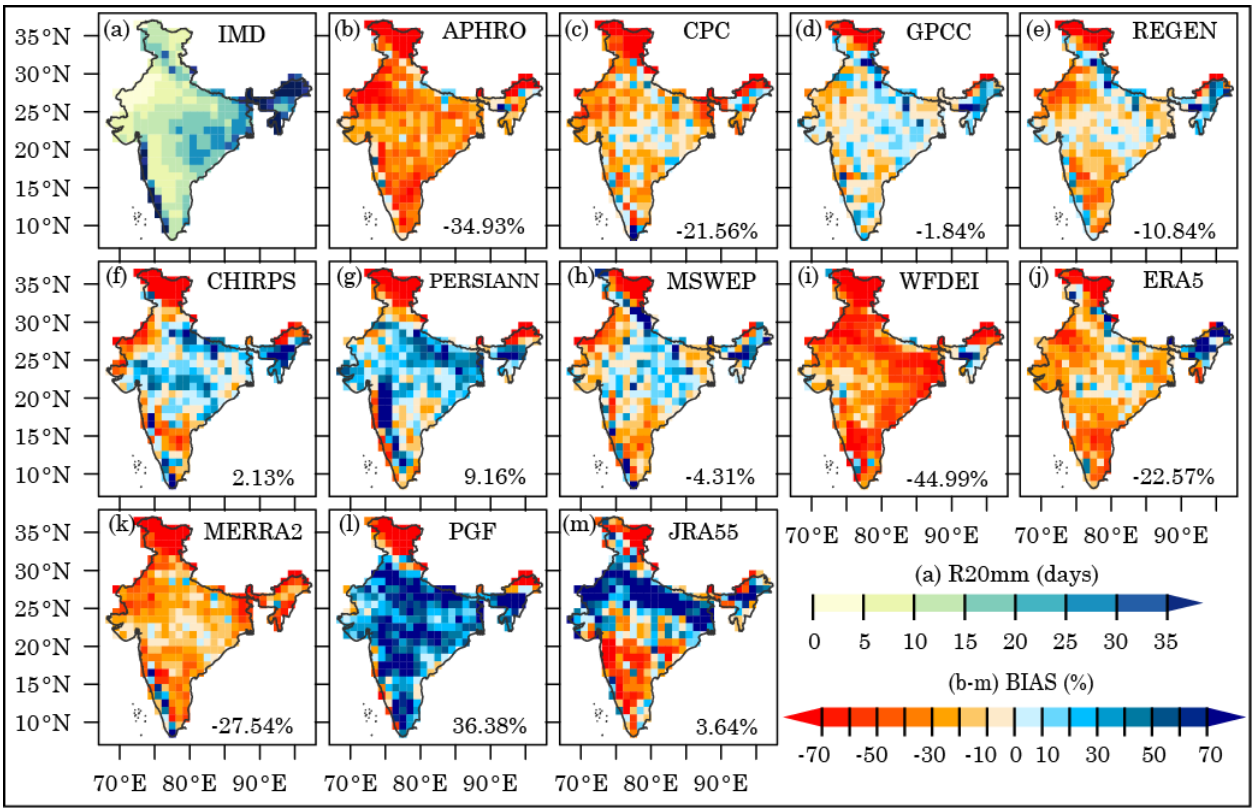


Fig. 5. Same as Fig. 2 but for R20mm.

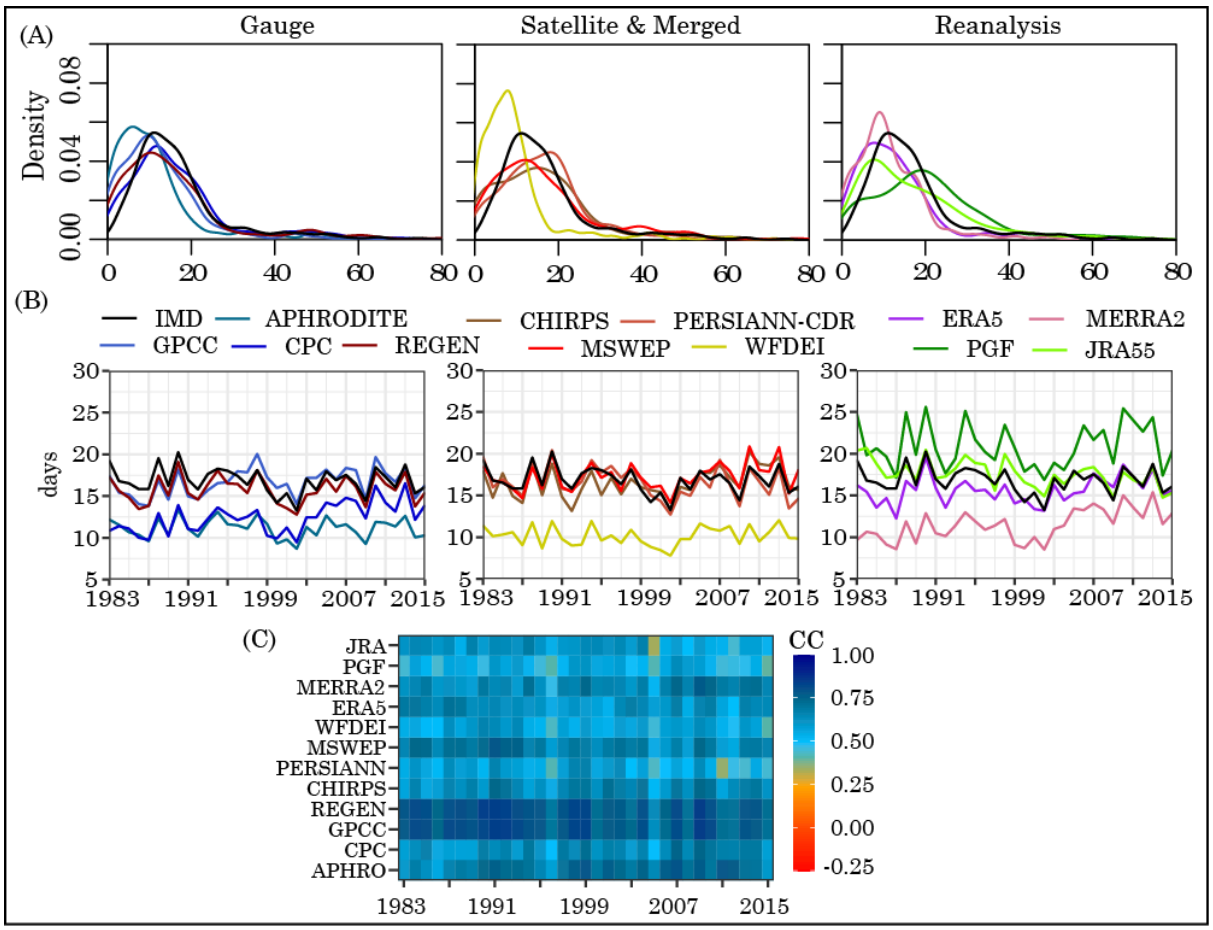


Fig. 6. Same as Fig. 3 but for R20mm.

3.3 Heavy, very heavy, and extremely heavy rainfall days

Heavy rainfall (HR) and very heavy rainfall (VHR) events in India are mainly concentrated in the foothills of the Himalayas, western side of WG, EC, and in parts of the CI and EP region (Fig. 7). Strong orographic control is found to exist in the occurrences of extreme rainfall events in India where in parts of WG and NE India, total frequency of HR and VHR are above 80 and 50 events respectively, during the study period. Moreover, HR and VHR events are less frequent in dry parts of TD, SP, and NH region, resulting in a lower annual rainfall amount in these areas. Similar to magnitude-based indices, HR and VHR events are also greatly underestimated by these datasets. The HR days in the central and eastern peninsular areas of India are not well captured by the APHRODITE, which may be due to lower station density in these regions (Fig. 7a). In the satellite-based data, CHIRPS better represents frequency of HR and VHR than PERSIANN-CDR but overestimates HR frequency in the Himalayan foothills. MSWEP better estimates HR and VHR and is

comparable to gauge-based IMD and GPCC but also overestimates HR frequency over the Himalayan foothills (Fig. 7). The WFDEI is worst among the products analyzed which may stem from the incorporation of ERA-Interim reanalysis in this merged product which is known to underrepresent extreme rainfall in India (Kim et al., 2019).

Extremely heavy rainfall (EHR) days (>205mm) are very rare in India but have relatively greater impacts in damaging infrastructure and crops. Similar to HR and VHR, spatial occurrences of EHR only from GPCC, MSWEP, and ERA5 datasets are comparable to IMD (Fig. S6). Only the ERA-5 reanalysis data identified some EHR days over NE, CI, and EP. Overall, the GPCC, MSWEP, and ERA5 give better estimates of higher extreme rainfall, however, with some overestimation in the orographic belts of WG and WH. The improvements in capturing extreme rainfall in ERA-5 over other reanalysis are also noted by (Mahato and Mishra, 2019). In MSWEP, various satellite rainfall datasets are incorporated which are known to overestimate extreme rainfall in the orographic belts in India (Gupta et al., 2019).

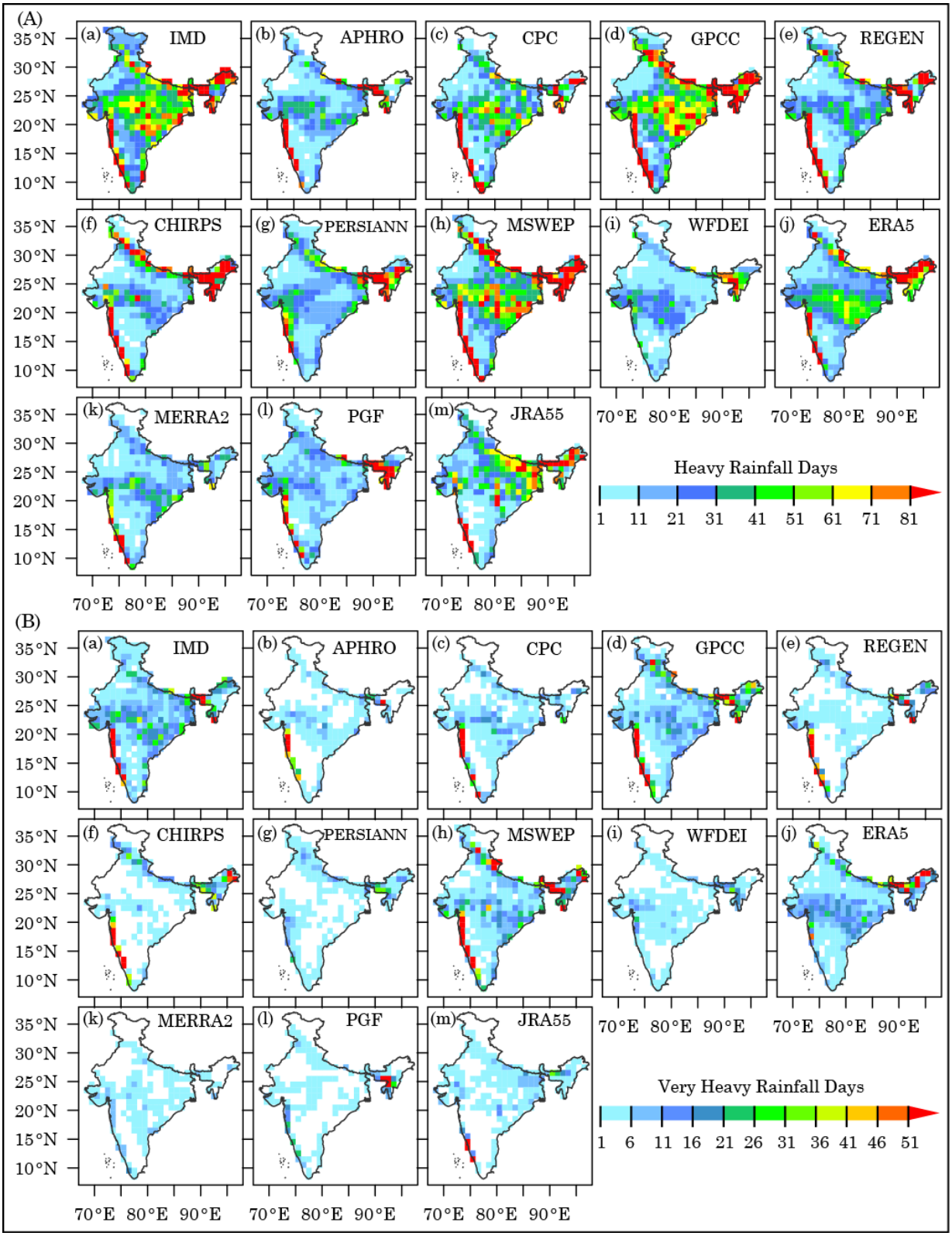


Fig. 7 Total number of heavy rainfall (HR) and very heavy rainfall (VHR) events in India during the period of 1983 – 2015.

3.4 Duration based extreme Indices

Dry day duration (CDD) is quite high (>150days) in the arid and semi-arid areas of WI, and is comparatively short (<50 days) in the NE, southern WG, and NH parts of India (Fig. 8). Lower CDD in the NH is due to the intermittent rainfall-snowfall occurrences during the monsoon-winter continuum, influenced by the monsoon and western disturbances respectively. Except for the PGF, other gridded products underestimate CDD over most parts of India (Fig. 8). Compared to the IMD dataset, CDD in the PGF is higher (>200 days) over the WI and SP. GPCC, REGEN and MSWEP better captured the spatial distribution of CDD and have median PBIAS less than 10% in India. In general, dry day lengths are underestimated by the selected datasets in most parts of India.

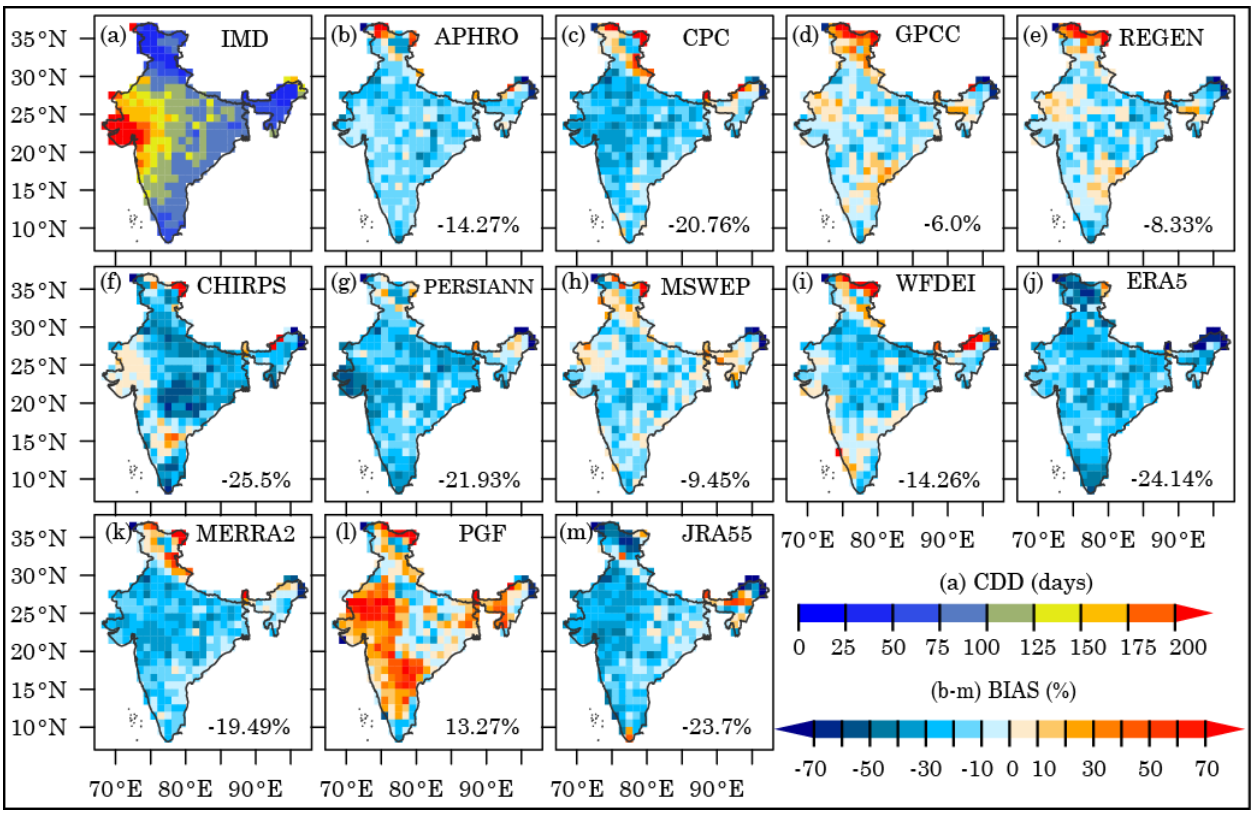


Fig. 8. Same as Fig. 2. But For CDD.

In contrast to CDD, higher CWD is found over the higher rainfall receiving zones (the WG and NE parts) and lower CWD values are observed over the dry-regions of western parts of India, in and around the TD (Fig. 9). The southern WG and NE parts of India are the wettest because of prolonged rainfall spells during monsoon. In the western parts and

southern peninsula, the rainfall is sporadic even during monsoon and this explains the lower CWD. In the core monsoon region and lower Gangetic plain, wet spell lengths are moderate and affected by the oscillation of the monsoon trough (Singh et al., 2019). Overall, CHIRPS and GPCC show strong performance in capturing spatial and temporal variations (Fig.10) of CWD in India, followed by CPC and MSWEP. Estimated PDFs from these three datasets (CHIRPS, CPC, and GPCC) are also close to the PDF from IMD. Except for the PGF, all other reanalyses greatly overestimate CWD in India with median bias above 70% whereas the PGF underestimates CWD by a similar magnitude.

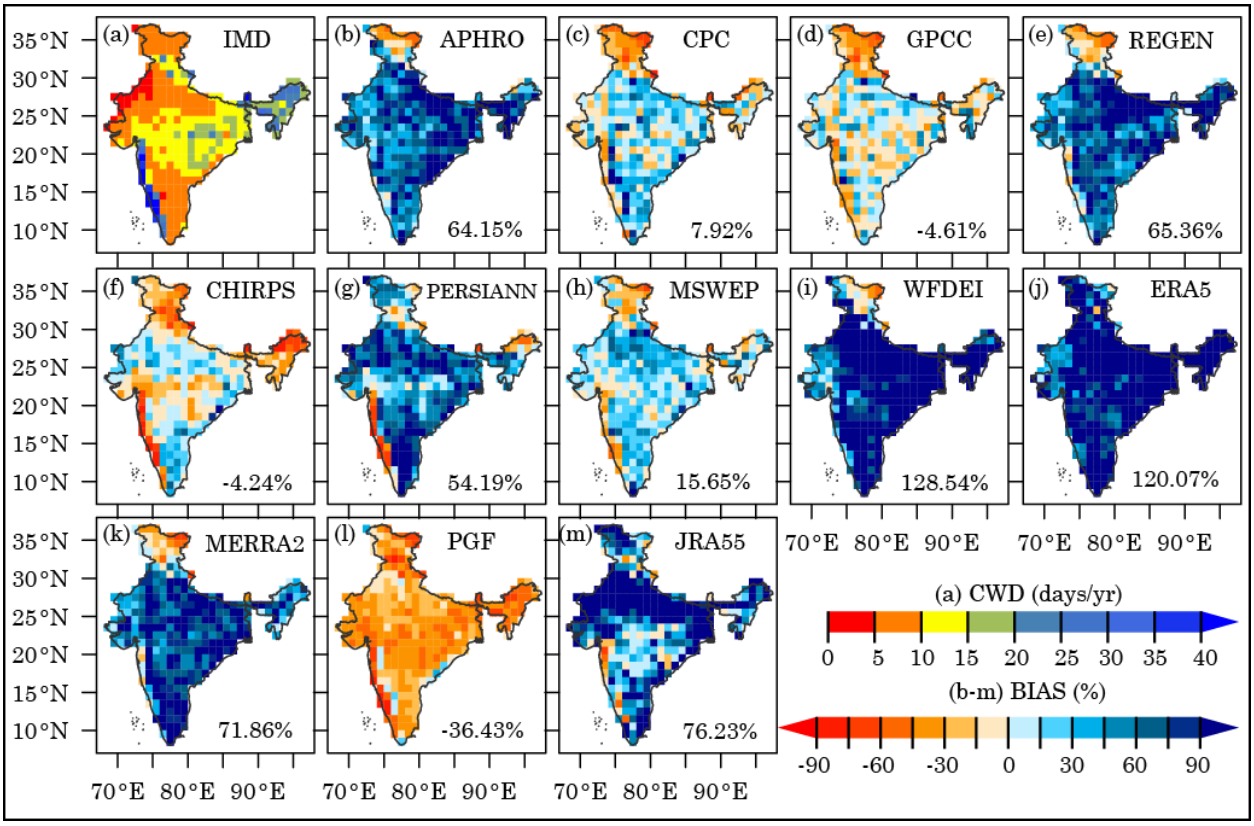


Fig. 9. Same as Fig. 2. But for CWD.

The gauge-based datasets have better agreement with IMD in estimating spatial and temporal variation in CDD and CWD (Fig. 10). Also, gauge-based and satellite datasets better estimate CWD than the CDD (except the WFDEI). However, inter-product spread in reanalysis datasets is relatively higher for both of these indices (Fig. 10). Overestimation of too many wet days with little rainfall in reanalysis products may be due the numerical

forecast model and uncertainties associated with parameterization schemes. This also affects the representation of dry days in these products. Overall, the spatial and temporal variability in (Fig. 10) dry days is better represented by the selected rainfall products than the wet days. Prolonged wet spells in the windward side of Western Ghats and NE during monsoon are due to the mountain-cloud interaction. However, satellite rainfall estimates are based on the relationship of rain rate with cold cloud top temperature measurements. This generates large bias and explains the underestimation of wet day length in the Western Ghats and NE India.

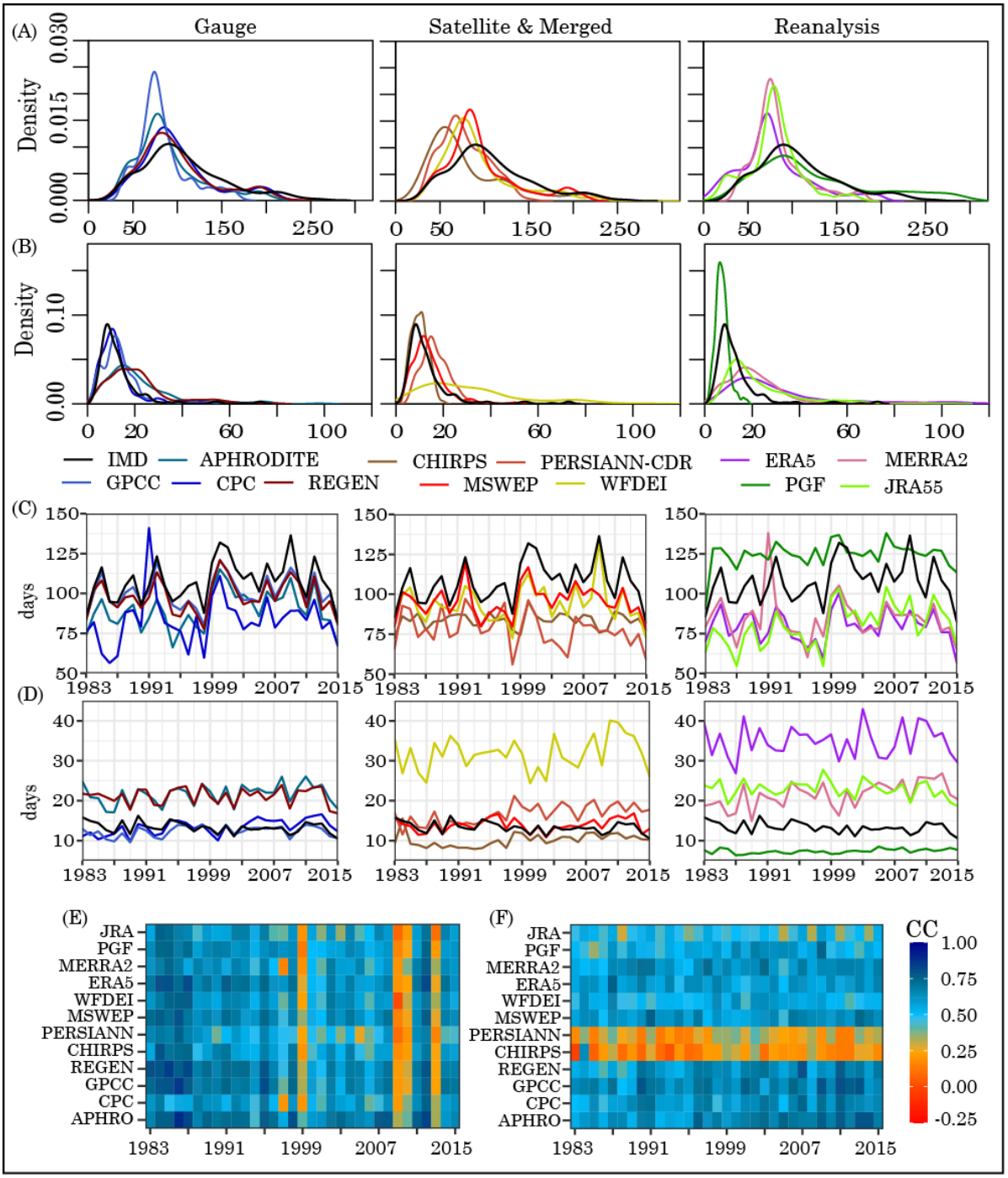


Fig. 10 Probability Density Functions represents climatological values CDD (A) and CWD (B) in India during 1983 – 2015. Temporal variation of area averaged CDD (C) and CWD rainfall (D) in different in gauge-based (left), satellite & merged (middle) and Reanalysis (right) datasets. Spatial correlation in representing CDD (E) and CWD rainfall (F) in India between IMD and other gridded dataset in representing.

3.5 Comparison based on trends in extreme rainfall

3.5.1 Trend in extreme rainfall magnitude

RX5day and RX1day rainfall has significantly increased in parts of western India, EP, and south-eastern parts of NH during the study period, whereas it has decreased over large parts of NH, GP, NE, and parts of WG region (Fig. 11 & Fig. S?). Estimated trends in magnitude-based indices in other gridded datasets show largest contrast with respect to the IMD dataset. It should be noted that the significant increasing and decreasing trend points for magnitude based indices are found in isolated places for the IMD dataset, however, these are clustered and found over larger areas in other gridded datasets. The wetting trend over western parts of India and drying trend in NE is present in all datasets (except CPC and MERRA2) with some over and underestimated areas. Trends in RX5day by CPC and MERRA2 are similar and they mostly overestimate increasing (wetting) trend areas over NW, GP, CI, and EP region. Thus, except CPC, other gauge-based datasets are consistent in representing the general pattern of increasing and decreasing trend, especially the wetting trends over EP and western parts of India and drying trend over NE and WG. However, the drying trend over GP and NH is underrepresented by the gauge-based datasets (Fig. 11). The PERSIANN-CDR noticeably shows a drying trend over the orographic belts and other parts of India, however, with the exception in the western parts where the wetting trend is present in almost in all datasets. The MSWEP gives more similar estimates of trend magnitude in RX5day and Rx1dayin India and better than other satellite, reanalysis and merged datasets when compared with the IMD dataset. In the reanalysis group, ERA5 and JRA55 also represent the drying and wetting trends in RX5day and Rx1day rainfall over NE and western India respectively. CPC and MERRA-2 exhibited wetting trends whereas the PERSIANN-CDR showed drying trend in most parts of India.

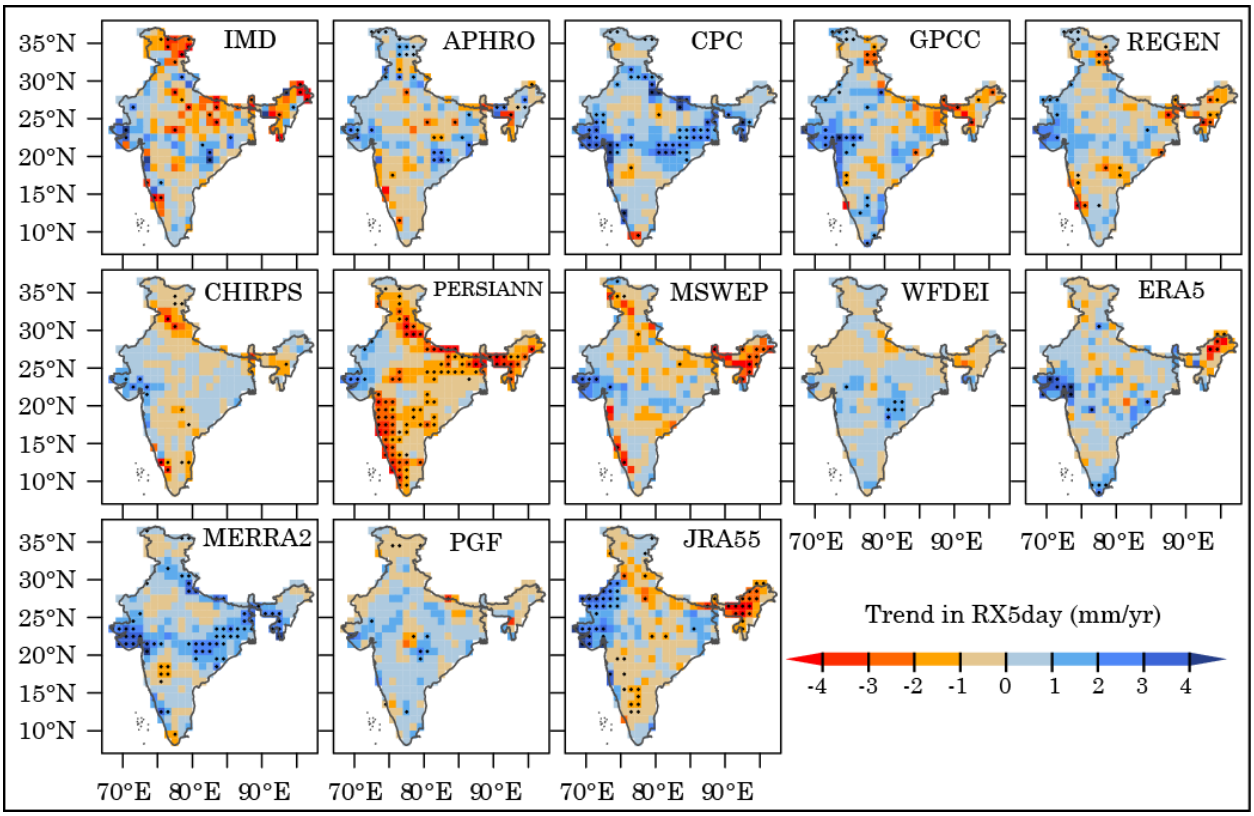


Fig. 11. Trend in RX5day rainfall during 1986-2015 in India. Black-dots showing grid-cells with significant trend at 95% level.

Regional patterns of trend direction in R95p are also variable and incoherent in the IMD datasets but the magnitude of decrease in R95p is relatively higher than RX1day and RX5day (Fig. 12). This is also true for most datasets, albeit with some showing more increasing trends (e.g. MERRA2 and CPC) and others more decreasing trends (PERSIANN-CDR).

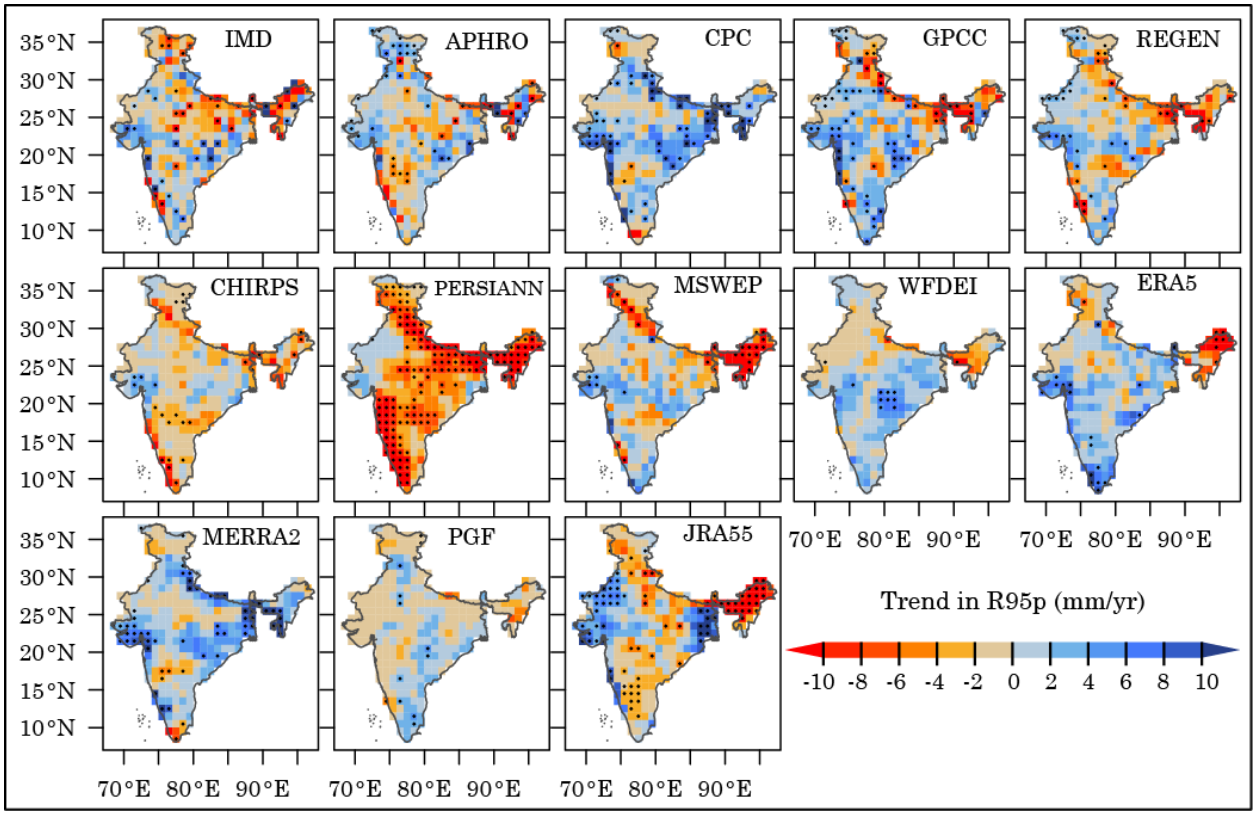


Fig. 12. Same as Fig. 11 but for R95p.

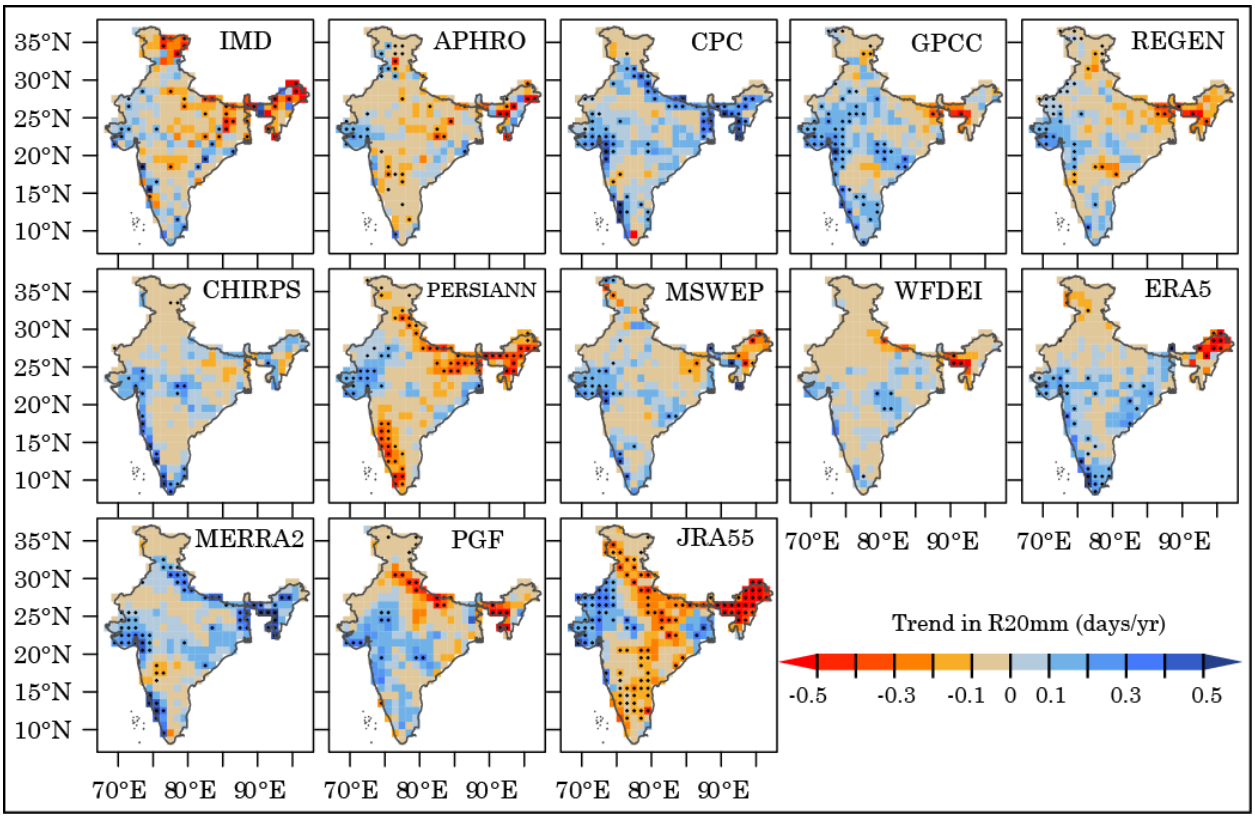
3.5.2 Trend in extreme rainfall frequency

Significant decreasing trends in R20mmand R10mm (Fig.13 & Fig.) days are observed mostly in NH, GP, and NE India whereas increasing trends are found over the WG and EP region of India. This indicates that the drying and wetting trends are consistent with magnitude based indices resulting in changes in monsoonal rainfall in these regions (Mahato and Mishra, 2020; Singh et al., 2019). CPC, GPCC, and MERRA2 have mostly showed wetting trend over most part India in contrast to IMD. Besides, the PERSIANN-CDR which show drying trend R20mm and other magnitude-based indices, has wetting trends for relative low rainfall days (R10mm).

Fig. 13 Same as Fig. 11 but for R20mm.

3.5.3 Trend in extreme rainfall duration

For the trends in CWD, large uncertainties are observed across different datasets. Some datasets (e.g. CPC and MERRA2) has strong wetting trend for all the indices. Most of the datasets show pattern of increasing trend in CWD over most parts of India in contrast to the isolated patches of increasing trend of IMD. Compared to other extreme indices, for CWD higher inconsistencies are noted with the IMD. This may be due to the higher bias estimating CWD in these datasets. In contrast to that, spatial pattern of trends in CDD are



consistent across most of the datasets. However, the JRA-55 has strong increasing trend in CDD dry days. Overall, the gauge-based datasets (except the CPC) are more consistent with the IMD in estimating trends in CDD than other products.

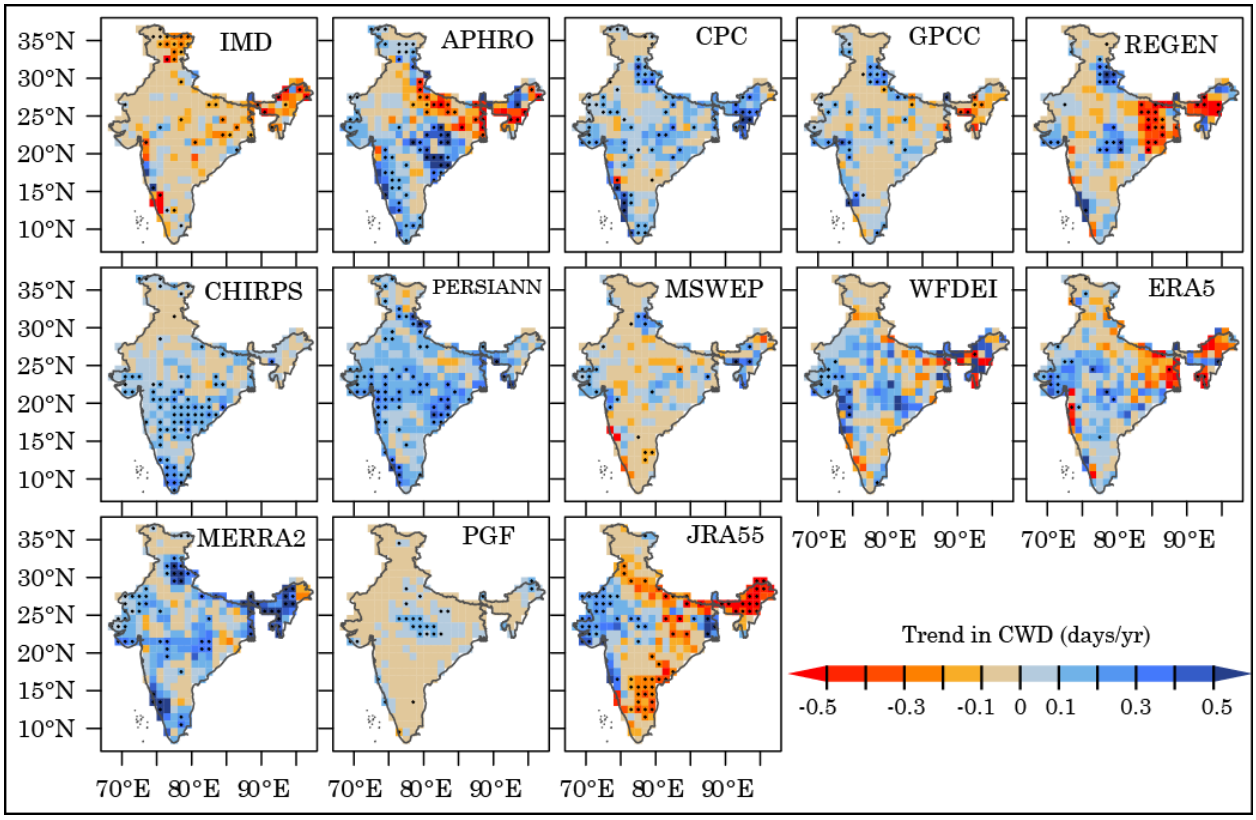


Fig. 14. Same as Fig. 11 but for CWD.

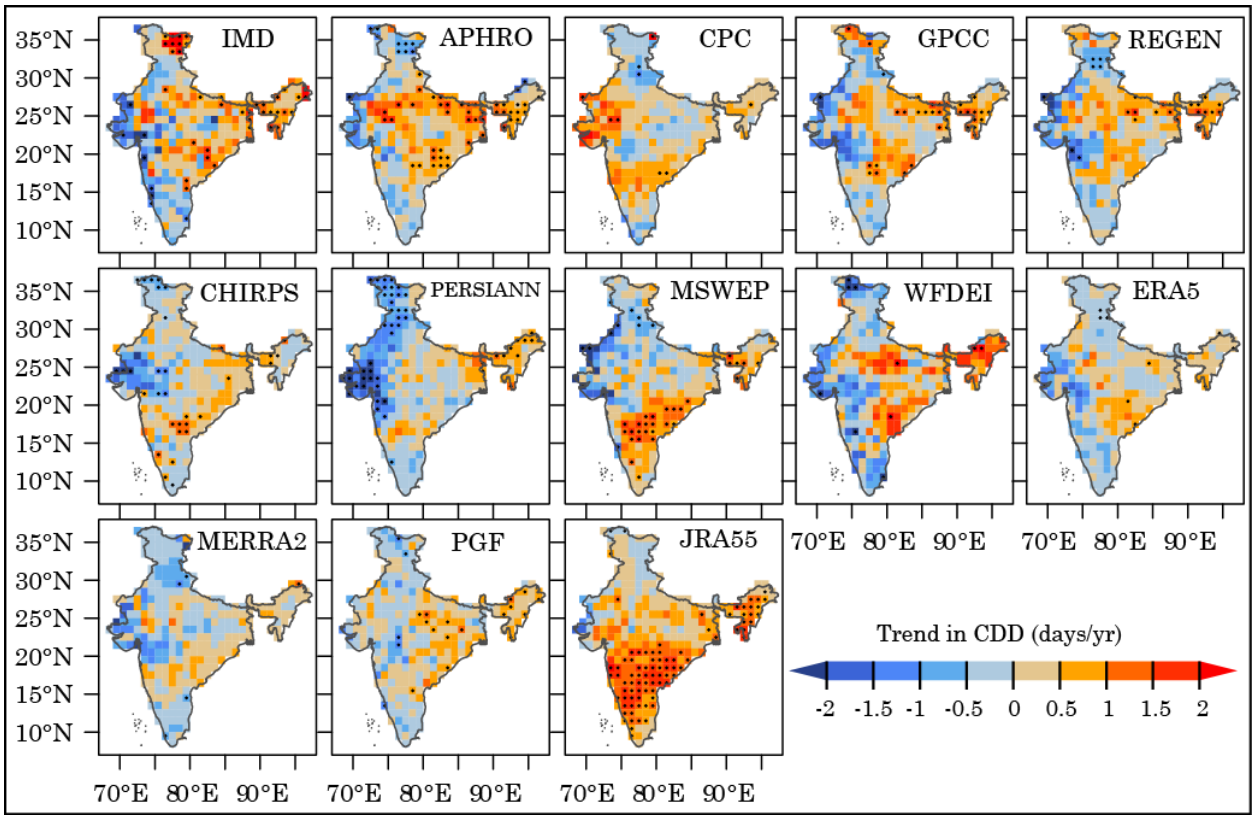


Fig. 15 Same as Fig. 11 but for CDD.

4. Discussion

From the above analysis, it is evident that the relative performance of gridded datasets varies in India and with the choice of extreme rainfall indices. The dry bias was highest for higher extreme indices (i.e RX1day and R99p) compared to relatively lower extreme (i.e. RX5day and R995p. This tail-dependent nature of extreme rainfall bias is a general feature of the satellite and reanalysis rainfall datasets. Analysis of frequency-based indices also confirms this, where heavy and very heavy rainfall days highly underrepresented in these products but R20mm overestimated. This means that the underestimation of extreme rainfall is mainly compensated by overestimating lower rainfall amounts in these datasets, which also explain the closer approximation of annual wet day rainfall (not presented in this study). Underestimation of extreme rainfall in India is noted in all datasets considering the high-resolution IMD gridded data as reference. However, considering another high-resolution (APHRODITE) gridded data as reference, Nguyen et al., (2020) found that extreme rainfall is overestimated over Asian domain as well as in India. Therefore, highlighting the importance of considering regional dataset such as IMD gridded-data, as it has higher station density than any other gauge-based dataset in India.

the representation of extreme rainfall among the selected gridded datasets varied markedly in India. Among the gauge-based gridded datasets GPCC shows the best agreement with the IMD dataset ahead of REGEN, APHRODITE, and CPC. This is quite surprising given higher station density in APHRODITE in India than GPCC (Fig. 1). APHRODITE has relatively poor coverage over Eastern peninsula and western dry parts of India. GPCC has a higher station density and a homogenous spatial coverage in India (especially in CI and EP region) compared to APHRODITE and CPC (Rana et al., 2015; Schneider et al., 2014). Therefore, GPCC gives close estimate to IMD for most of the extreme indices and also better preserve the spatial variation of rainfall extreme in India. Another source of uncertainty may be due to the differences in interpolation techniques used to construct these datasets. The Sheremap interpolation technique used by GPCC and APHRODITE is found to more robust over complex terrain than the optimal interpolation technique used in CPC (Ahmed et al., 2019; Salman et al., 2019). The gauge-based datasets failed to capture extreme rainfall dynamics over orographic belts, mainly in the eastern parts of the NH. This is mainly due to mere absence of gauge records in these gridded datasets in this region during construction (Pai et al., 2014).

Among the satellite rainfall datasets, CHIRPS performs better than PERSIANN-CDR in reproducing extreme rainfall behaviour in India. Similar findings for CHIRPS are also reported by Gupta et al., (2019) in reproducing extreme rainfall in India. Inadequate representation of extreme rainfall over the WG and foothills of NH is a limitation of satellite-derived rainfall as the remotely-sensed precipitation measurements fail to detect orographic rainfall resulting from atmosphere-mountain interactions (Gupta et al., 2019). PERSIANN-CDR uses infrared (IR) measurements of cloud top temperature and its relationship with precipitation rates for providing daily precipitation estimates. To avoid large unrealistic estimates of precipitation, maximum estimates are capped in PERSIANN-CDR system by setting an arbitrary limit, which can explain underestimation in extreme precipitation. Another constraint is that the training of artificial neural network relies solely on the IR measurement and a high-resolution data which is limited over the continental United States only. On the other hand, the CHIRPS precipitation estimates are derived by subsuming data from multiple sources (gauge-based, IR measurements, T3B42, and CFS2). Besides, the CHIRPS uses gauge-based GPCC data for calibration, while the PERSIANN-CDR estimates are calibrated using the GPCP satellite-derived precipitation

product. However, these two datasets are inadequate in representing the spatial pattern of extreme rainfall trends in India. The PERSIANN-CDR and CHIRPS are mainly developed to provide temporally homogeneous precipitation records rather than the best instantaneous estimates of precipitation rates. The MSWEP merged product performs reasonably well in representing extreme rainfall events in India and bias is also lower and similar to GPCC. However, over orographic belts it overestimated heavy rainfall events which are similar to GPCC. Chen et al., (2020) noted that WFDEI better capture RX1day over the globe when compared to GPCC. However, this study finds higher bias in India for this dataset. Higher extreme rainfall events as well as the magnitudes of their changes are mostly under-captured by this dataset when compared to the IMD. The WFDEI is developed using ERA-Interim reanalysis and bias-corrected using GPCC dataset. Therefore, subdued monsoon rainfall in India which is noted in ERA-Interim (Kim et al., 2019) may explain this underestimation.

The reanalysis datasets showed the largest discrepancies among other precipitation products when compared with the IMD dataset. Overestimation of extreme rainfall over the GP in JRA-55 may be due to the spin-down problem, which simulates excessive precipitation at the start at the forecast (Kobayashi et al., 2015). The PGF reanalysis highly overestimated CWD, and underestimated CDD in India, which may be due to the presence of too little wet days in the dataset. Performance of MERRA-2 is comparatively better than the JRA-55 reanalysis, especially in capturing heavy rainfall amount, frequency of R10mm and CDD in India. Mahato and Mishra et al. 2019 also find similar results while analyzing extreme monsoon season rainfall in India. An improved precipitation correction algorithm and incorporation of merged gauge-satellite data may be the reason for that (Reichle et al. 2017). The ERA-5 shows improvements with the sophisticated data assimilation methods and has benefited from improvements in model physics and core development of forecast models (Nogueira, 2020). As discussed above, the difference in grid-resolution also reduces the performance of reanalysis datasets in reproducing extreme precipitation.

5. Conclusion

Understanding extreme rainfall characteristics is crucial as they can have great societal impacts especially under recent warming. Gridded rainfall datasets for studying extreme rainfall are quite an attractive choice as they provide daily precipitation estimates at a high

spatial resolution over most parts of the globe. However, their performance must be assessed first before using in hydro-climatological studies. Twelve such daily gridded rainfall datasets from four different sources (comprising gauge-based, satellite, reanalysis, and merged products) are compared with a high-resolution regional dataset from IMD. The paper has the following objectives. First, to assess the spatio-temporal representation of different frequency, magnitude, and duration based extreme rainfall events in these datasets across India. Second, to assess the performance of these datasets in reproducing the spatial pattern of observed trends in frequency, duration, and magnitude based extreme rainfall indices. Third, to identify better performing datasets among the selected ones for extreme rainfall studies in India. The main findings are as follows:

Spatially higher extreme rainfall indices (e.g. RX1day, RX5day) are mostly underestimated by these datasets. The amount of dry bias is relatively high for higher extreme indices that are located further into the tail of the daily rainfall distribution (e.g. RX1day and R99tp). The amount of wet bias increases for moderate and lower rainfall extremes (e.g. R20mm and R10mm) as frequency of these indices is overestimated in most parts of India. It is also found that the amount of bias in estimating extreme rainfall is relatively higher over complex topography e.g. Western Ghats, Himalaya, and NE India. Besides, a consistent overestimation of extreme rainfall in the dry parts of Southern Peninsula (leeward side of Western Ghats) is noted in PERSIANN-CDR and JRA-55 over the NW India. The inter-product spread is lower among the gauge-based products and it is highest for reanalysis. However, the ERA-5 reanalysis captures the spatio-temporal variability of extreme rainfall indices better than other reanalyses and even sometimes outperforms other product types (e.g. CPC, WFDEI). Duration-based extreme indices are better captured by the gauge-based datasets than other data types. Due to overestimation of very low rainfall days, CWD is overestimated in these data products. In contrast, the CDD are better captured than CWD. The gauge-based, satellite, and merged products better capture the spatial and temporal variation in dry days.

Trends in extreme rainfall indices are quite patchy and found in isolated places in the IMD dataset. This inhomogeneous trend pattern can also be noted in other datasets, although, with some notable exception like the PERSIANN-CDR shows strong drying trend for almost

all the extreme indices. In contrast, the CPC and MERRA-2 have wetting trend over India across all the extreme indices, which is in large contrast to the IMD dataset.

The study finds that the gauge based GPCC better captures extreme rainfall in India than other datasets. In the satellite-reanalysis group, CHIRPS, and ERA-5 outperformed other datasets, respectively. It is interesting to note that the MSWEP merged datasets is in better agreement with IMD than the satellite reanalysis products. However, there is less consistency among the datasets in estimating trends in extreme rainfall indices over India. Although, regional wetting (EP and western India) and drying trend (GP and NE India) trend patters are consistent in most of the datasets.

Moreover, some of the gridded datasets used in this study are often used to validate global and regional climate models for climate change impact assessment studies and the underestimation of extreme rainfall, which is inherent in these datasets, may introduce larger uncertainties in climate change studies, especially those with an emphasis on extreme precipitation. Therefore, we argue that assessment ability to capture extreme rainfall by gridded datasets over the region of interest is a prerequisite before conducting any research on changing pattern of regional rainfall characteristics in a warming world.

Author contributions

Suman Bhattacharyya: Conceptualization, Methodology, Data curation, Formal analysis, Visualization, Writing- original draft. **S Sreekesh:** Conceptualization, methodology, Supervision, Writing- Review & Editing. **Andrew King:** Writing- Review & Editing

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