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A Comparison and Ranking Study of Monthly Average Rainfall Datasets with IMD Gridded Data in India

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Abstract: Precise rainfall measurement is essential for achieving reliable results in hydrologic applications. The technological advancement has brought numerous rainfall datasets that can be available to assess rainfall patterns. However, the suitability of a given dataset for a specific location remains an open question. The objective of this study is to find which rainfall datasets perform well in India at various spatial resolutions: pixel level, meteorological sub-divisions (MSDs) level, and India as a whole and temporal resolutions: monthly and yearly. This study performs skill metrics analysis on seven widely used rainfall datasets—GPM, CRU, CHIRPS, GLDAS, PERSIANN-CDR, SM2RAIN, and TerraClimate—using the Indian Meteorological Department's (IMD) gridded data as a reference. The rule-based decision tree techniques are employed on the obtained skill metrics analysis values to find the good-performing rainfall dataset at each pixel value among all the datasets used. The MSD and pixel-wise analyses reveal that GPM performs well, while TerraClimate performed the most poorly in almost all MSDs. The analysis suggests that of the satellite-derived, gauged, and merged datasets, merged-type are the good-performing datasets at the MSD level, with approximately 17 MSDs demonstrating the same. The temporal analysis (in both month- and year-wise scales) also suggests that GPM is a good-performing dataset. This study obtained the optimal dataset for each pixel among the seven selected datasets. The GPM dataset typically ranks as a good-performing fit, followed by CHIRPS and then PERSIANN-CDR. Despite its finer resolution, the TerraClimate dataset ranks lowest at the pixel level. This research will aid in selecting the optimal dataset for MSDs and pixels to obtain reliable results for hydrologic and agricultural applications, which will contribute to sustainable development.

Keywords: skill metric analysis; rainfall; MSDs; hydrology; satellite-derived; GPM; CRU; CHIRPS; GLDAS; PERSIANN-CDR; SM2RAIN

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1. Introduction

Rainfall significantly impacts the earth's hydrological cycle and energy balance. Precise rainfall measurement is essential to hydrologic modelling, agriculture, drought monitoring, water resource management, numerical weather forecasting, moisture budget calculations, and other hydro-meteorological applications [1–8]. It also helps us enhance our insight into rainfall's impact in various domains.

Rain gauges are the principal source of direct rainfall data [9]. The uneven and scattered distribution of rain gauges in remote areas is the main reason for inadequate spatial coverage, reducing the overall accuracy of rainfall estimation over large regions [10]. Earth observation technology helps to overcome these limitations, as advancements in remote sensing and science have made it possible to retrieve rainfall estimates from satellite observations [11]. Remote sensing is a cost-effective, continuous, and uninterrupted technique for retrieving a worldwide rainfall dataset with passive radiative sources at various spatial and temporal resolutions, even in data-scarce regions and under adverse conditions [12–14].

The accuracy of satellite-derived rainfall datasets requires attention, as rainfall is a significant input for many applications. In this regard, rigorous evaluation and validation are necessary to ensure that datasets accurately represent rainfall in various physiographic locations [15–17]. Several studies have assessed the suitability of satellite rainfall data in a particular region or country, application, and time duration by comparing it to rain gauge data. For the Indian subcontinent during the Indian summer monsoon, Kumar Singh et al. [18] examined the HE (Hydro Estimator) and IMSRA (INSAT Multispectral Rainfall Algorithm) datasets based on the Indian National Satellite System (INSAT), Global Precipitation Measurement (GPM) and Global Land Data Assimilation System (GLDAS) datasets. They found that GLDAS gives the best results among all selected datasets, and GPM gives the best results in the satellite datasets category at a monthly temporal resolution. Kumar Singh et al. [19] evaluated INSAT HE & IMSRA, GPM, and National Center for Medium-Range Weather Forecasting (NCMRWF), Merged Satellite Gauge (NMSG) of IMD for the southwest monsoon season of 2016 at a weekly temporal resolution. Their study showed that NMSG and GPM are the best datasets among all the datasets. Thakur et al. [20] evaluated Integrated MultisatellitE Retrievals (IMERG) of GPM data in India during the southwest monsoon between 2014 and 2017 against IMD gridded data and found that it was good to use for weather forecasting and hazard management. Kumar et al. [21] employed the Tropical Rainfall Measuring Mission (TRMM) Multi-satellite Precipitation Analysis (TMPA), and IMERG data were employed against IMD data also during the monsoon, between 1998 and 2017, and suggested that both were the best datasets. V. Pandey et al. [22] used Climate Hazards Group Infrared Precipitation with Station (CHIRPS) and TRMM datasets for drought monitoring in the Bundelkhand region, India and found that TRMM yielded better results when evaluated against ground-measured IMD data. Singh et al. [23] used INSAT-3D HE & IMSRA and GPM datasets for heavy rainfall events during the winter monsoon over peninsular India. Their results showed that GPM better estimated heavy rainfall compared to INSAT-3D HE and IMSRA. Kommu et al. [24] validated monthly CHIRPS, PERSIANN-CDR and TRMM datasets against IMD gridded data between 2000 and 2012 in the Tungabhadra basin, India, using skill metrics such as the coefficient of correlation, percent bias (PBIAS) and Nash–Sutcliffe efficiency (NSE). The study found that TRMM was best able to mimic high rainfall patterns precisely, whereas the PERSIANN-CDR dataset better captured low precipitation. Later, Gupta et al. [25] evaluated and validated CHIRPS, SM2RAIN-Advanced SCATterometer (SM2RAIN-ASCAT) and TRMM/GPM datasets with IMD gridded data between 2007 and 2016 and found that the TRMM and CHIRPS performed well across most regions in India, while the SM2RAIN-ASCAT dataset underperformed, especially for extreme rainfall cases. The TRMM satellite rainfall was also compared with the IMD rainfall over Maharashtra, India, for monsoon months from 2004 to 2013 [26], and it was found that TRMM correlates well with IMD data, where the western ghat (mountain range) impact is more significant [6].

Various studies have evaluated satellite rainfall datasets derived from TRMM [27–30] and the Indian satellite INSAT [23,31], INSAT HE and IMSRA, GPM and GLDAS [18], TMPA and IMERG [21] using ground-based rainfall measurements obtained across different regions of the Indian subcontinent. The GPM-based (IMERG-V4 and Global Satellite Mapping of Precipitation (GSMaP) GSMaP-V6), INSAT3D Multispectral Rainfall Algorithm (IMR) and Hydro-Estimator (HE) method and IMD–National Centre for Medium-Range Weather Forecasting (NCMRWF) merged products have been evaluated using gridded gauge-based IMD rainfall data on daily, monthly and seasonal scales [32]. All of the datasets show a noticeable bias in producing rainfall over orographic regions (i.e., the Western Ghats and foothills of the Himalayas) and North-East India. However, there exists a significant difference among the satellite measurements. Overall, IMERG-FNL (GPM) datasets showed promising results with gauge-based IMD data compared to GSMaP and INSAT3D estimates.

Researchers have examined the suitability of various rainfall products for other parts of the world. Liu et al. [33] compared GSMaP, IMERG, and CHIRPS data for Bali, and the results suggested IMERG was more suitable. Wang et al. [34] applied the CPC MORPHing technique (CMORPH), TMPA-RT (TRMM), and Precipitation Estimation from Remotely

Sensed Information using Artificial Neural Networks (PERSIANN) data in Northwest China during periods of heavy rainfall. The former two were found to be more accurate than PERSIANN. Ayehu et al. [7] used CHIRPS and TAMSAT 1, 2 and 3 datasets for the Upper Blue Nile Basin in Ethiopia, and their results showed a more accurate performance from CHIRPS. The breadth of research signifies that GPM, CHIRPS, and PERSIANN are widely used datasets across diverse topographical regions.

However, validating datasets at the sub-divisional level is also necessary in addition to at national or political levels [29]. Researchers have evaluated rainfall datasets on a seasonal [19,20,32,35], monthly [5,6,22], ten-day [7], weekly [19] and daily time steps [19,23,31,36,37]. The validation of available rainfall datasets at a monthly scale and MSD level, and pixel level in India gives the scientific community more confidence in selecting rainfall products for various applications. It helps to choose the best-performing rainfall dataset for different applications and provides more information about the rainfall blueprint of a region. Hence, it also provides useful guidance for agricultural stakeholders making operational decisions.

To date, rainfall comparison research has aimed to find good-performing datasets out of two or three selected datasets. Few studies use more than four rainfall datasets; furthermore, these rainfall products have only been examined India as a whole. There is also a research gap in the ranking various rainfall products based on their suitability at each pixel level and MSD level. The primary objectives of this study are: (1) to compare the monthly rainfall datasets such as GPM, Climatic Research Unit (CRU), CHIRPS, GLDAS, PERSIANN-CDR, SM2RAIN, and TerraClimate with IMD gridded rainfall data, and (2) to understand their suitability for India and to choose the most suitable rainfall dataset at each pixel level and MSD level.

2. Study Area, Datasets Used and Methodology

2.1. Study Area

India's MSDs were chosen as the spatial resolution of interest because India has diverse climate zones and four seasons (winter, pre-monsoon, monsoon and post-monsoon). Moreover, most of the agricultural area falls into the rainfed agricultural region (around 56%) and uses more water per unit of agricultural yield than other nations [38]. Hence, studying Indian rainfall variation can contribute to sustainable water resource management. There are currently 36 sub-divisions in India; they are largely delineated based on India's historical weather and climate, with certain attention given to practical concerns, the compilation of statistics, the issuance of weather alerts to government functionaries, and the education of the general public [39]. This study considers 34 MSDs; the current resampling resolution of the employed data fails to capture the 1st and 36th MSD, AN and I and Lakshadweep since they have a small area. Hence, 34 MSDs are considered in this study. The study area's pictorial representation is shown in Figure 1, and the acronyms of MSDs are mentioned in Table 1.

2.2. Datasets

This study uses IMD gridded monthly rainfall data for the years 2015–2019 to validate seven rainfall datasets: CHIRPS, CRU, GLDAS, GPM, PERSIANN-CDR, SM2RAIN, and TerraClimate. Out of the seven datasets, three are merged datasets (CHIRPS, GPM, and GLDAS), two are gauged (CRU and TerraClimate), and the remaining two are satellite-derived (PERSIANN-CDR and SM2RAIN). The datasets used, their data sources, spatial and temporal resolution, and data availability are listed in Table 2. These datasets are chosen for this study as they are widely used in the Indian context for various hydrologic and agricultural applications [18,19,22,24,40–42].

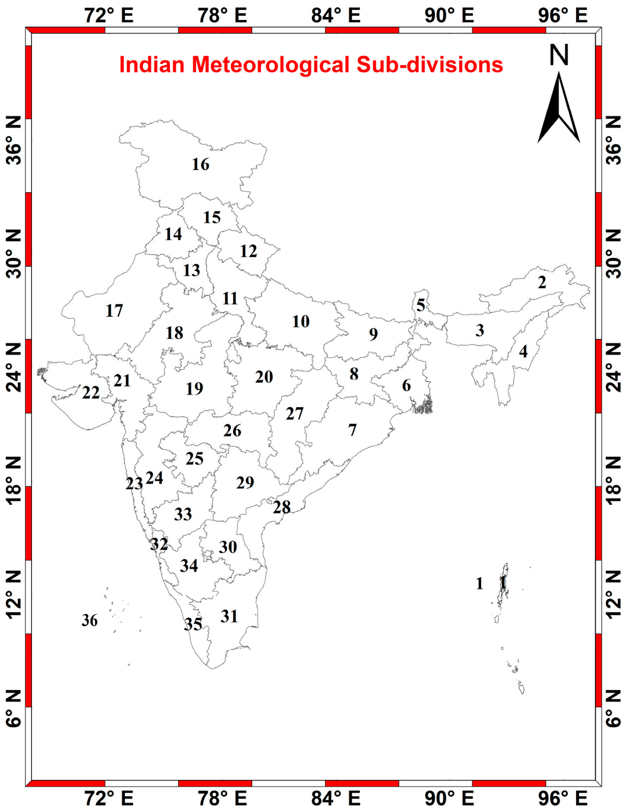

Figure 1. Study area: Indian meteorological sub divisions.

Table 1. List of Indian meteorological sub divisions.

1	Andaman and Nicobar Islands (A and N I)	13	Haryana, Chandigarh and Delhi (HC and D)	25	Marathwada (MW)
2	Arunachal Pradesh (ARP)	14	Punjab (PN)	26	Vidarbha (VB)
3	Assam & Meghalaya (A and M)	15	Himachal Pradesh (HP)	27	Chhattisgarh (CG)
4	Nagaland, Manipur, Mizoram and Tripura (NMMT)	16	Jammu and Kashmir and Ladakh (JK and L)	28	Coastal Andhra Pradesh and Yanam (C-AP and Y)
5	Sub-Himalayan West Bengal and Sikkim (SHWB)	17	West Rajasthan (W R)	29	Telangana (TS)
6	Gangetic West Bengal (GWB)	18	East Rajasthan (E R)	30	Rayalaseema (RS)
7	Odisha (OD)	19	West Madhya Pradesh (W MP)	31	Tamil Nadu and Puducherry and Karaikal (TN and P)
8	Jharkhand (JH)	20	East Madhya Pradesh (E MP)	32	Coastal Karnataka (C-KA)
9	Bihar (BH)	21	Gujarat region (GJ)	33	N.I. Karnataka (NI KA)
10	East Uttar Pradesh (E UP)	22	Saurashtra and Kutch (S and K)	34	S.I. Karnataka (SI KA)
11	West Uttar Pradesh (W UP)	23	Konkan and Goa (K and G)	35	Kerala and Mahe (KL)
12	Uttarakhand (UK)	24	Madhya Maharashtra (MH)	36	Lakshadweep (L)

Table 2. Datasets and Sources.

Parameter	Dataset and Source	Spatial Resolution	Temporal Resolution	Data Availability
Rainfall	**IMD Gridded Data** https://www.imdpune.gov.in/Clim_Pred_LRF_New/Grided_Data_Download.html (accessed on 15 September 2020)	0.25°	Daily	1901–Present
	CHIRPS (Merged gauge + satellite) https://data.chc.ucsb.edu/products/CHIRPS-2.0/global_monthly/tifs/ (accessed on 15 September 2020)	0.05°	Monthly	1981–Present
	CRU (Gauged data) https://crudata.uea.ac.uk/cru/data/hrg/cru_ts_4.05/cruts.2103051243.v4.05/ (accessed on 19 June 2021)	0.5°	Monthly	1901–Present
	GLDAS 2.1 Rain Precipitation Rate (Combination of Model and Gauged data) https://giovanni.gsfc.nasa.gov/ (accessed on 15 September 2020)	0.25°	Monthly	2000–Present
	GPM (Merged satellite-gauge precipitation estimate - Final Run) https://giovanni.gsfc.nasa.gov/ (accessed on 15 September 2020)	0.1°	Monthly	2000–Present
	PERSIANN-CDR (Satellite) http://chrsdata.eng.uci.edu/ (accessed on 19 June 2021)	0.25°	Monthly	1983–Present
	SM2RAIN (Satellite) https://zenodo.org/record/4570192#.YORPVOgzY2x (accessed on 19 June 2021)	0.25°	Monthly	2007–Present
	TerraClimate (Gauged data) https://www.climatologylab.org/terraclimate.html (accessed on 19 June 2021)	0.05°	Monthly	1958–Present

(a) IMD Gridded rainfall datasets

The IMD rainfall gridded dataset is prepared from daily rainfall data and archived at the National Data Centre, IMD, Pune, using the Shepard method [43], which uses rainfall records of 6955 rain gauge stations [44]. These datasets are prepared with a spatial resolution of 25 km and a one-day temporal resolution.

(b) CHIRPS

The CHIRPS dataset has a 0.05° resolution and covers 1981 to the present. This dataset is available in daily, pentad, dekad, monthly, 2-monthly, 3-monthly, and annual time scales [45].

(c) CRU

The CRU TS (Climatic Research Unit gridded Time Series) is an extensively used climate dataset with a 0.5° * 0.5° on a monthly temporal resolution. This study uses the CRU TS v4.05 dataset, available from 1901 to 2021. It is derived by interpolating monthly climate anomalies from weather station observations [41].

(d) GLDAS

The Global Land Data Assimilation System (GLDAS) aims to use advanced surface modelling and data assimilation techniques to build optimum fields of land surface states and fluxes by ingesting satellite and ground-based observational data sources [46]. This analysis uses the GLDAS model-derived rain precipitation rate monthly averaged product with 0.25° spatial resolution.

(e) GPM

The GPM mission core satellite was launched in 2014 to provide global quantitative precipitation estimates (QPE). With the help of an international constellation of satellites, the Integrated Multi-satellite Retrievals for GPM (IMERG) produces precipitation estimates at 0.1° resolution in the range 60°N-S every half hour. The IMERG precipitation dataset is calibrated to the GPM Microwave Imager/Dual-frequency Precipitation Radar combined product to provide the best possible estimates of precipitation [47]. The GPM IMERG final run product was employed in this study.

(f) PERSIANN-CDR

The PERSIANN-CDR dataset was developed by the Center for Hydrometeorology and Remote Sensing (CHRS). The PERSIANN-CDR dataset is created from the PERSIANN algorithm using GridSat-B1 infrared data and corrected using the Global Precipitation Climatology Project (GPCP) monthly product at 0.25° spatial resolution from 1983 to the present [48,49].

(g) SM2RAIN

SM2RAIN-ASCAT rainfall datasets were obtained from the ASCAT satellite soil moisture data through the SM2RAIN algorithm [50,51] at 0.25° resolution from 2007 to the present at a monthly temporal resolution [51].

(h) TerraClimate

TerraClimate combines WorldClim datasets with time-varying and coarser spatial resolution datasets (CRU Ts4.0 and JRA55) for generating various datasets. TerraClimate rainfall data are available from 1958 to 2021 and used in this study [52].

2.3. Methodology

IMD gridded rainfall data are used as reference data to validate selected rainfall datasets for MSDs in India between 2015 and 2019. The source data of IMD is available on a daily scale; for this research purpose, it needs to be converted to a monthly scale. The daily gridded data of IMD is converted to monthly data through summation; the number of days of the month and leap year conditions are considered for this purpose. Python code is written for performing this task. The selected datasets come in various spatial resolutions; therefore, they are resampled into 0.25° resolution using the nearest neighbour technique to match the reference dataset. The discrepancy between selected datasets and reference dataset was measured using skill metrics such as the correlation coefficient (γ), the root mean square error (RMSE), the Nash–Sutcliffe efficiency (NSE), the percent bias (PBIAS), and the ratio of the standard deviation of the observation to the root mean square error (RSR). Skill metrics analysis is performed to assess the suitability of seven widely used rainfall datasets for each MSD, pixel, dataset and dataset type wise. Rule-based decision tree techniques are employed on obtained results to find the good-performing datasets among all the selected datasets at each pixel level and MSD level. The methodology followed for this research work is shown in Figure 2, and skill metrics used for rainfall dataset comparison, their equations range, and sources are mentioned in Table 3.

Skill metrics need to be classified into good-performing, moderate-performing, and low-performing fits to evaluate dataset-wise suitability. Table 4 summarises the five skill metrics used and their classification criteria. The basis for the range selection was taken from [53]. The skill metrics values for individual MSDs for selected datasets are represented in Figure 3, and Figure 4 summarises the classification of MSDs. The MSDs are categorised as good-, moderate-, and low-performing based on the five skill metrics ranges, as mentioned in Table 3. The datasets are classified as good-performing if a minimum of three skill metrics are in a good-performance range, and if more than two parameters are low, it is regarded as low-performing. The intermediate state is considered a moderate-performing fit.

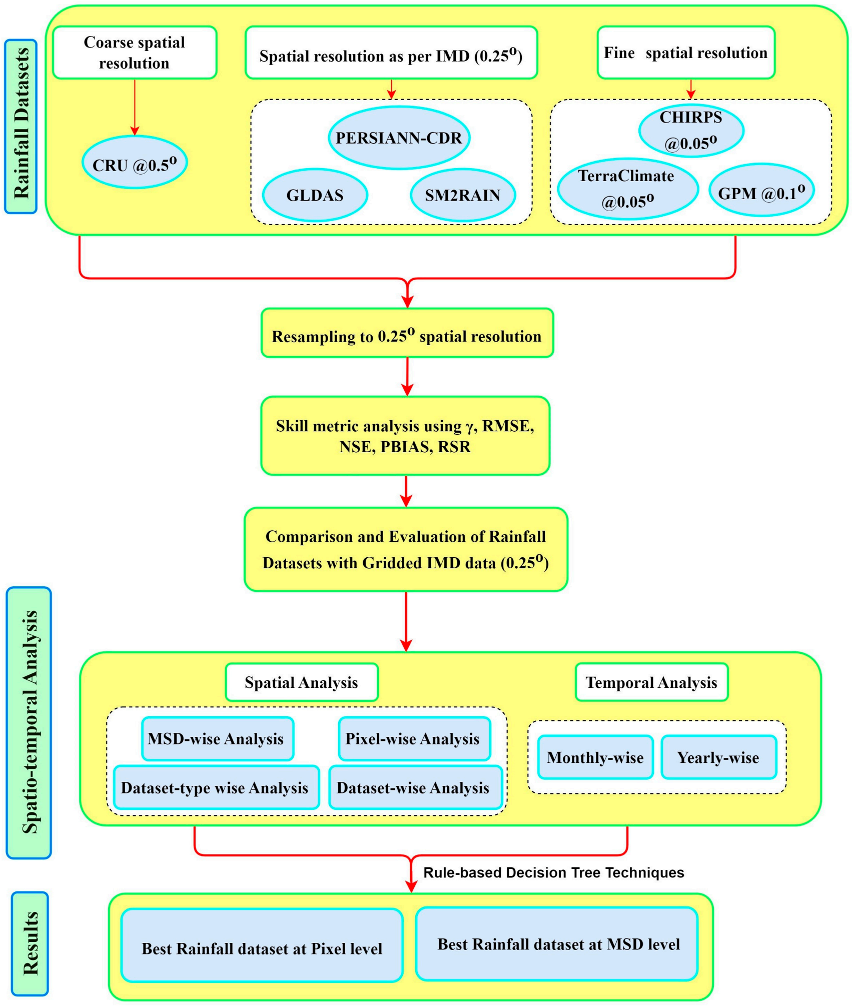

Figure 2. Flowchart of methodology.

Table 3. Skill metrics used for rainfall dataset comparison. y_i and $\acute{y}_i$ represent the actual and predicted values, respectively, and $\overline{y}$ and $\overline{\acute{y}_i}$ are averages of the actual and predicted values, respectively.

S.No	Skill Metrics	Equation	Range	Source
1	**Pearson Correlation Coefficient (γ)**	$\gamma = \frac{\sum_{i=1}^{n}(y_i - \overline{y}) \times (\acute{y}_i - \overline{\acute{y}_i})}{\sqrt{\sum_{i=1}^{n}(y_i - \overline{y})^2 \times (\acute{y}_i - \overline{\acute{y}_i})^2}}$	−1 and 1. Where 0 is no correlation, 1 is a total positive correlation, and −1 is a total negative correlation	(Pearson 1895) [54]
2	**Root Mean Square Error (RMSE)**	$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \acute{y}_i)^2}$	A smaller value indicates good performance.	(Moriasi et al. 1983) [53]
3	**Nash–Sutcliffe Efficiencies (NSE)**	$NSE = 1 - \frac{\sum_{i=1}^{n}(y_i - \acute{y}_i)^2}{\sum_{i=1}^{n}(y_i - \overline{y})^2}$	-Infinity to 1. If this parameter is closer to 1, the model is further accurate.	(Nash and Sutcliffe 1970) [55]
4	**Percentage Bias**	$PBIAS = \frac{\sum_{i=1}^{n}(y_i - \acute{y}_i)}{\sum_{i=1}^{n}\acute{y}_i} * 100$	A smaller percentage indicates good performance.	(Gupta et al. 1999) [56]
5	**RMSE-observations standard deviation ratio (RSR)**	$RSR = \frac{\sqrt{\sum_{i=1}^{n}(y_i - \acute{y}_i)^2}}{\sqrt{\sum_{i=1}^{n}\left(y_i - \overline{\acute{y}_i}\right)^2}}$	0 to ∞. ≤0.7 indicating a good-performing range.	(Chu and Shirmo-hammadi 2004) [57]

Table 4. Skill metrics and their ranges.

Skill Metrics	Good-Performing Range	Moderate-Performing Range	Low-Performing Range
γ	>0.8	0.4–0.80	<0.4
NSE	>0.75	0.5–0.75	<0.50
RMSE	<25	25–75	>75
PBIAS	−10 to +10	10 to 25 or −10 to −25	>25 or <−25
RSR	0–0.5	0.5–0.7	>0.7

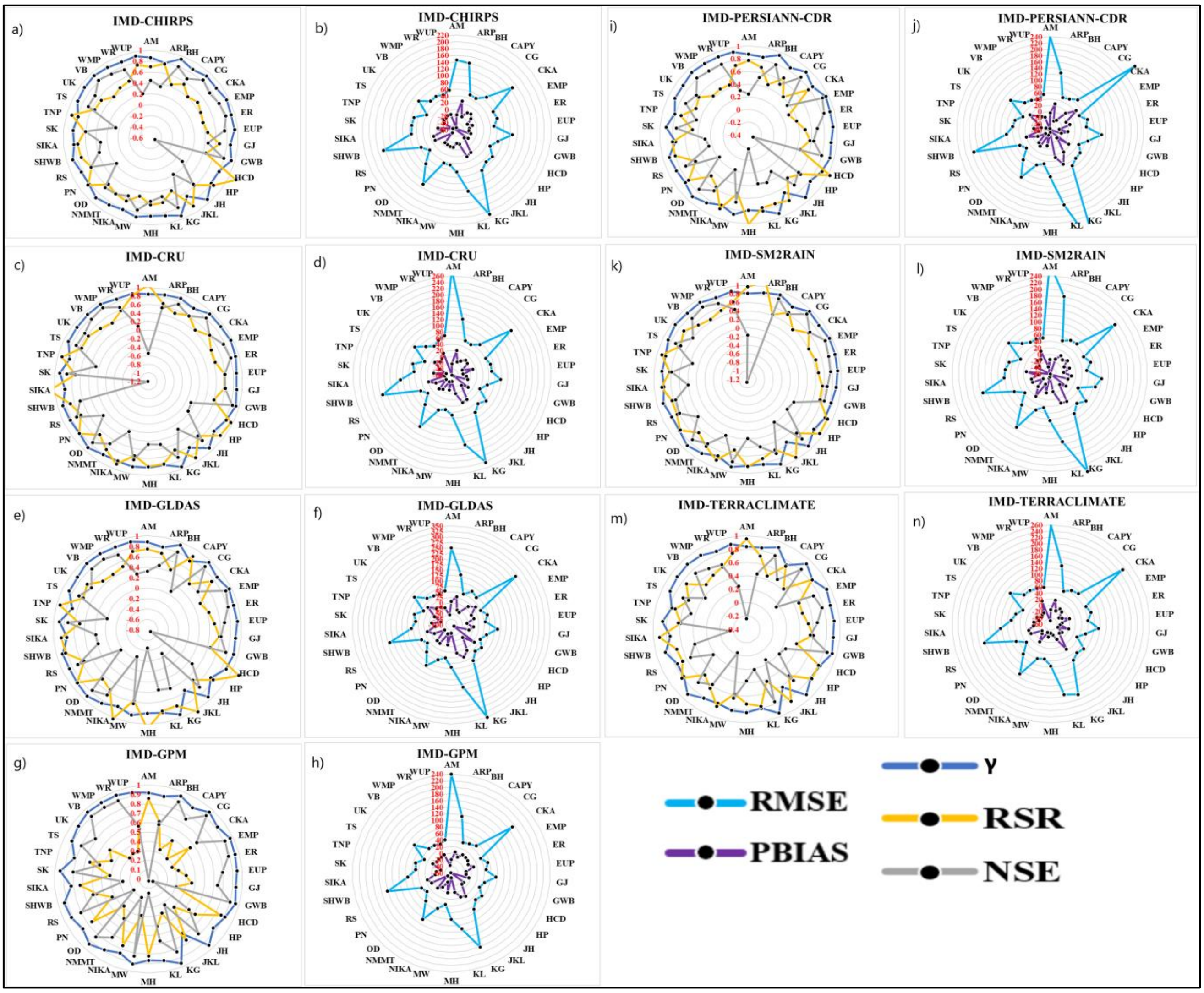

Figure 3. (**a**–**n**) Skill metrics representation of each dataset with IMD gridded data in 34 MSDs. Graphs (**a**,**c**,**e**,**g**,**i**,**k**,**m**) show the γ, NSE, and RSR variation, and graphs (**b**,**d**,**f**,**h**,**j**,**l**,**n**) shows the RMSE and PBIAS in chosen datasets over 34 MSDs.

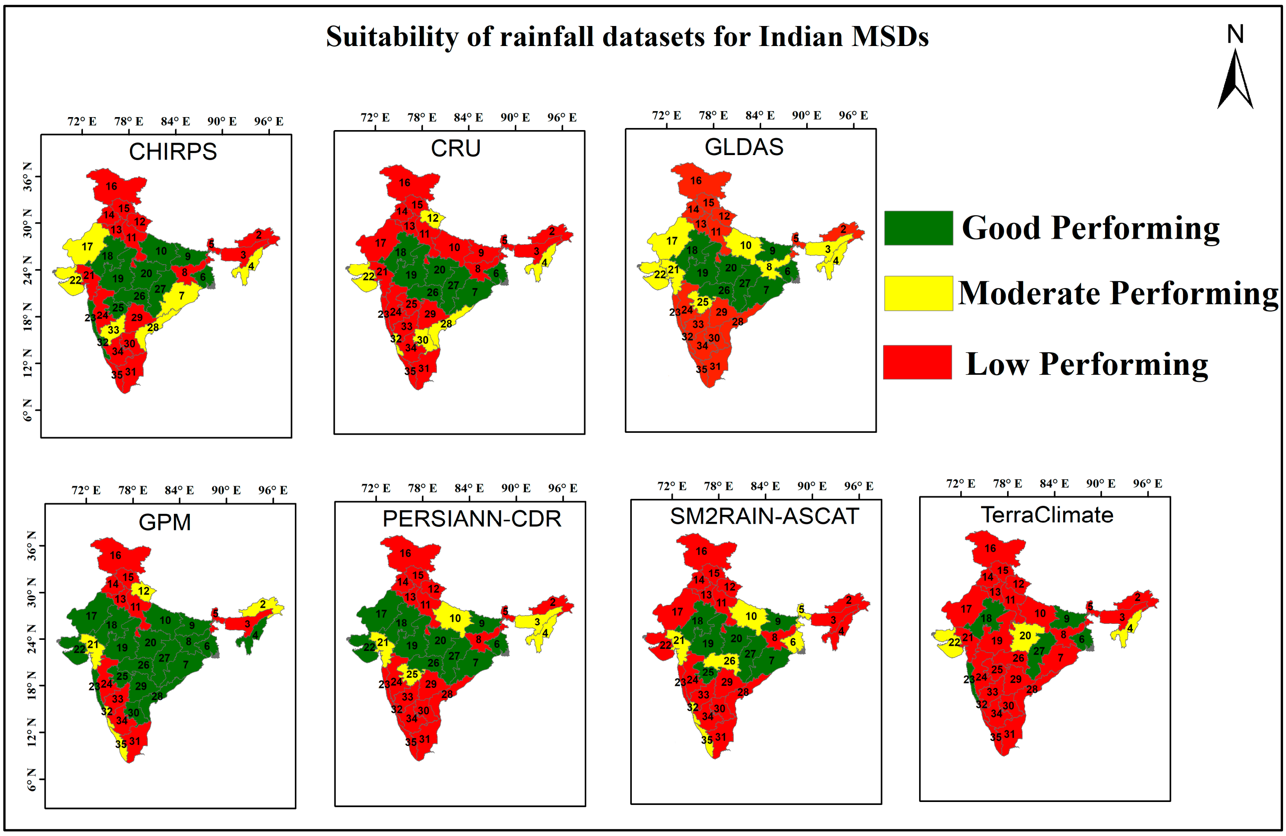

Figure 4. Dataset-wise suitability over Indian MSDs from 2015 to 2019. (The numbers 1–34 represent MSDs; their names are listed in Table 1).

3. Results

3.1. Dataset-Wise Suitability Analysis

The dataset suitability for each MSD is assessed and illustrated in Figures 3 and 4. The results of this study are elaborated upon in the following sections. The datasets are classified into three categories, i.e., good-performing, moderate-performing, and low-performing and are defined in the Section 2.3.

3.1.1. CHIRPS

Out of 34 MSDs, this dataset performed well in 11, moderately in 6, and low in 17 MSDs. The results reveal that this product is suitable for half of MSDs (18), concentrated in the central part of India, and not for the northern, southern, and northeastern regions (except the NMMT) of India. This can be attributed to uncertainty in the dataset that occurred because of merging CHIRP and station data using inverse distance weighting, as the scattered distribution of rain gauges might be the reason for the uncertainty [45].

3.1.2. CRU

Overall, CRU performed well in 7 MSDs, moderately in 6 MSDs, and low in 21 MSDs. Similar to CHIRPS, skill metrics analysis showed that this dataset is not suitable for the northern, southern (except RS, CKA, and CAPY), and northeastern parts of India, as for (except NMMT) of India, and suitable for the central regions of India. The low performance of this dataset can be attributed to the reduced coverage of rain gauges in the northern and northeastern states and uncertainty in the dataset [41].

3.1.3. GLDAS

Skill metric analysis showed that GLDAS is suitable for 8 MSDs in India, moderately suitable for 8 MSDs, and low-performing for 18 MSDs. The results suggest that this dataset is low performing for the northern and southern parts of India and good-performing in the central parts of India. This is the only dataset that performs moderately in desert regions, whereas all other datasets are low performing in those regions.

3.1.4. GPM

This is dataset is overall the most suitable across MSDs, as it performed well in 18 MSDs, moderately in 5 MSDs, and low in only 11. However, it is not suitable for northern India and is best performing in the central parts of India. This dataset might not be viable to use in hilly regions. These results are in agreement with those of Thakur et al., 2020, which found that the GPM dataset performed poorly in hilly regions [20].

3.1.5. PERSIANN-CDR

The analysis shows that this dataset performed well in 10 MSDs, had moderate performance in 5 MSDs, and was low-performing in 19 MSDs. This suggests that this dataset performs low for southern and northern India but performs moderately for the northeast. Except for JH, it is suitable for all central parts of India. Performance in MSDs across the eastern coast, aside from TNP, is well.

3.1.6. SM2RAIN

Overall, out of the 34 MSDs, SM2RAIN performed well in 7, moderately in 7, and low in 20 MSDs. This dataset is not suitable for the north, south, and northeastern areas but moderately suitable for regions along the west coast. It is only suitable in a few centrally located MSDs (CG, MW, ER, WMP, EMP, OD, and BH). This dataset is suitable for drought-prone MSD, MW, indicating that it can be useful for measuring small levels of rainfall.

3.1.7. TerraClimate

The TerraClimate dataset performed the most poorly among the datasets; it performs poorly in 26 MSDs. This dataset only performed well in five MSDs and moderately in three MSDs. Regionally, the TerraClimate dataset performed poorly in northern regions, northeastern states, and across the south. It also performs poorly in central India, with the exception of CG, ER, GWB, and BH.

3.2. Rainfall Dataset Type Suitability for MSDs

The chosen datasets were divided based on satellite-derived, gauged, and merged types to determine which type provided the best compatibility (Figure 5). This analysis demonstrates that none of the dataset types are suitable for 16 MSDs, and only the merged type is suitable for three MSDs. The satellite-derived-type datasets are found to be suitable only in one MSD (GJ), while both merged and gauged-type datasets are suitable for two MSDs (K and G and NMMT). All types of datasets are suitable for nine MSDs (ER, WMP, EMP, VB, CG, BH, SK, OD, and GWB). Overall, the merged type is the most suitable dataset type (17 MSDs).

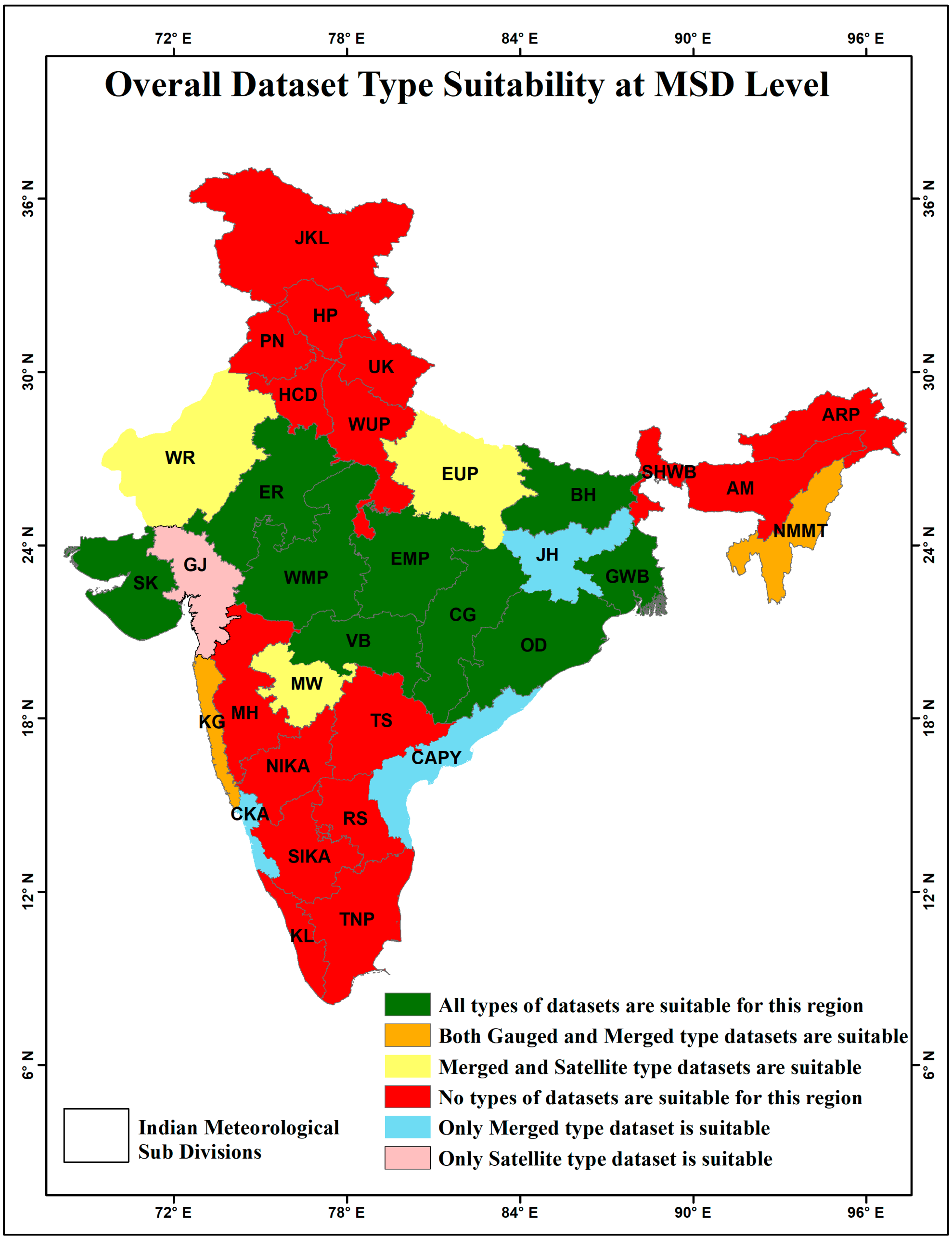

Figure 5. Rainfall dataset type suitability for MSDs from 2015 to 2019.

3.3. Pixel Wise Analysis

Pixel-wise skill metrics analysis is performed over MSDs in India, using three well-known continuous skill metrics, γ, RSR, and the NSE; Figures 6–8 show results for the seven datasets. Based on γ and NSE, none of the datasets is suitable for JK and L (Figures 6 and 7). In addition, NSE results suggest that none of the datasets are suitable for the Western Ghats and parts of northeastern states (Figure 7). Based on RSR values for the west coast and northeast, none of the datasets is suitable (Figure 8). Considering RMSE, no dataset performed well in the western coast or northeast (Figure 9). Based on PBIAS, the datasets only perform well in central India (Figure 10).

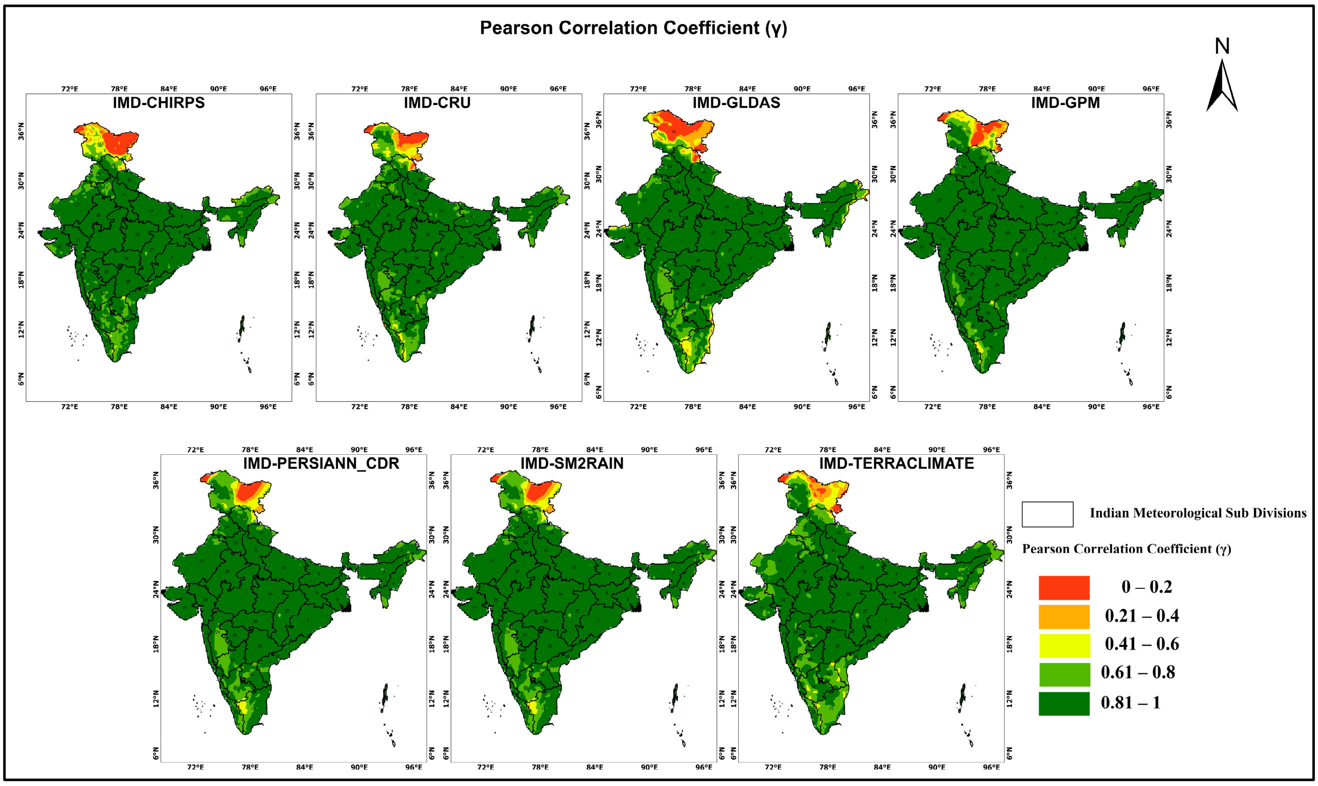

Figure 6. Coefficient of correlation (γ) maps of various datasets with respect to IMD.

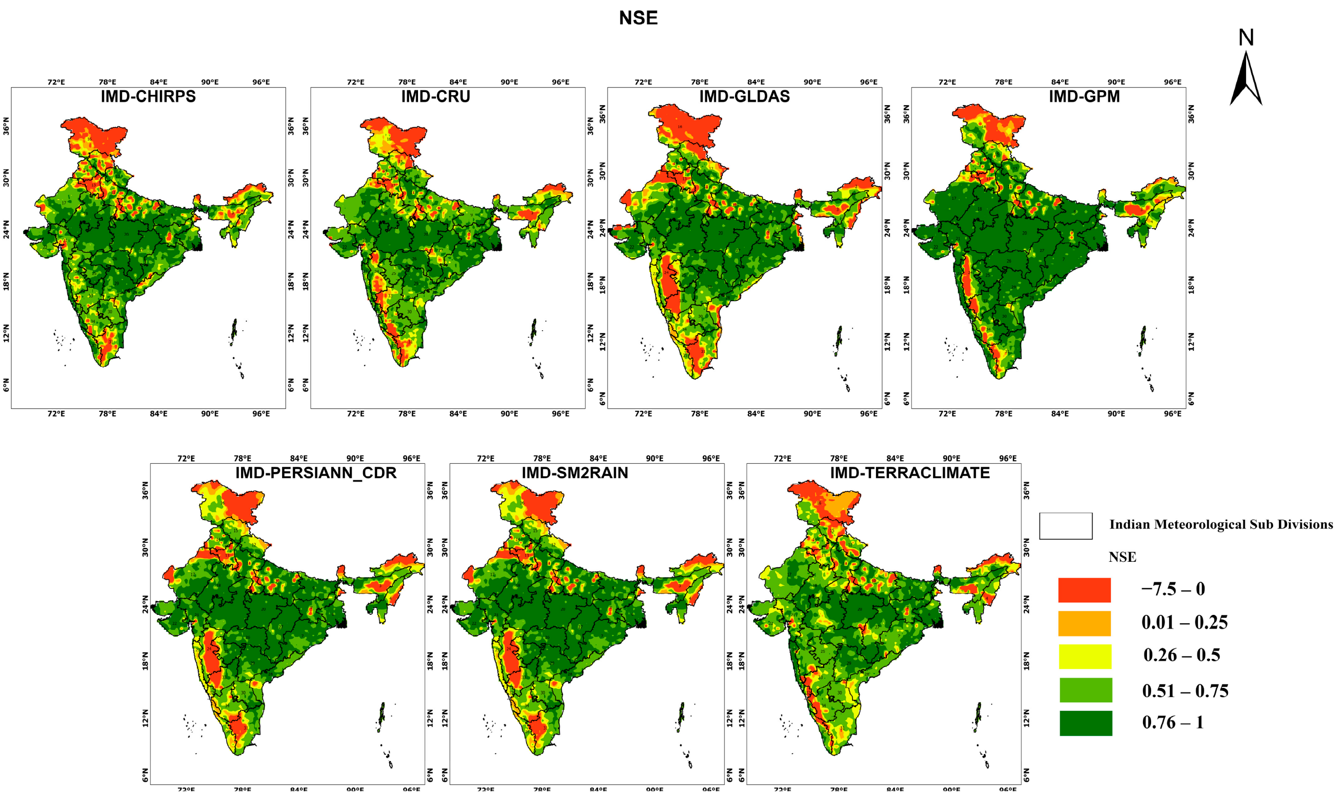

Figure 7. NSE maps of various datasets with respect to IMD.

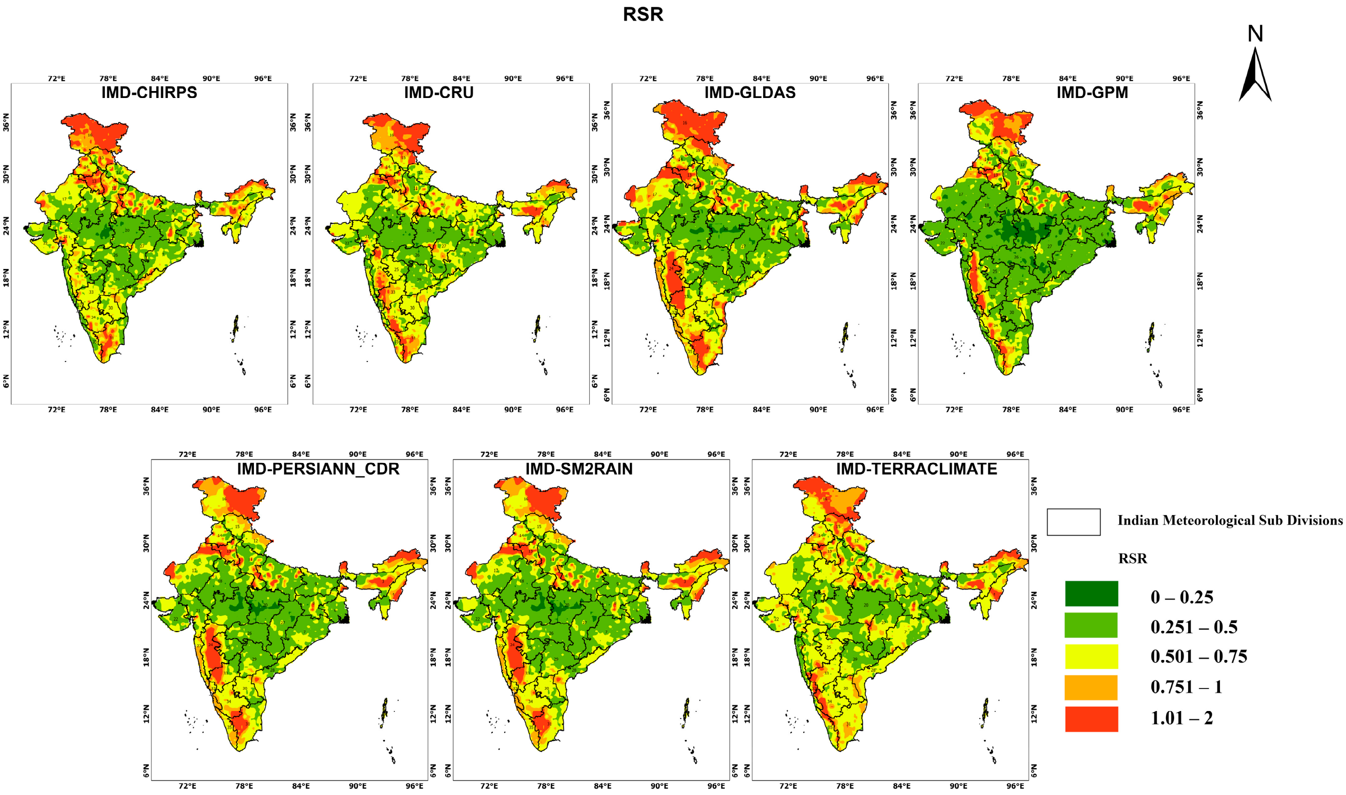

Figure 8. RSR maps of various datasets with respect to IMD (in mm).

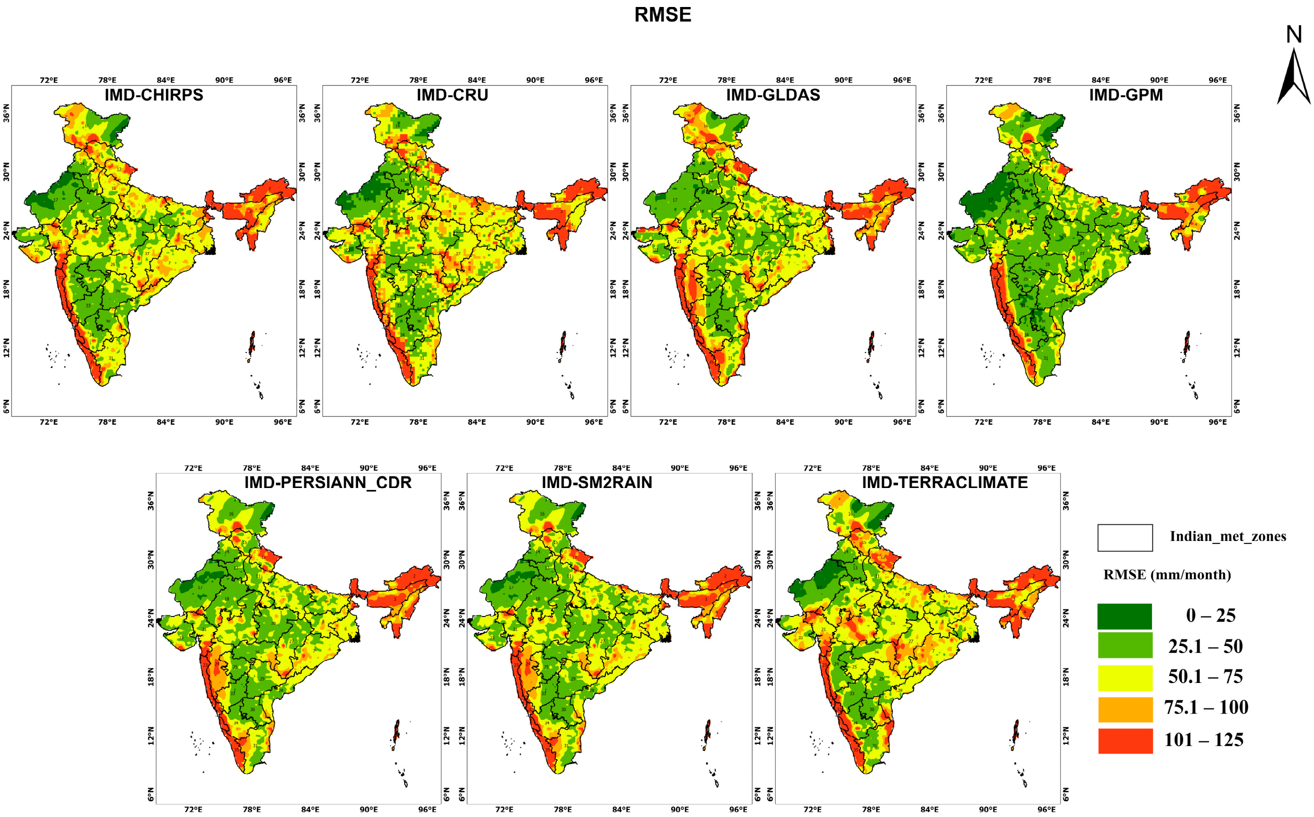

Figure 9. RMSE maps of various datasets with respect to IMD (in mm).

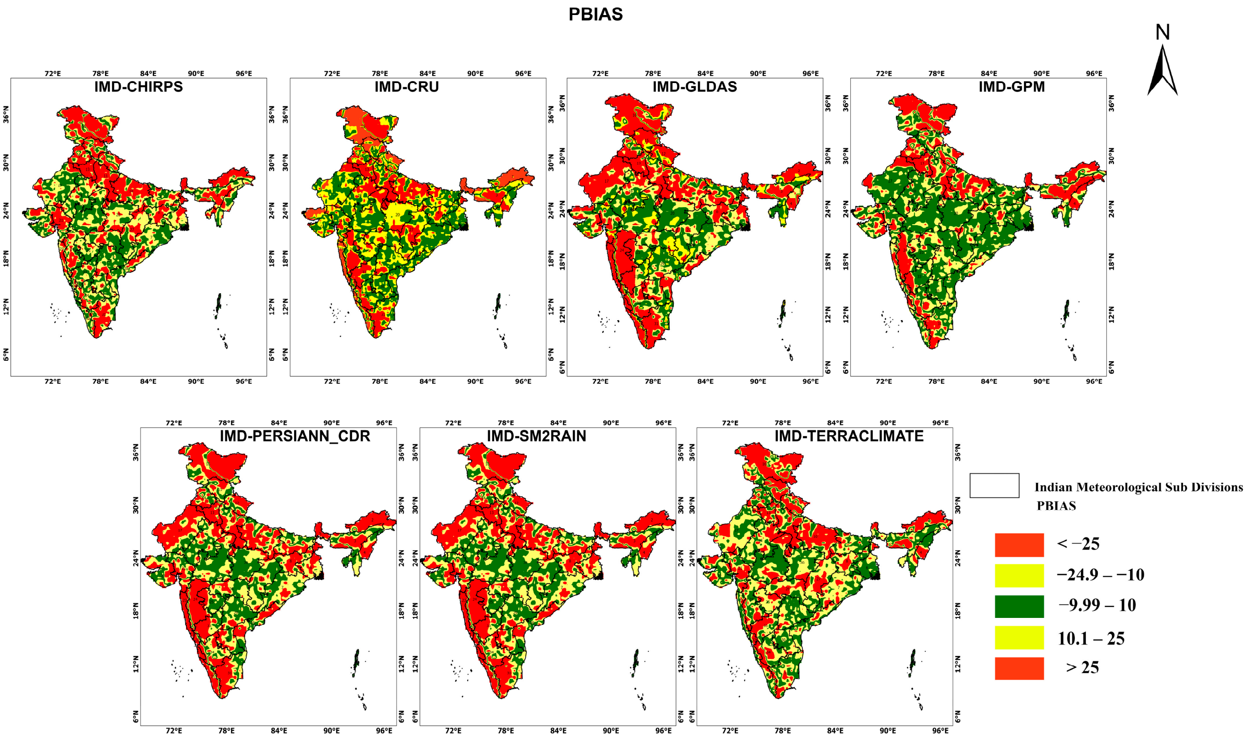

Figure 10. PBIAS maps of various datasets with respect to IMD (in mm).

India as a Whole

A pixel-wise comparison of India as a whole is performed to understand the suitability of selected datasets for the entire country using five skill metrics. This study reveals that among all datasets, GPM is the best-performing, with average values of 0.89, 064, 57.98 mm/month, 0.51 and −8.36 for γ, NSE, RMSE, RSR, and PBIAS, respectively. It shows that GLDAS is a low-performing dataset, as skill metrics γ, NSE, RMSE, RSR, and PBIAS average values over India were depicted as 0.83, 0.36, 75.99 mm/month, 0.67, and −12.42, respectively (Table 5). The best suited to most poorly suited datasets are: GPM > CHIRPS > PERSIANN-CDR > TerraClimate > CRU > SM2RAIN > GLDAS.

Table 5. Summary of the dataset's suitability for overall India.

Dataset	γ	NSE	RMSE	RSR	PBIAS	Suitability
CHIRPS	0.84	0.52	69.44	0.62	−14.48	Moderate-Performing
CRU	0.84	0.48	73.38	0.64	−10.45	Moderate-Performing
GLDAS	0.83	0.36	75.99	0.67	−12.42	Low-Performing
GPM	0.89	0.64	57.98	0.51	−8.36	Good-Performing
PERSIANN-CDR	0.86	0.5	71.54	0.62	−17.12	Moderate-Performing
SM2RAIN	0.82	0.46	74.42	0.65	−8.02	Moderate-Performing
Terraclimate	0.84	0.51	74.04	0.63	−7.33	Moderate-Performing

3.4. Temporal Analysis of Rainfall Datasets for India

The temporal analysis of rainfall datasets is performed from 2015 to 2019 for India. For this analysis, the five skill metrics values are used to find the suitability of the dataset both monthly and yearly (Figures 11 and 12). The rainy months, such as SE monsoon rainfall months (June to September) and NE monsoon months (October to December), are considered for monthly temporal analysis. The five years monthly average values are considered for identifying the dataset's suitability purpose. It is found that for July, August, September, October and December, the GPM is a good-performing dataset as their skill metrics values much better than other selected datasets. GPM outperformed the other datasets except with PBIAS values in all other skill metrics. Whereas for June, CHIRPS emerges as the best dataset, and for December, it is CRU. The reason behind CHIRPS emerging as a well-performing dataset in June and CRU in December might be due to considering of whole India instead of considering only SE monsoon or NE monsoon occurred regions alone. The temporal analysis based on year-wise analysis was performed by considering the yearly rainfall of selected datasets compared with the IMD gridded dataset for the years 2015 to 2019 for the whole India (Figure 12). The results revealed that GPM is the best-performing dataset for all the years.

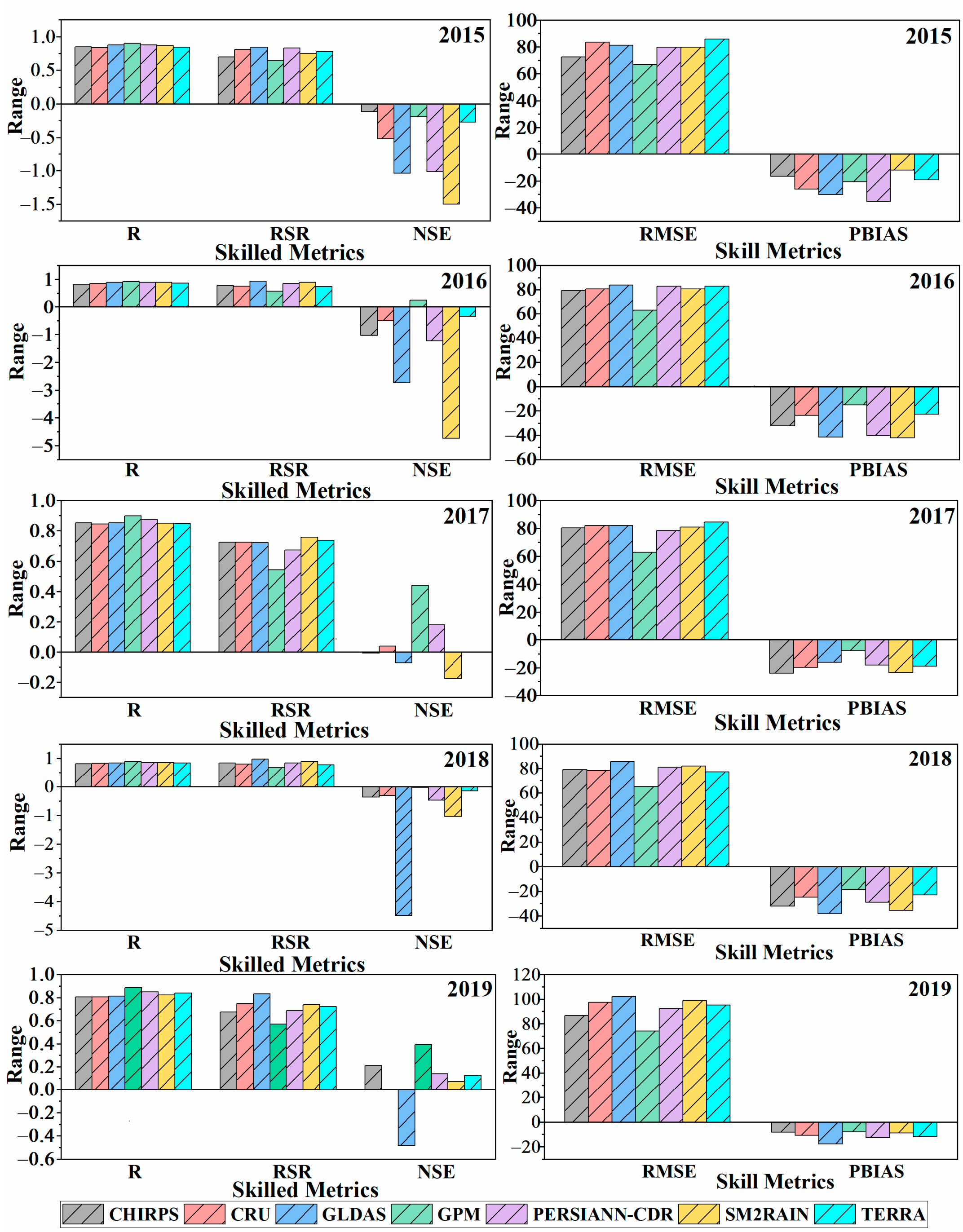

Figure 11. Barchart of skill metrics for GPM, CRU, CHIRPS, GLDAS, PERSIANN-CDR, SM2RAIN, and TerraClimate with respect to IMD gridded dataset from June to December from 2015 to 2019.

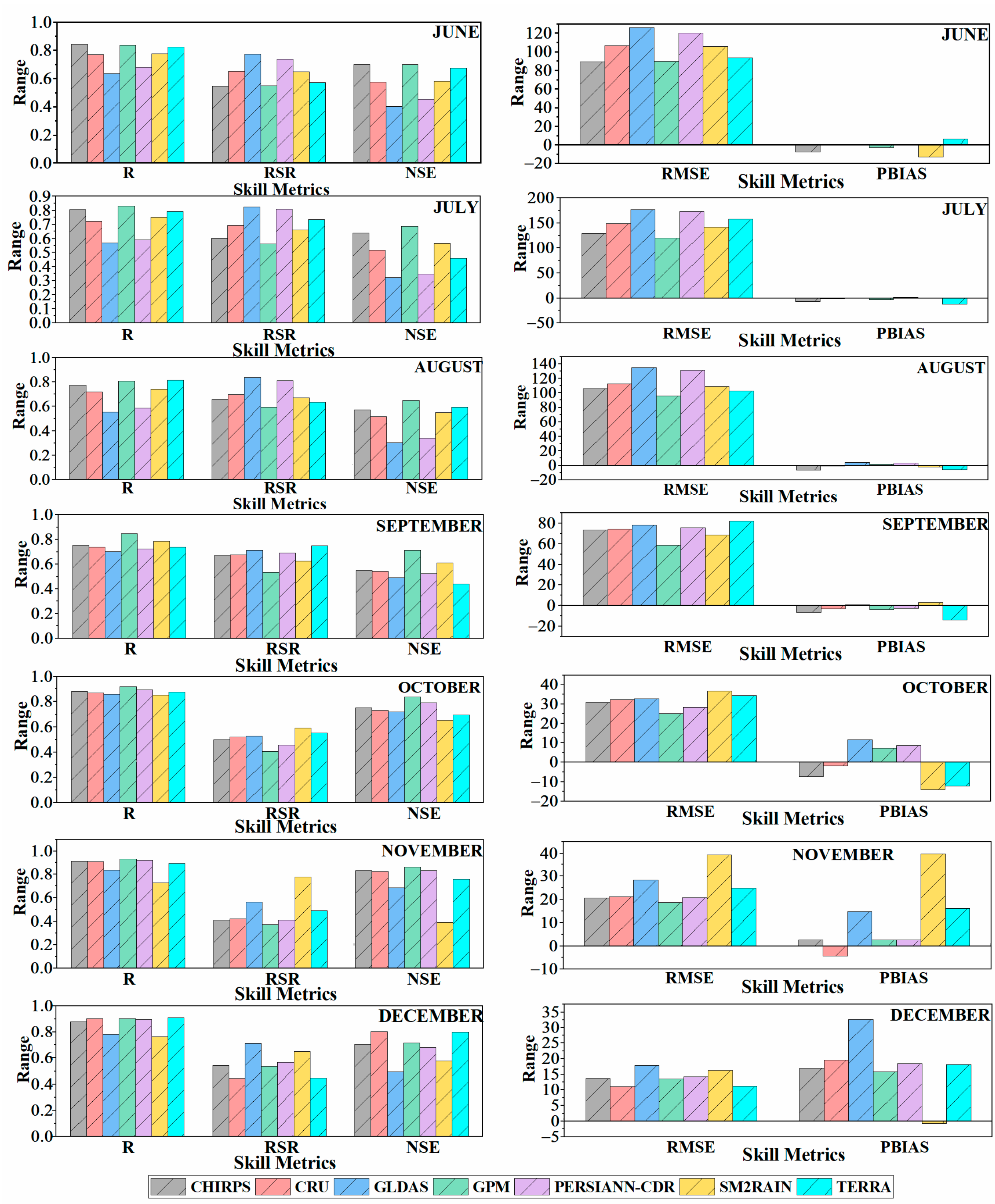

Figure 12. Barchart of skill metrics for GPM, CRU, CHIRPS, GLDAS, PERSIANN-CDR, SM2RAIN, and TerraClimate with respect to IMD gridded dataset from 2015 to 2019.

3.5. Good-Performing Datasets at the Pixel Level for India

Rule-based decision tree techniques are employed on three continuous skill metrics results. The rule-based decision tree technique is a data mining technique in which the class decisions are taken based on multiple "if... then . . . else" rules and conditions. In the current study, the skill metrics values are taken, and a set of "if... then . . . else" conditions are applied to obtain the desired classifications such as good-performing, moderate-performing, and low-performing. Based on the range classification given in Table 4, the rules are designed and employed to find India's good-performing dataset at each pixel level. Datasets vary in their performance in the 4641 pixels analysed. More specifically, CHIRPS, CRU, GLDAS, GPM, PERSIANN-CDR, SM2RAIN and TerraClimate fit well in 1989 pixels, 1718 pixels, 1986 pixels, 3105 pixels, 2166 pixels, 1649 pixels, and 1579 pixels respectively (Figure 13). The order of good-performing datasets is as follows: GPM > CHIRPS > PERSIANN-CDR > TERRACLIMATE > CRU > SM2RAIN > GLDAS.

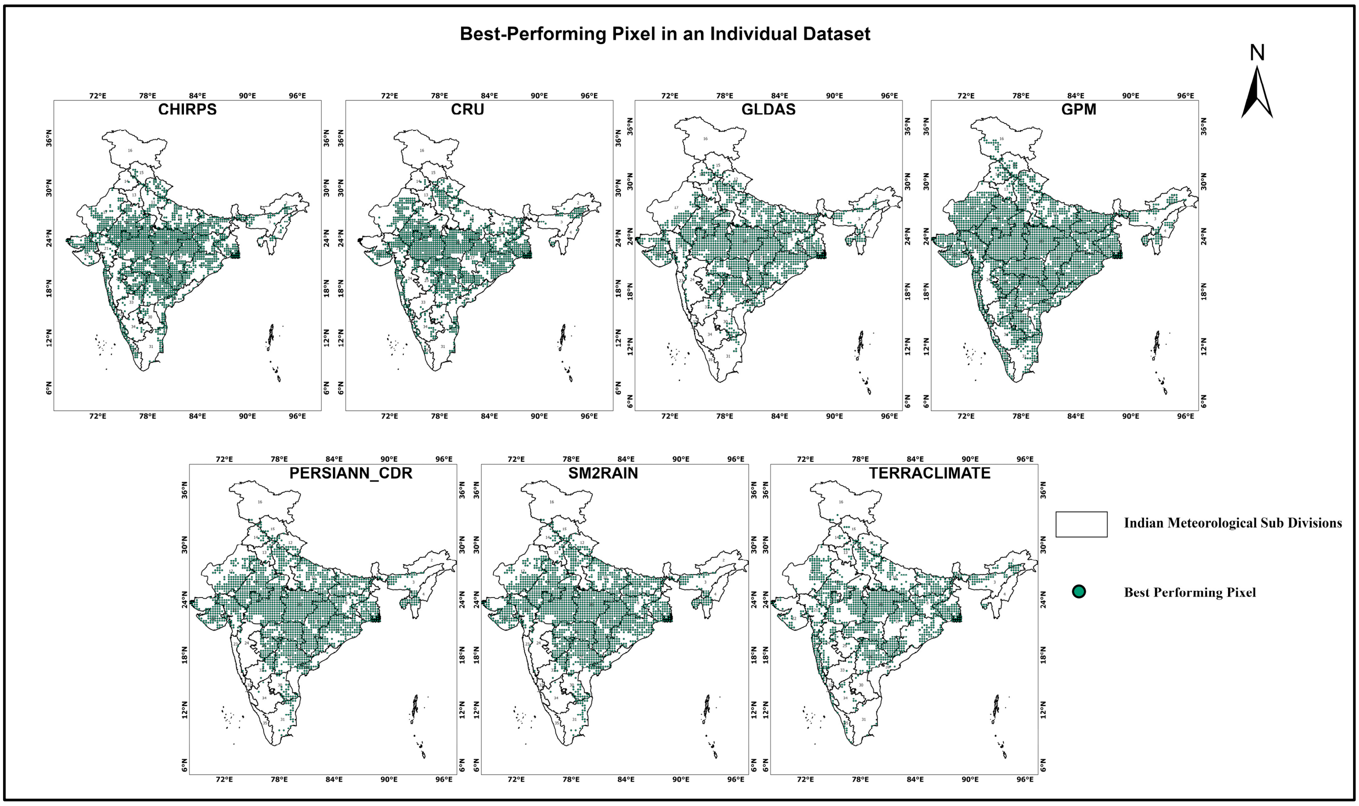

Figure 13. Good-performing pixels in individual datasets for India from 2015 to 2019.

We find that the datasets analysed here are only suitable in 3428 pixels out of 4641 pixels. This indicates that 1213 pixels do not have a suitable dataset. Out of 3428 pixels, each dataset was ranked at the pixel level. This shows which dataset performs the best at each pixel. Results show that CHIRPS, CRU, GLDAS, GPM, PERSIANN-CDR, SM2RAIN, and TerraClimate are suitable in 269, 150, 196, 2185, 254, 208, and 166 pixels, respectively. It was found that GPM is the best-performing dataset for most of the pixels, followed by CHIRPS and then PERSIANN-CDR. The CRU dataset's 150 pixels imply that it is unsuitable for most pixels and is inferior to other datasets (Figure 14). The order of the good-performing datasets is as follows: GPM > PERSIANN-CDR > CHIRPS > GLDAS > CRU > SM2RAIN > TERRACLIMATE.

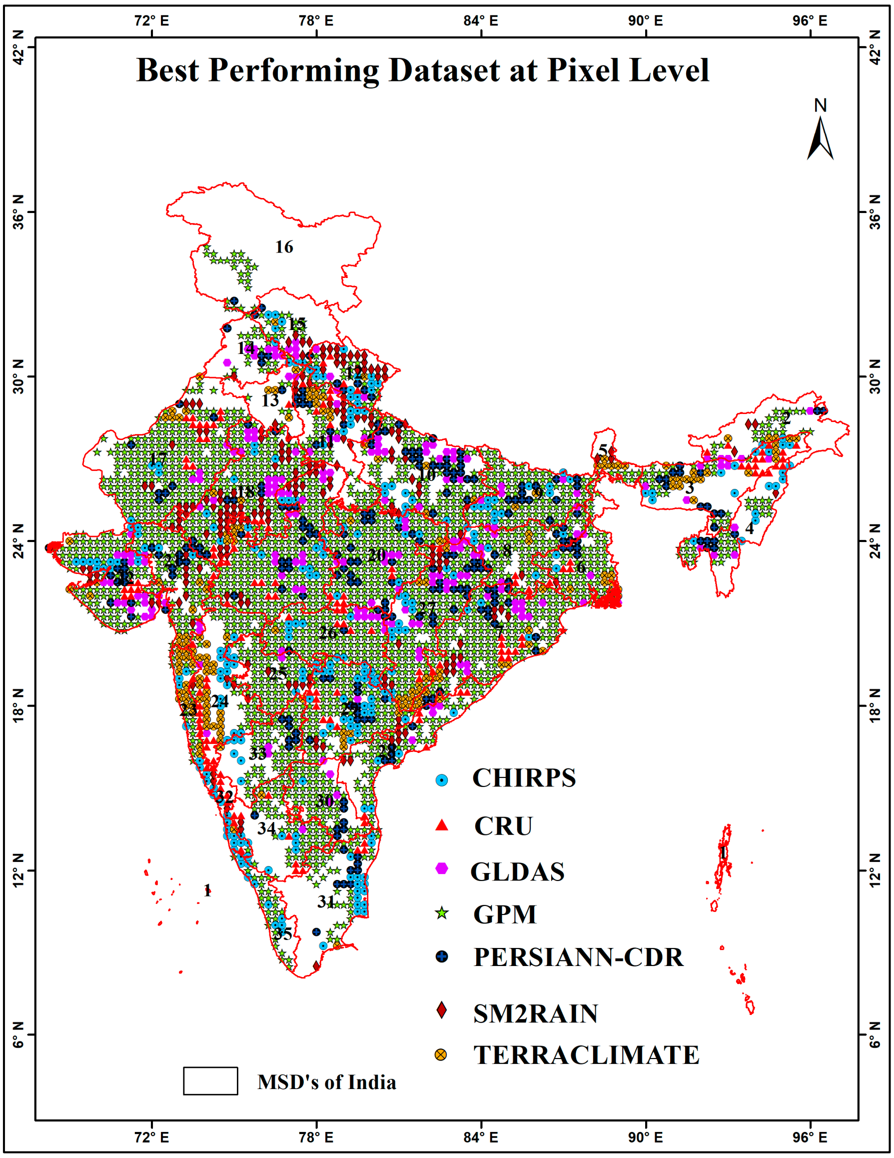

Figure 14. Good-performing datasets at the pixel level for India from 2015 to 2019.

4. Discussion

The present work is necessary for hydrologic and agricultural applications because an analysis' results will vary and can be significantly biased based on which datasets are used. This analysis provides evidence to help choose the most appropriate dataset for a specific region. These findings are in contrast to similar work (Kumar Singh et al., 2018), which found that GLDAS is a better-performing dataset for India than GPM. However, our results show that GPM performed better than the other datasets evaluated for most parts of India. Therefore, employing a modified methodology with advanced data mining techniques, more number of skill metrics (5), and the inclusion of a longer time period might be the reason for our findings differing from those of Kumar Singh et al., 2018. Pixel-wise analysis was also undertaken, which reveals that no dataset is suitable for more than 50% of pixels. The existing literature suggests that GPM is best for India as a whole, but when it comes to the pixel level, it is outperformed by other datasets in a few pixel locations. Even though the aim is to find the good-performing datasets in India, out of the seven most widely used datasets, not even one dataset fits those particular 1213 pixels based on skill metrics analysis. It has been found that leeward (in the Western Ghats) and mountainous regions (north and northeastern regions) are where blank pixels are predominant. The reason for blank pixels is due to the limitations and uncertainties of the datasets in those pixels. This analysis identified the good-performing datasets in 3428 pixel locations out of 4641 pixel locations in India.

5. Summary and Conclusions

The present work investigates CHIRPS, CRU, GLDAS, GPM, PERSIANN-CDR, SM2RAIN, and TerraClimate's suitability for rainfall measurement in India. Skill metrics (γ, RMSE, NSE, RSR, and PBIAS) are used to understand suitability and choose the most appropriate rainfall dataset at each pixel level. The study analysed rainfall datasets, comparing and validating results in terms of spatially (dataset, pixel, dataset type, and overall, national level suitability) and temporally (month-wise and year-wise).

The dataset-wise analysis shows that GPM performs better in 18 Indian MSDs than other datasets. Of all the datasets, the TerraClimate dataset is the lowest-performing. Most of the datasets (i.e., CRU, GLDAS, SM2RAIN, and TerraClimate) failed to give good performance results in high and low rainfall areas as well as hilly regions. The most suitable dataset type is merged, which performs well for 17 MSDs. Surprisingly, the satellite-derived type dataset is the most suitable for GJ. The temporal analysis shows that GPM is best among all datasets when considering both month-wise and year-wise.

A pixel-wise comparison across India reveals that, among all datasets, GPM performs the best while GLDAS performs the worst. Good-fitting pixels among the selected datasets were identified in this study. This study found that in 3105 pixels out of 4641 pixels, GPM correlated well with the IMD dataset, whereas TerraClimate correlated well only 1579 pixels. Furthermore, rule-based decision tree techniques are applied to skill metrics in order to rank the datasets. Results show that GPM is a good-performing dataset for most of the pixels, followed by CHIRPS, and then PERSIANN-CDR. In contrast, CRU is ranked as superior to other datasets in only 150 instances. Pixelwise analysis reveals that no dataset is suitable in over 50% of pixels. It also shows that very few datasets are suitable in certain locations. Future work can find the good-performing datasets in those blank pixels by considering a longer temporal aspect at the daily timestep.

Our results suggest that it is necessary to analyse a dataset's suitability at various spatial scales, such as the national level, MSD level, and pixel level. This systematic analysis was needed to choose suitable rainfall datasets. These findings contribute to efforts to improve hydrologic modelling, agricultural modelling and decision-making, drought monitoring, water resource management, numerical weather forecasting, moisture budget calculations, effective rainfall measurements, and water footprint mapping. This monthly accumulated rainfall analysis provides more information about the rainfall blueprint of the region of interest and should thus be helpful for agricultural stakeholders in decision-making. Finally, the findings of this study will be beneficial to satellite data developers in improving an algorithm that is suitable for diverse topographical regions of India.

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