Evaluation of gridded precipitation products in the selected sub-basins of Lower Mekong River Basin

Santosh Dhungana (santosh.dhung@gmail.com)
Asian Institute of Technology https://orcid.org/0000-0003-2549-2390

Sangam Shrestha
Asian Institute of Technology (AIT), Pathum Thani, 12120, Thailand

Tuan Pham Van
Asian Institute of Technology (AIT), Pathum Thani, 12120, Thailand

KC Saurav
Asian Institute of Technology (AIT), Pathum Thani, 12120, Thailand

Ashim Das Gupta
Asian Institute of Technology (AIT), Pathum Thani, 12120, Thailand

Thi Phuoc Lai
Asian Institute of Technology (AIT), Pathum Thani, 12120, Thailand

---

Research Article

Keywords: gridded precipitation products, entropy method, compromise programming, evaluation

Posted Date: February 18th, 2022

DOI: https://doi.org/10.21203/rs.3.rs-1302010/v1

Evaluation of gridded precipitation products in the selected sub-basins of Lower Mekong River Basin

Santosh Dhungana[a], Sangam Shrestha[a,c], Tuan Pham Van[a], Saurav KC[a], Ashim Das Gupta[a], Thi Phuoc Lai Nguyen[b]

[a]Water Engineering and Management (WEM), Department of Civil and Infrastructure Engineering (CIE), School of Environment and Technology (SET), Asian Institute of Technology (AIT),
Pathum Thani, 12120, Thailand

[b]Development Planning Management and Innovation (DPMI)
Department of Development and Sustainability
School of Environment, Resources and Development
Asian Institute of Technology (AIT),
Pathum Thani, 12120, Thailand

[c]Stockholm Environment Institute, Asia Centre, Chulalongkorn Soi 64, Phyathai Road, Pathumwan, Bangkok, 1033 Thailand

Corresponding Author: Santosh Dhungana
santosh.dhung@gmail.com

ABSTRACT

Hydrological and meteorological studies demand accurate, continuous long-term reliable and uniformly distributed precipitation datasets. A plethora of gridded precipitation products (GPPs) has made their place as an alternate to rain gauge records. However, GPPs house inherent depending on the type of data, data density, gridding algorithm, etc. Hence it is crucial to evaluate them prior to their application. This study evaluated eight GPPs: Asian Precipitation Highly Resolved Observational Data Integration towards Evaluation data (APHRODITE), Climate Prediction Center (CPC), Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS), Southeast Asian Observed dataset (SA-OBS), Climate Prediction Center Morphing Technique (CMORPH), The Tropical Rainfall Measuring Mission (TRMM) -daily products and Climate Research Unit (CRU) and Global Precipitation Climatology Center (GPCC)- monthly products for 17 years (1998-2014). An entropy-based weight calculation for each statistical indices and compromise programming was employed to rank GPPs in the selected sub-basins basins (Nam Ngum River Basin (NRB) and Vietnam Mekong Delta (VMD)) of Lower Mekong Region (LMR) for mean and six extreme precipitation indices. The correlation coefficient (r), Root Mean Square Error (RMSE), and skilled score (SS) were the statistical indices used in this study. In terms of capturing mean monthly precipitation, GPCC outweighed all other products for both the studied basin. However, APHRODITE ranked first on a daily based product based on compromise programming for NRB. APHRODITE consistently recorded r between 0.85 to 0.95, RMSE in between 50 and 100 mm/month and SS between 0.72 to 0.90 for the 5 observed stations. Similarly, in case of VMD, TRMM ranked first for the daily precipitation products with r in between 0.8 to 0.95, RMSE between 50 to 70 mm/month and SS between 0.56 to 0.9 when evaluated with 11 observed stations. The APHRODITE for NRB and TRMM for VMD could be reliable GPPs for hydrological and meteorological studies.

Keywords— gridded precipitation products, entropy method, compromise programming, evaluation

1 INTRODUCTION

Precipitation, a key environmental variable, finds itself in a multitude of applications making it central to scientific research (Sun et al., 2018; Try et al., 2020). Direct gauge precipitation is the most reliable and accurate data source that reflects the precipitation at the earth's surface.

However, in many regions, availability of the gauge-based data is dire, even though available for some, they may not be complete and are often costlier. Also, they too are erroneous attributed to instrumentation relocation, observation gaps and errors, data transmission, inability to represent single large event, etc. Weather radar could be an alternative to the gauge-precipitation. However, they demand wider coverage and calibration according to precipitation type. Further, they could be the costlier option, especially in developing nations, and have limitations in capturing the precipitation in mountainous areas (Arshad et al., 2021; Lee, 2006). To overcome these gaps, the large-scale varying spatio-temporal satellite, gauge-based interpolated products, or a blend of both have garnered wider attention from the scientific communities.

Leveraging the use of satellite and the evolving state-of-the-art computing techniques has opened up a new window to reliably estimate and develop the hydroclimatic series for a longer period especially in the areas with scarce to no data. The gridded precipitation products (GPPs) find their way to application owing to their easy access and as cost-free resources. GPPs can be broadly categorized into interpolated gauge-based, satellite estimates, and reanalyzed products. There is a plethora of GPPs (Darand & Khandu, 2020) to choose from and no one-size-fits-all dataset is available. These datasets are usually available in different spatial and temporal (sub-daily, daily, and monthly) scales. The performance of GPPs is also not uniform across the globe (Camici et al., 2018). Saying that, the GPP that reflects the observed dataset well in one basin may not be representative for another basin in the same region as well. They further possess a high level of uncertainty owing to their gridding algorithms, reliability and number of data sources used, models used for precipitation estimates, gauge adjustment techniques, etc. (Aliyar et al., 2021; Ebert et al., 2007). Thus, the credibility of the GPPs is subjective to the time, region, and climate and the technology and methods involved in their development. Hence, evaluation of GPPs is not only important to the users but also to the developers or producers for further improvement as these products are still evolving and continue to evolve. This certainly indicates the need for evaluation before their usage.

Evaluation and ranking techniques span across a multifaceted spectrum ranging between the use of single criteria like (CC or RMSE) to multi-criteria decision making (MCDM) like Compromise programming (Komaragiri & Kumar, 2014; Zeleny, 1973), Cooperative Game Theory (Gershon & Duckstein, 1983), Preference Ranking Organization Method of Enrichment Evaluation(PROMETHEE-2) (Brans et al., 1986), and Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) (Opricovic & Tzeng, 2004). These methods are constantly evolving and being improved. As the precipitation is inherent with the intrinsic errors of missing data, instrumentation errors, instrument relocation, observation errors, etc. It is often difficult to rank the dataset only based on the statistical indicators as different statistical indices may suggest different GPPs. Further, the conventional method of evaluation of GPPs based on the statistical indices is subjective to the evaluation skill of the researcher. Thus, this indicates the need for an approach that seeks the tradeoffs among the indicators and ranks the GPPs based on the weight they received for different indicators.

Zeleny, (1973) introduced compromised programming (CP) to automatically devise the solution closest to the reference dataset. This approach tends to obtain the best solution by finding the optimum values of evaluation indices under consideration. The search for the optimum value is guided by the entropy method to weigh each indicator (Komaragiri & Kumar, 2014). The main advantage of the entropy method is that it calculates the weight for each indicator without intervention from the evaluator avoiding unintentional bias. Further, the method weighs each indicator based on the information available which is given by its entropy value. The higher the entropy value higher is the uncertainty. The abundance of the studies on the evaluation of gridded-dataset, their evaluation, and application are available (Darand &

Khandu, 2020; Ebert et al., 2007; Sun et al., 2018). The evaluation of GPPs spans across a wide assortment of spatial coverage from global (Hobeichi et al., 2020; Shen et al., 2020; Yong et al., 2015), continental-scale (Awange et al., 2016; Tarek et al., 2021), national-scale (Aliyar et al., 2021; Darand & Khandu, 2020; Prakash et al., 2016), regional-scale (Ahmed et al., 2019; Camici et al., 2018; Satgé et al., 2020) and to basin-scale(Duan et al., 2016; Fallah et al., 2020; Yan Yang et al., 2014).

However, there are very few studies across the Mekong River Basin (MRB) on the evaluation of the GPPs. Evaluation studies of GPPs across MRB can broadly be categorized into a) Ability to characterize the spatio-temporal distribution of precipitation (and its extremes in some cases) and b) Blend of spatio-temporal characterization and hydrological application (ability to simulate hydrology). For instance, Chen et al. (2017) evaluated four grid-based precipitation products: Asian Precipitation Highly Resolved Observational Data Integration Towards Evaluation (APHRODITE), Climate Prediction Center Morphing (CMORPH), Tropical Rainfall Measuring Mission (TRMM), and Climatic Research Unit (CRU) by comparing 242 rain gauges on a daily scale over the Greater Mekong Subregion. The study revealed that APHRODITE had the highest correlation with the gauge-based rainfall observations, while the other three products indicated a slightly high false alarm ratio. Similarly, Chen et al. (2018) assessed the performance of different satellites (TRMM and Precipitation Estimation From Remotely Sensed Information Using Artificial Neural Networks - Climate Data Record (PERSIAN-CDR)) and reanalysis datasets (Modern-Era Retrospective analysis for Research and Applications, Version 2 (MERRA2), ERA-Interim, and Climate Forecast System and Reanalysis (CFSR)) with the gauge-based APHRODITE dataset as reference for MRB. The study revealed that the satellite products were reliable in capturing the climatological features. Likewise, Dandridge et al. (2019) assessed two satellite-based rainfall products (TRMM Multi-satellite Precipitation Analysis (TMPA) and Climate Hazard Group InfraRed Precipitation with Station (CHIRPS)) for Lower MBR (LMRB) based on their ability to detect precipitation for the dry and wet season. These studies mostly used continuous statistical indices like relative bias (Bias), correlation coefficient (r), root mean squared error (RMSE), random error, and systematic error) and three categorical indices namely probability of detection (POD), false alarm ratio (FAR), and critical success index (CSI) to evaluate the performance of GPPs.

On the other hand, most of the studies over MRB fit into the latter category housing the blend of spatio-temporal characterization and hydrological application. For example, Tian et al. (2021) evaluated six precipitation products against the observed gauge-based precipitation (using r, PBIAS, RMSE, and Kling-Gupta efficiency (KGE) as evaluation indicators) and the ability to simulate the hydrology of the Mekong River Basin (Nash Sutcliffe Efficiency (NSE) as evaluation metrics). Based on their results, APHRODITE outperformed another dataset for the Basin. Similarly, Tang et al. (2019) evaluated five GPPs (APHRODITE, China Meteorological Administration (CMA), CHIRPS, Agricultural Model Intercomparison and Improvement Project based on NASA Modern-Era Retrospective Analysis for Research and Applications (AgMERRA) and CFSR) for 11 basins and 46 sub-basins in MRB using four continuous statistical indices (Mean Error (ME), BIAS, r, R^2) and three categorical indices (POD, FAR and CSI) and their skill to simulate hydrology using NSE and RE. Their study revealed that APHRODITE was best suited for rugged terrain whereas almost all datasets had similar performance on the flat terrain. Likewise, Dang Dinh et al. (2020) evaluated four GPPs: the Climate Prediction Center (CPC) Unified Gauge-Based Analysis of Global Daily Precipitation, CMORPH, TRMM, and the Global Satellite Mapping of Precipitation (GSMaP) and their ability to capture the hydrology of the basin. The study found out that the TRMM outperformed other GPPs in terms of simulating hydrology. Similarly, Tang et al. (2021) used a novel approach towards the error correction of the GPPs. However, these evaluation approaches were subjective to the evaluation skill of the researcher. Likewise, Li et al. (2019)

evaluated three satellite-based precipitation products (Global Precipitation Measurement (GPM), TRMM, and PERSIANN-CDR) across Lower MRB (LMRB). A pixel-point comparison was made between the satellite products and 116 rain gauges for a monthly and daily and daily discharge for 6 stream gauges. The GPM proved to be skilled in terms of simulating precipitation and hydrology for the basin.

All former studies mostly focused on evaluating the GPPs based on their ability to reproduce the mean precipitation and skill to simulate the discharge in the basin. None of this study considered the ability of GPPs to reproduce the extreme indices. Further, they were mostly carried out considering MRB as a whole. For the basin covering a wide assortment of terrain from rugged mountainous to flat terrain, the performance of GPPs is not uniform (Alexander et al., 2020). All previous studies just focus on the continuous statistical indicators and categorical indices and evaluation mostly relied on the skill of the evaluator. Hence, the main objective of this study is to evaluate eight GPPs namely: APHRODITE, CHIRPS, CMORPH, CRU, CPC, Southeast Asian OBServed (SAOBS), TRMM, Global Precipitation Climatology Center (GPCC) for Nam Ngum River Basin (NRB) and Vietnam Mekong Delta (VMD) two sub-basins of LMRB featuring different characteristics in terms of climate and terrain. The evaluation of GPPs also involves the use of automated entropy-compromise programming (ECP) to weight evaluation indicators and rank them. Since a limited number of gauge-based stations are available for the NRB, the pixel-to-point comparison is made between the GPPs and the observed dataset.

2 STUDY AREA

The study area comprises of two basins of the LMRB: Nam Ngum River Basin in Lao PDR and Mekong delta in Vietnam as presented in figure 1.

2.1 Nam Ngum River Basin

The Nam Ngum River Basin (NRB) is a one of the important Mekong tributary sub-basins in central Lao PDR housing an area of 16,8000 km2 accounting for 7% of the country's area. The basin lies approximately between 17.9° N to 19.8° N and 101.85° E to 103.5° E. The main tributary of the basin, Nam Ngum River, traverses 420 km southwards before draining into Mekong River. It further discharges 40 % of the country's flow to Mekong River which accounts for 14 % of its flow (Meema et al., 2021). The basin is characterized by relatively flat in the southern part and steep topography with undulating terrain in the northeast part. The elevation for the Nam Ngum ranges between 151 m to 2698.

The basin is characterized by the tropical climate with distinct wet (June to September) and dry (October to April) seasons. March and April months usually witness the highest temperature with the average temperature ranging between 30 °C to 38 °C considering the altitude and location. The average annual precipitation across basin ranges between 1,450 mm to 3,500 mm with basin average of 2,000mm (Meema et al., 2021).

The basin is of significant importance as it has tremendous potential for hydropower and already houses four dams and other may under construction or planned with Nam Ngum 1 being the largest one. The mean annual river flow of the NRB is approximately 21,000 Mm^3 which attains its lowest level during March-April and reaches the peak during August-September.

2.2 Vietnam Mekong Delta

The Vietnam Mekong Delta (VMD) lies approximately between 8.55°N to 11.05 °N and

104.45°E to 106.85 °E in the southern Vietnam bounded by the East Sea in the South and southeast, Cambodia in the north and Gulf of Thailand in the southwest. The basin is spread across an area of 40,000 square kilometers and is drained by a complex network of the canals, rivers and dykes.

The VMD is characterized by the relatively flat terrain <5 m. It observes tropical climate with distinct wet (May to November) and dry season (December to April). About 30- 40 % of the delta is inundated during rainy (wet) season influenced by the Indian Summer Monsoon (Duy et al., 2021). The average annual precipitation across the basin ranges between 1,300 mm to 2,500 mm of which 80-90% is attributed by the precipitation during the wet season accounting for a discharge load of 75-85 % (Le et al., 2021).

The VMD is well known for the aquaculture and rice production occupying about 50% (~1.9 million ha) of the agricultural land (Sebesvari et al., 2012). However, the annual floods from the Mekong River inundates the large parts of the VMD.

3 DATASETS

3.1 Observation Datasets

The observed gauge-based precipitation dataset in the NRB were very limited. Only six stations data were made available by the Department of Meteorology, Laos that were mostly concentrated around the Central region of the Basin along the Nam Ngum River. The spatial distribution of the observed dataset is presented in figure 1. Only five stations having the overlapping observed data were considered of this study. In case of the VMD, eleven rain gauges stations covering entire area were made available. The daily observed gauge-based precipitation dataset was available for the reference period of 1998 to 2014.

3.2 Gridded Precipitation Products

In this study, we evaluated eight GPPs that comprises five gauge-based, one satellite-based and two reanalyzed precipitation products with different spatial and temporal resolutions Different GPPs have different temporal resolution, an overlapping reference period of 1998-2014 was considered for the study. Details of products, their description and source from where they can be retrieved are presented in table 1.

3.2.1 Gauge-based Precipitation Products

APHRODITE

Asian Precipitation Highly Resolved Observational Data Integration Towards Evaluation (APHRODITE) is a observed gauge-based interpolated precipitation product using improved Angular-Distance-Weighting interpolation technique that covers three spatial domains (Monsoon Asia, Middle Ease and Russia) at the spatial resolution of 0.25° and of daily temporal resolution (Yatagai et al., 2012). The Meteorological Research Institute of Japan Meteorological Agency and the Research Institute for Humanity and Nature are the developers of the dataset. Daily based precipitation records form a wide assortment of sources including the global telemetric stations, individual researcher's collections, meteorological stations records of the National Climatic Data Center, etc. were obtained in order to develop the APHRODITE. Two versions of products are available: V1101 is available from 1951-2007 and V1101EX_R1 from 2007-2015).

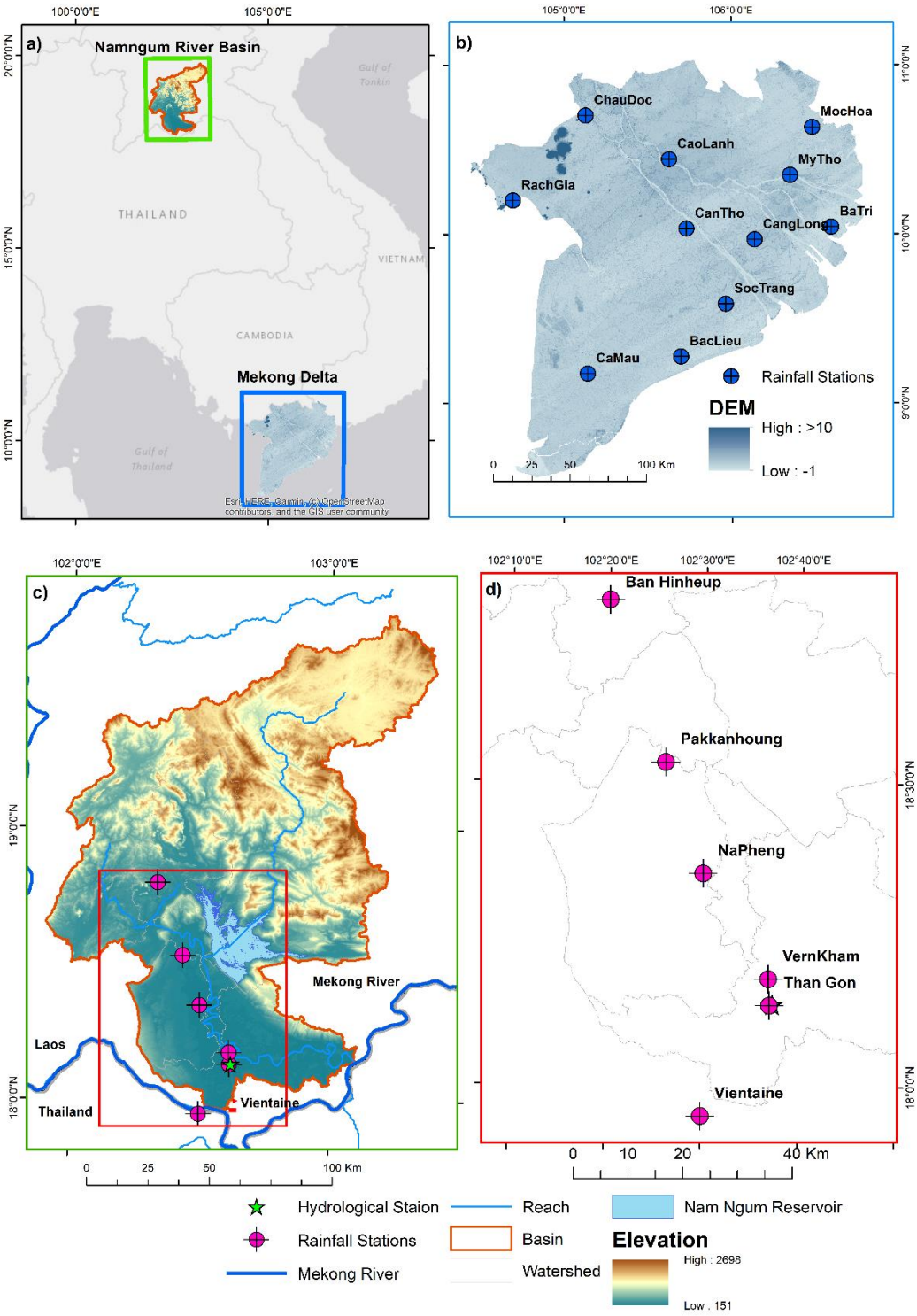


Figure 1: a) Location Map of Nam Ngum River Basin and Vietnam Mekong Delta b) Elevation profile along with the spatial distribution of reference precipitation gauges across the Vietnam Mekong Delta c) Elevation profile of Nam Ngum River Basin d) Spatial distribution of the reference precipitation gauges in the Nam Ngum River Basin.

CPC

The Climate Prediction Center (CPC) precipitation product is a quality controlled observed gauge-based interpolated daily scale dataset produced by the National Oceanic and Atmospheric Administration (NOAA) at the spatial resolution of 0.5° covering a period of 1979 until present (Xie et al., 2007). The data sources used in developing this products house more

than 30,000 gauge stations data provided by Cooperative Observer Network (COOP), GTS and numerous national and international organizations.

CRU

The Climate Research Unit (CRU) is a meteorological stations based interpolated terrestrial only (except Antarctica) monthly dataset at a spatial resolution of 0.5° covering a period of 1901 to 2020(I Harris et al., 2014; Ian Harris et al., 2020). The anomalies for the gauge-based precipitation data were gridded using the angular distance weighting (ADW) interpolation algorithm and were converted to the actual values of precipitation (not anomalies). The data set is developed by the University of East Anglia with a support from Natural Environment Research Council (NERC), United Kingdom (UK), the United State (US) Department of Energy and the UK National Center for Atmospheric Sciences (NCAS). In this study the CRU gridded Time Series version 4.05 (CRU TS v4.05) was used.

GPCC

The Global Precipitation Climatology Center (GPCC) is a gauge-based interpolated long-term gridded monthly dataset with a spatial resolution of 0.25° covering a period of 1891-2016. The data set houses about 50,000 stations per month throughout the globe (Zandler et al., 2019). The raw gauge-based dataset for the production of GPCC was supported by several institutions including national meteorological institutions (NMAs), the World Meteorological Organization (WMO), the Food and Agricultural Organization (FAO), the Climate Research Unit (CRU), etc.

SAOBS

The Southeast Asian OBServed (SAOBS), a product of Southeast Asia Climate Assessment and Dataset (SACAD), is a observed gauge-based interpolated daily dataset for Southeast Asia at two spatial resolution of 0.25° and 0.5° from 1981 until 2014 (van den Besselaar et al., 2017). About 4,000 gauge-based precipitation datasets from Southeast Asian countries were used to develop the SAOBS. This study used the dataset of 0.25° spatial resolution.

3.2.2 Satellite-based Precipitation Product

TRMM

The Tropical Rainfall Measuring Mission (TRMM) is a satellite-based precipitation estimates developed by a joint mission between the National Space Development Agency (NASDA), Japan and the US National Aeronautics and Space Administration (NASA) with an aim to estimate rainfall in the tropical and subtropical regions. This daily dataset is available at the spatial resolution of 0.25° between 1998 until 2020 (Huffman & Bolvin, 2018).

3.2.3 Reanalyzed Precipitation Products

CHIRPS

The Climate Hazard Group InfraRed Precipitation with Station (CHIRPS) is a reanalyzed precipitation product developed from the blend of multiple sources of dataset including observed rain gauge data, precipitation based on cold cloud duration (CCD) infrared data of National Oceanic and Atmospheric Administration (NOAA) - National Climate Data Center (NCDC), TRMM 3B42 and Version 2 atmospheric model rainfall of NOAA- Climate Forecast

System (CFS). The dataset is available at two spatial resolutions (0.05° and 0.25°). The CHIRPS25 is the daily precipitation product at the spatial resolution of 0.25° spanning across a period of 1981 until present (Funk et al., 2015) was used in this study.

CMORPH

The NOAA CPC MORPHing (CMORPH) dataset is a bias-corrected precipitation data product developed by blending gauge-based observation with passive microwave-based infrared satellite precipitation estimates using CPC Morphing Technique. CMORPH data is available at three spatial resolutions of 8 km (only December 2002 onwards), 0.25° and 0.5° and three temporal resolution of 30 min, 3- hourly and daily from 1998 until present (Xie et al., 2017). This study used the CMORPH with 0.25° spatial resolution and daily temporal resolution.

Table 1: Different GPPs categorized according to their type they fit in, their spatial and temporal resolutions, period of their availability and sources from where they can be retrieved

Type	Products	Spatial Resolution	Temporal Resolution	Spatial Coverage	Period of Record	Data Source
Gauge-based	APHRODITE (V1101 and V1101EX_R1)	0.25°	Daily	Monsoon Asia, Russia and Middle East	1951-2015	Data can be downloaded from: http://aphrodite.st.hirosaki-u.ac.jp/download/ (user registration is required)
	CPC	0.5°	Daily	Global	1979-present	Data can be downloaded from: https://www.esrl.noaa.gov/psd/data/gridded/Tables/precipitation.html
	CRU TS4.05	0.5°	Monthly	Global	1901-2015	Data can be downloaded from: https://data.ceda.ac.uk/badc/cru/data/cru_ts/cru_ts_4.05/data (registration required to access data)
	GPCC	0.25°	Monthly	Global	1891-2016	Data can be downloaded from: https://opendata.dwd.de/climate_environment/GPCC/html/fulldata-monthly_v2018_doi_download.html
	SAOBS	0.25°,0.5°	Daily	Southeast Asia	1981-2014	Data can be downloaded from: https://sacad.database.bmkg.go.id/download/grid/download.php
Reanalyzed	CHIRPS25	0.25°	Daily	50°N- 50°S	1981-present	Data can be downloaded from: https://data.chc.ucsb.edu/products/CHIRPS-2.0/
	CMORPH	0.25°,0.5°	Daily	60°N- 60°S	1998-present	Data can be downloaded from: https://www.ncei.noaa.gov/data/cmorph-high-resolution-global-precipitation-estimates/access/daily/

Satellite-based	TRMM 3B42_7	0.25°	Daily	50°N- 50°S	1998-present	Data can be downloaded from: https://disc.gsfc.nasa.gov/datasets/TRMM_3B42_Daily_7/summary?keywords=TRMM_3B42

4 METHODOLOGY

The series of steps adopted for evaluation and ranking of the gridded dataset is illustrated in figure 2. It starts with the collection of observed and gridded datasets. The methodology adopts the point-to-point comparison for which the gridded datasets were extracted to station's coordinates. Following the data extraction, extreme indices were computed. Five extreme indices proposed by Experts Team on Climate Change Detection Indices (ETCCDI) of World Meteorological Organization (WMO) were computed for each dataset. List of extreme indices used in this study are presented in Table 2. A payoff matrix was then formulated by normalized the evaluation metrics obtained for each EI in addition to mean precipitation for each station. Metrics normalization was carried out to avoid the dominance of the larger value indicators. Entropy method(Komaragiri & Kumar, 2014) was employed to weigh each evaluation criteria. The payoff matrix along with the weights obtained from entropy method were then supplied to the compromise programming to obtain station wise ranked dataset. To obtain one final ranked dataset, sum of ranks for individual indices were computed and the one with the least value was ranked 1st, second least value was ranked 2nd and so on.

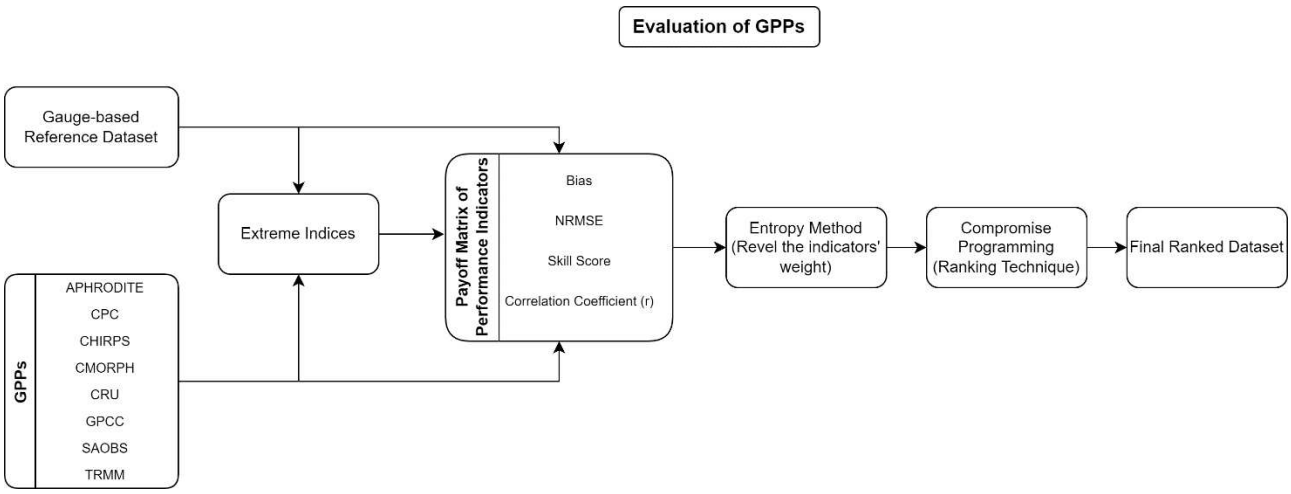


Figure 2: Flowchart displaying the GPP evaluation and ranking techniques adopted in this study

4.1 Extreme Indices

The Expert Team on Climate Change Detection and Indices (ETCCDI) of the WMO has developed 27 core extreme climate indices to analyze and standardize the climate extremes (Zhang et al., 2011). Of proposed 27 indices, five indices corresponding to precipitation extreme analysis used in this study are presented in the table 2 below:

Table 2: ETCCDI Extreme Precipitation Indices

Index	Descriptive Name	Definition	Unit
CDD	Consecutive Dry Days	Maximum number of consecutive dry days when precipitation is less than a specified threshold (precipitation <1mm)	Days

CWD	Consecutive Wet Days	Maximum number of consecutive dry days when precipitation is above a specified threshold (precipitation >1mm)	Days
R10mm	Heavy Precipitation Days	Annual count of days when daily rainfall rate (RR)>10mm	Days
R20mm	Very Heavy Precipitation Days	Annual count of days when daily rainfall rate (RR)>10mm	Days
RX1day	Maximum 1-Day Precipitation Amount	Annual maximum 1-day precipitation	mm
RX5day	Maximum 5-day Precipitation Amount	Annual maximum 5-day precipitation	mm

4.2 Continuous Statistical Indices

To evaluate the GPPs against the available observed dataset following continuous statistical indices are used:

Pearson correlation coefficient (r)

$$r = \frac{\sum_{i=1}^{n}(o_i-\bar{o})(p_i-\bar{p})}{\sqrt{\sum_{i=1}^{n}(o_i-\bar{o})^2}\sqrt{\sum_{i=1}^{n}(p_i-\bar{p})^2}} \quad 1$$

Where o_i, $\bar{o}$, p_i, $\bar{p}$ and n are observed precipitation for ith position, observed mean for the studied period, gridded precipitation for ith position, average gridded precipitation data for the studied period and n is the total amount of data in the timeseries. Pearson correlation coefficient measures the degree of similarity between the observed and gridded dataset. It's value ranges between -1 to 1. Value of 1 (-1) represent a perfect positive (negative) correlation.

Bias

$$Bias = \sum_{i=1}^{n} p_i - o_i \quad 2$$

Where p_i and o_i are gridded and observation precipitation data at ith position and n is the total number of datapoints in timeseries. The positive (negative) value of Bias indicates overestimation (underestimation) by the gridded dataset while the value of zero shows perfect estimation. The closer the value of Bias to zero better is the estimation.

Root Mean Squared Error

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(x_i-y_i)^2}{n}} \quad 3$$

Where x_i, y_i are the observed and gridded data points at ith position and n is the total number of datapoints in the timeseries. RMSE measures the differences between the observed and gridded dataset and estimates the averaged error magnitude. Value of RMSE close to zero indicate the better agreement between gridded and observed dataset.

Skill Score

The skill score compares the probability density function (pdf) of the GPPs with the pdf of the

observed/reference dataset and measure the common area between the pdfs.

$$S_{\text{score}} = \sum_i^N \left[min\left(P_i^{\text{GPP}}, P_i^{\text{reference}}\right)\right] \quad 4$$

Where S_{score} is the skill score, N is the number of bins to calculate pdf, P_i^{GPP} and $P_i^{\text{reference}}$ are the frequencies of values in a bin of the GPP and observed dataset respectively. A skill score of 1 indicate a complete overlap between the pdfs of GPP and observed and a value of 0 indicate no overlap at all.

4.3 Performance Evaluation Based on Categorical Indices

Apart from the continuous statistical indices, three categorical indices: probability of detection (POD), false alarm ratio (FAR) and critical success index (CSI) are used to evaluate the skills of GPPs in accurately prediction the rain/ no rain. POD measures the ability of the GPPs to correctly estimate the precipitation of a given threshold. It is also commonly known as the hit ratio. Similarly, FAR measures the number of false precipitation that GPPs detected that were not present in the observed. Likewise, the CIS measures the ability of GPPs to estimate the precipitation skill. The POD, FAR and CSI are calculated using equations 5,6, and 7.

$$POD = \frac{R}{R+M} \quad 5$$

$$FAR = \frac{F}{R+F} \quad 6$$

$$CSI = \frac{R}{R+F+M} \quad 7$$

Where R is the number of hits, F is the number of false alarm and M is the number of misses. The POD, FAR and CSI ranges between 0 to 1 where 1 indicates perfect skill in detecting the precipitation for POD and CSI. In contrast 0 represents the perfect score for FAR indicating GPPs did not give any false alarm.

4.4 Entropy Method

Entropy method assigns weights to each evaluation criteria under study. Equations 8-11 are used to compute weights using entropy method.

$$\text{En}_j = -\frac{1}{\ln(T)} \sum_{a=1}^{T} k_{aj} \ln\left(k_{aj}\right) \text{ for } j = 1,2, \dots \dots J \quad 8$$

$$k_{aj} = \frac{k_j(a)}{\sum_{a=1}^{T} k_j(a)} \quad 9$$

Where En_j is the entropy for each evalutaion criteria j, T is the number of gridded precipitation datasets and k_{aj} is the value of the jth indicator for ath gridded dataset.

The entropy (En_j) is then used to compute the degree of diversification and weights for each index as given by following equations.

$$Dd_j = 1 - En_j \quad 10$$

$$r_j = \frac{Dd_j}{\sum_{j=1}^{J} Dd_j} \quad 11$$

Where Dd_j and r_j represent the degree of diversification and normalized weight of indicator j respectively.
Higher the value of entropy higher is the uncertainty associated with the indicator and less is the weight.

4.5 Compromise Programming

Compromise Programming is the ranking technique that utilizes minimum distance of the indicator associated with GPP and the observed dataset. The distance formula for compromise programming is given by equation 12.

$$L_p(a) = \left[\sum_{j=1}^{J} w_j \left|f_j^* - f_j(a)\right|^p\right]^{\frac{1}{p}} \qquad 12$$

Where $L_p(a)$ is the minumum distance metric for the a gridded dataset, j is the indicator, f_j^* and $f_j(a)$ are normalized value of jth indicator for observed and a th gridded dataset respectively, w_j is the weight of jth indicator obtained from entropy method and p represents distance parameter (p=1 for linear and p=2 squared Euclidean distance). Lower the value L_p places the gridded dataset on the top and so on.

5 RESULTS

5.1 Performance of GPPs across NRB based on continuous statistical indices and CP

The comparison of the GPPs with the station data are made on a grid-to-point basis whereby nearest grid data are extracted to the station as enough stations were unavailable to cover the entire basin. Station wise evaluation indicators (r, Bias, RMSE and SS) are presented in table 3 and figure 3 for NRB. The APHRODITE in daily scale and CRU and GPCC at monthly time resolution show a good fit against the observed dataset with correlation coefficient ranging between 0.85 to 0.97. The GPCC, TRMM and APHRODITE have least bias among all the GPPs. The former two GPP represent positive bias ranging between1.21-38 mm/month indicating overestimation of precipitation while the later GPP underestimate the precipitation for 80 % of stations (-4.97 - -25.34 mm/month). Rest all GPPs (except CHIRPS) highly underestimate the precipitation in the NRB. CPC accounts for the highest negative bias in monthly precipitation for all stations followed by the CMORPH. The APHRODITE performs best in terms of RMSE with its values ranging between 45.32-111.55 mm/month followed by TRMM (48.83-109.87mm/month) and GPCC (34.73-126.37 mm/month). Rest all GPPs are relatively erroneous.

The skill score (SS) represents the coincidence of two PDFs. The SS of APHRODITE and TRMM ranged between 0.69 to 0.90 outperforms the other datasets. The CPC, CMOPRH and SAOBS exhibited larger differences between the PDFs against observed dataset. The worst was exhibited by the CPC with SS value ranging between -0.12 to 0.4 (except for Vientiane). Rest GPPs exhibited moderate SS. The discrepancies in the evaluation indices between GPPs can also be attributed to the different interpolation techniques and the station density available for interpolation (Hu et al., 2018).

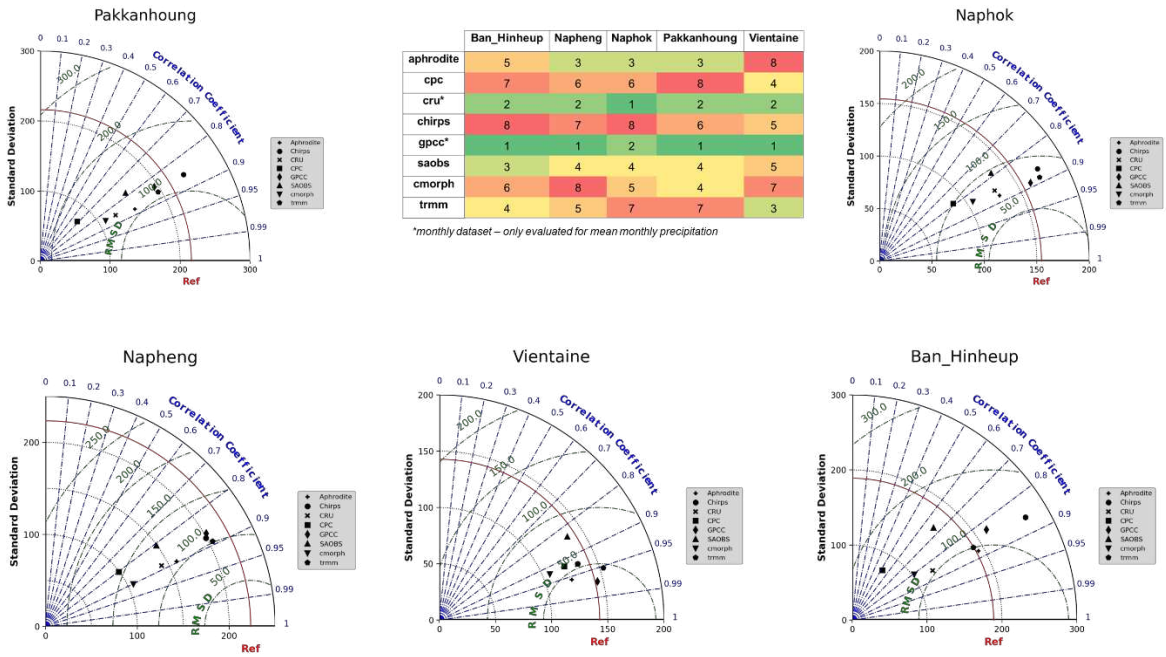
Table 3: Statistical measures of GPPs for different statistical indices across stations of NRB

		Bias	RMSE	r	SS
APHRODITE	**Ban_Hinheup**	25.53	97.53	0.88	0.73

	Napheng	-25.34	109.96	0.90	0.76
	Naphok	-4.97	73.93	0.88	0.77
	Pakkanhoung	-22.00	111.55	0.88	0.73
	Vientiane	-13.06	45.32	0.96	0.90
CHIRPS	**Ban_Hinheup**	100.97	175.26	0.86	0.14
	Napheng	0.95	107.30	0.88	0.77
	Naphok	33.22	93.91	0.86	0.63
	Pakkanhoung	55.08	135.59	0.86	0.61
	Vientiane	-3.89	53.67	0.93	0.86
CRU	**Ban_Hinheup**	-43.25	113.06	0.85	0.64
	Napheng	-45.10	125.52	0.89	0.68
	Naphok	-8.96	80.85	0.85	0.73
	Pakkanhoung	-49.78	135.95	0.85	0.60
	Vientiane	-5.26	53.12	0.93	0.86
CPC	**Ban_Hinheup**	-116.82	200.11	0.52	-0.12
	Napheng	-101.02	184.96	0.80	0.31
	Naphok	-65.03	119.28	0.79	0.40
	Pakkanhoung	-123.35	211.93	0.68	0.04
	Vientiane	-20.61	60.63	0.92	0.82
GPCC	**Ban_Hinheup**	38.28	126.37	0.83	0.55
	Napheng	5.11	111.82	0.87	0.75
	Naphok	19.75	77.48	0.89	0.75
	Pakkanhoung	1.21	118.07	0.84	0.70
	Vientiane	6.54	34.73	0.97	0.94
SAOBS	**Ban_Hinheup**	-43.61	152.80	0.66	0.35
	Napheng	-60.74	147.85	0.81	0.56
	Naphok	-24.18	99.31	0.79	0.59
	Pakkanhoung	-52.78	144.96	0.78	0.55
	Vientiane	-22.51	82.32	0.84	0.67
CMORPH	**Ban_Hinheup**	-74.16	142.60	0.81	0.43
	Napheng	-90.35	162.85	0.90	0.47
	Naphok	-40.75	95.49	0.84	0.62
	Pakkanhoung	-78.51	156.21	0.85	0.48
	Vientiane	-37.71	70.94	0.92	0.75
TRMM	**Ban_Hinheup**	14.48	101.13	0.86	0.71
	Napheng	10.24	101.58	0.89	0.79
	Naphok	31.42	85.66	0.89	0.69
	Pakkanhoung	12.94	109.87	0.86	0.74
	Vientiane	15.28	48.83	0.95	0.88

The Taylor diagram(Taylor, 2001) in figure 3 visually illustrates the performance of different gridded dataset against the observed dataset with three different evaluation indicator (r, RMSE, SD) and a table in the middle shows the final rank of the dataset. Before obtaining the final rank, datasets with daily temporal resolution were further evaluated for the extreme climate indices. The performance of individual dataset against the observed dataset for different EIs is presented in figure 4. As monthly dataset was evaluated against the mean precipitation, their score summed up to minimum and placed themselves in the top order. It can be seen from the

figures and table, APHRODITE secured 3rd rank (overall) and 1st (at daily scale) for about 60 % stations of NRB.



	Ban_Hinheup	Napheng	Naphok	Pakkanhoung	Vientaine
aphrodite	5	3	3	3	8
cpc	7	6	6	8	4
cru*	2	2	1	2	2
chirps	8	7	8	6	5
gpcc*	1	1	2	1	1
saobs	3	4	4	4	5
cmorph	6	8	5	4	7
trmm	4	5	7	7	3

*monthly dataset – only evaluated for mean monthly precipitation

Figure 3: Taylor diagram displaying performance of different datasets against observed dataset for different evaluation indicators

Figure 4 houses the ranking of each GPP against the observed dataset obtained from entropy method and compromise programming while figure 5 presents the box and whisker plot of EIs for the different GPPs across stations under considerations. Varying degree of performances were observed for GPPs for different stations. For instance, SAOBS was able to capture the CDD for 60 % of stations followed by CPC. On the other hand, CPC and CHIRPS did well in capturing the CWD for 80 % of the stations combined. APHRODITE and CMORPH was able to capture the range of CDD and CWD, but they underestimated (overestimated) for CDD (CWD) for almost all the stations. For about 60 % of the stations, SAOBS was able to represent the R10mm precipitation followed by APHRODITE. Similarly, in case of R20mm precipitation, APHRODITE ranked itself in top order for 60 % of the stations. APHRODITE and TRMM were able to represent the Rx1day precipitation for 80 % of the stations combined. In contrast, SAOBS dominated the order for 60% of the stations for Rx5mm indices.

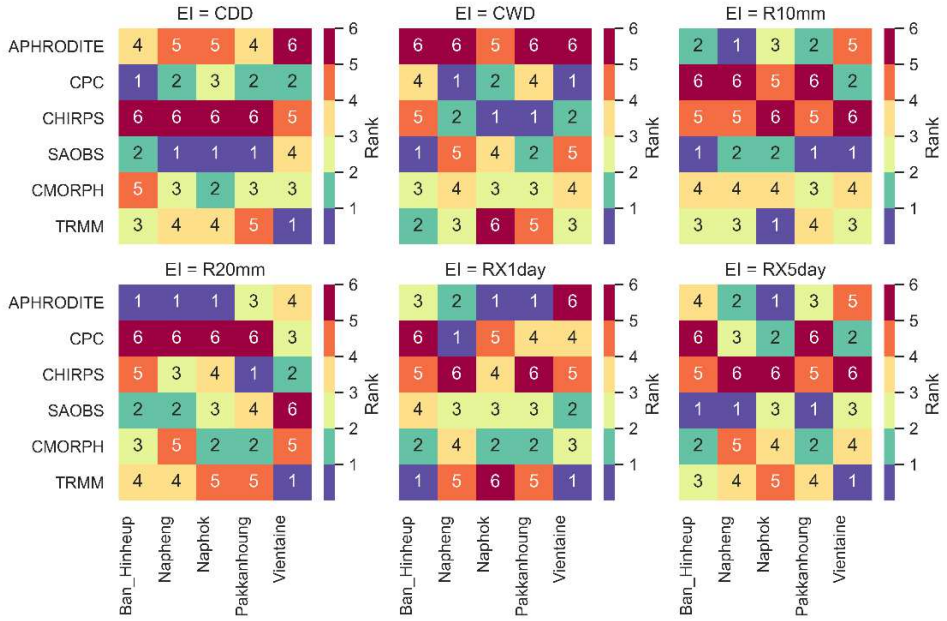


Figure 4: Heatmaps capturing rank of GPPs evaluated against the observed dataset for different EIS for all the stations in NRB

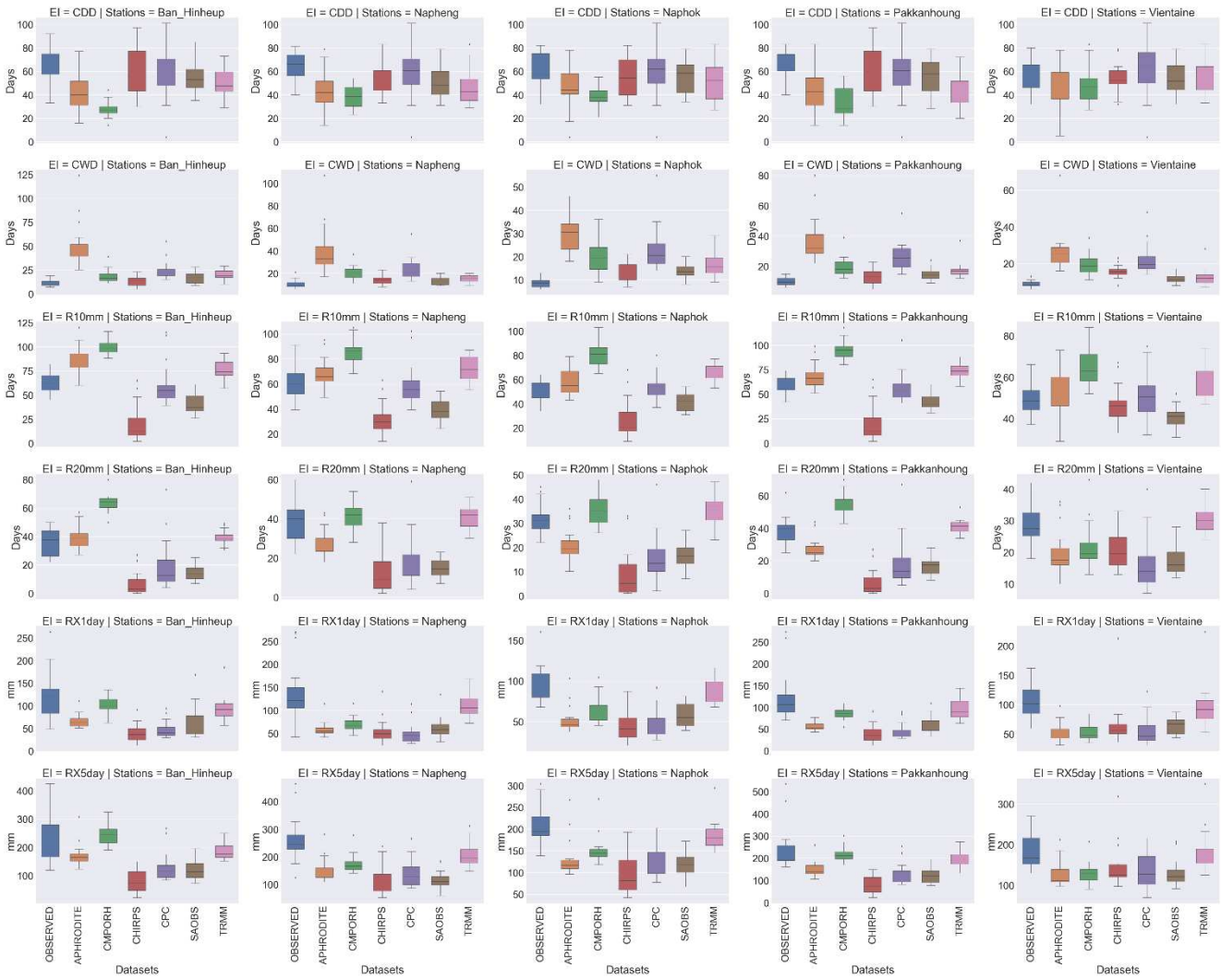


Figure 5: Box plot housing the performance of different datasets against observed dataset for different climate indices in NRB

5.2 Evaluation GPPs based on categorical Indices for NRB

The skill of individual GPPs to correctly discriminate the rain/no-rain were further tested using three categorical indices (POD, FAR and CSI) using 1mm as the precipitation threshold. The values of POD, FAR and CSI for each GPP is presented in table 4. APHRODITE dataset had the highest POD ranging between 0.96-0.98 while SAOBS had the least FAR value. The TRMM had the highest CSI value ranging between 0.44 to 0.64.

Table 4: Evaluation of GPPs based on the categorical indices (bold values represents better performance for each index)

Datasets	Categorical Indices	Ban_Hinheup	Napheng	Naphok	Pakkanhoung	Vientiane
APHRODITE	POD	**0.98**	**0.98**	**0.96**	**0.98**	**0.98**
	FAR	0.53	0.53	0.58	0.54	0.42
	CSI	0.46	0.47	0.41	0.46	0.57
CHIRPS	POD	0.79	0.82	0.83	0.80	0.83
	FAR	0.47	0.45	0.51	0.49	0.33
	CSI	0.47	0.49	0.45	0.45	0.59
CMORPH	POD	0.91	0.89	0.88	0.87	0.88
	FAR	0.42	0.42	0.47	0.45	0.28
	CSI	0.55	0.54	0.49	0.51	0.65
CPC	POD	0.84	0.88	0.91	0.83	0.95
	FAR	0.46	0.45	0.50	0.48	0.33
	CSI	0.49	0.51	0.48	0.47	0.65
SAOBS	POD	0.81	0.80	0.83	0.82	0.83
	FAR	**0.39**	**0.41**	**0.46**	**0.42**	**0.30**
	CSI	0.53	0.52	0.48	0.51	0.61
TRMM	POD	0.87	0.86	0.82	0.83	0.81
	FAR	0.41	0.42	0.47	0.52	0.25
	CSI	**0.54**	**0.53**	**0.48**	**0.44**	**0.64**

5.3 Performance of GPPs across VMD based on continuous statistical indices and CP

The results evaluation criteria of the different GPPs against the observed stations data for Mekong Delta is presented in table 1 of Annex I. APHRODITE, CHIRPS, GPCC and TRMM demonstrate least bias for almost all the stations ranging between ±23 mm/month. The former two GPPs mostly have the negative bias and later two GPPs with the positive bias. Similarly, CMORPH, CPC and SAOBS mostly underpredicted the precipitation in with as high as -184mm/month for RachGia station (SAOBS). Similarly in terms of RMSE, APHRODITE, GPCC and TRMM has the least RMSE with values less than 86 mm/month followed by CHIRPS, CMORPH, CPC and CRU. The SAOBS had poor RMSE ranging between 150 -241 mm/month. Likewise, except for the SAOBS, all GPPs demonstrated a good correlation (above 0.7 for 80% of stations) with the observed dataset at the monthly scale with higher correlation corresponding to TRMM and GPCC. The r values for SAOBS ranged between 0.16 -0.42 reveal very poor correlation at the monthly timescale. Figure 6 graphically illustrates the performance of each GPPs in terms of r, RMSD and SD for VMD.

The GPCC had the better coincidence of PDF with the observed indicated by the SS values ranging between 0.52- 0.98 for different stations. Rest all GPPs has the similar performances

in terms of SS except (CRU and SAOBS). The SAOBS has the least overlapping PDF with observed as indicated by the negative values of SS (-1.28 to -0.82).

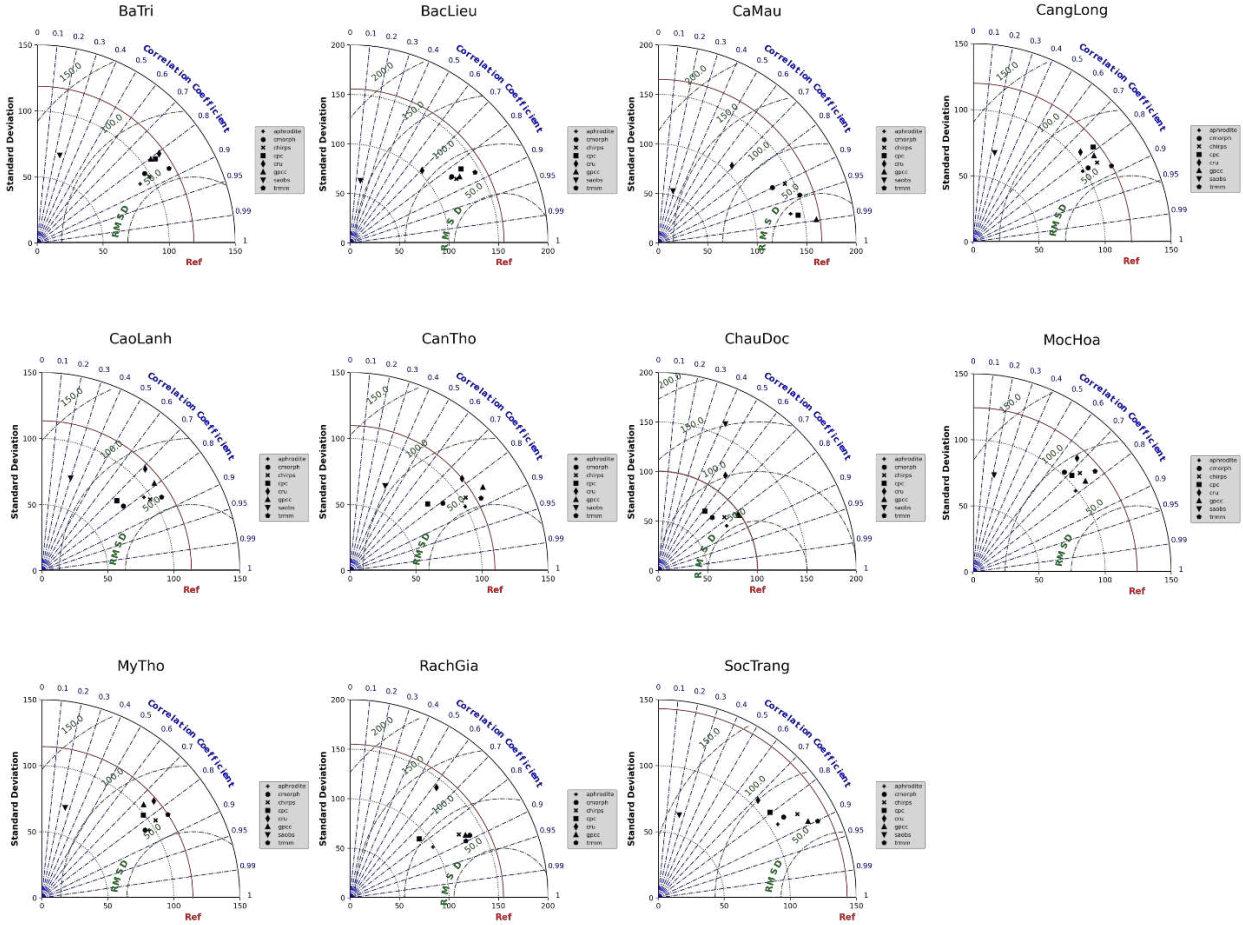


Figure 6: Taylor Diagram displaying performance evaluation of GPPs against observed dataset at different stations for Mekong Delta

Similarly, figure 7 below presents a box and whisker plot housing the performance of daily-scale GPPs against observed dataset for several climate EIs under study for stations covering entire VMD. During the study period from 1998-2014, TRMM outperformed all other GPPs in terms of representing the climate EIs against EIs of observed dataset for all the stations. Strong differences can be observed for other GPPs in representing the EIs. For instance, TRMM and CMORPH closely represent CDD (CWD) while other GPPs under estimate (over estimate) CDD(CWD)for almost all the stations. Similarly, TRMM and APHRODITE adequately represent the observed R10mm EI for almost all the stations while other GPPs underestimated R10mm EI except for CHIRPS which overestimated the R10mm EI for all stations. However, only TRMM seems to represent R20mm while other GPPs underestimate it for all the stations. Likewise, only TRMM and CMORPH sufficiently captured the Rx1day and Rx5day indices while other GPPs underestimated them.

Figure 7: Performance of daily-scale GPPs against observed dataset for EIs for different stations across Mekong Delta

The rank of each GPP based on its performance against the observed data set for different climate indices is presented by the heatmap in the figure 8.

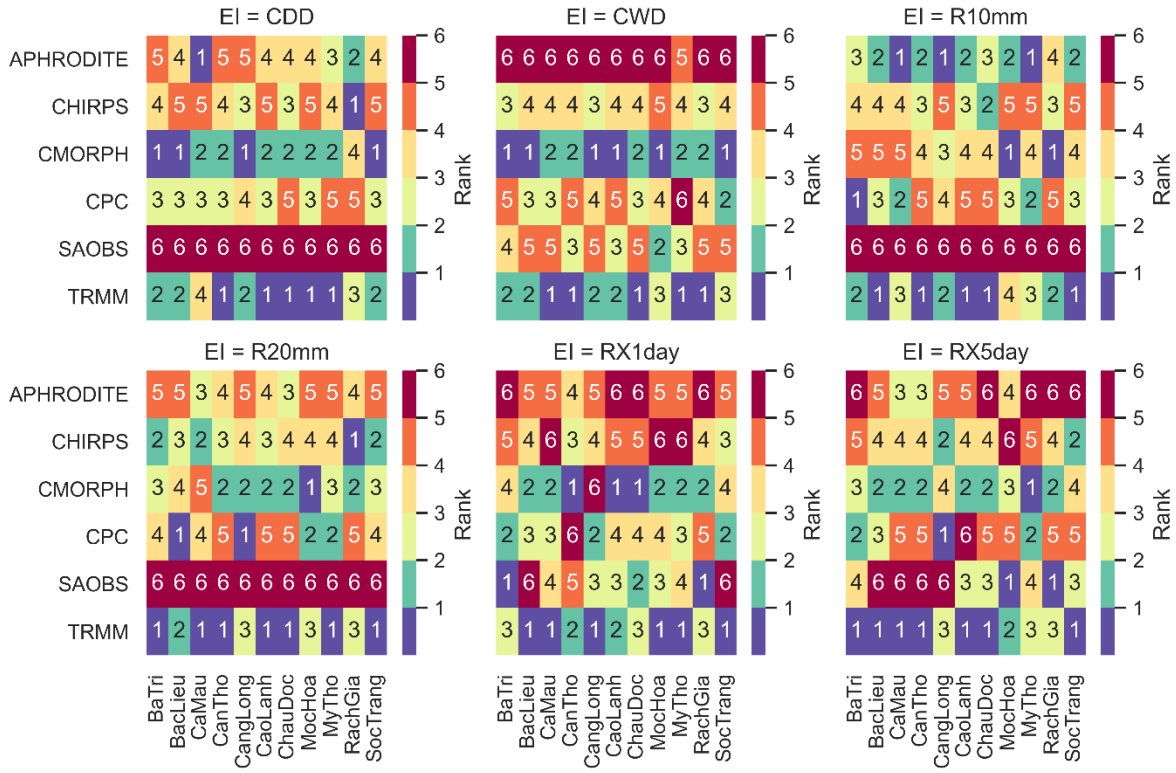


Figure 8:Heatmaps capturing rank of GPPs evaluated against the observed dataset for different EIS for all the stations in Mekong Delta

5.4 Evaluation of GPPs based on categorical indices

The threshold to discriminate rain/ no-rain was considered 1mm as recommended by WMO. Based on the different categorical indices used to evaluate the GPPs, Aphrodite seems to perform well in detecting the rainfall as indicated by the POD value greater than 0.85 for all stations as presented in table 5. The APHRODITE also has the higher FAR values ranging between 0.34 to 0.52. This can be attributed to the higher number of CWD and fewer CDD for APHRODITE. Satellite based estimate TRMM and reanalyzed dataset CMORPH have the least value for POD not above 0.71 for all stations. They also have relatively lower FAR compared to station based gridded dataset. However, the overall critical index is similar for all the datasets.

Table 5: Evaluation of GPPs based on categorical indices for Mekong Delta

Datasets	Categorical Indices	Bac Lieu	BaTri	Ca Mau	Cang Long	Can Tho	Cao Lanh	Chau Doc	Moc Hoa	My Tho	Soc Trang	Rach Gia
APHRODITE	POD	0.90	0.90	0.95	0.91	0.92	0.87	0.85	0.88	0.87	0.88	0.87
	FAR	0.45	0.50	0.34	0.48	0.47	0.51	0.51	0.49	0.52	0.42	0.45
	CSI	0.52	0.47	0.63	0.49	0.51	0.46	0.45	0.47	0.45	0.54	0.51
CMORPH	POD	0.70	0.66	0.70	0.70	0.63	0.58	0.55	0.61	0.66	0.69	0.71
	FAR	0.32	0.35	0.34	0.35	0.35	0.39	0.43	0.44	0.38	0.30	0.36
	CSI	0.53	0.49	0.52	0.51	0.47	0.42	0.39	0.41	0.47	0.53	0.51
CHIRPS	POD	0.80	0.77	0.79	0.81	0.82	0.80	0.77	0.77	0.81	0.79	0.78
	FAR	0.40	0.44	0.39	0.44	0.45	0.49	0.54	0.52	0.47	0.38	0.44
	CSI	0.52	0.48	0.52	0.50	0.49	0.45	0.41	0.42	0.47	0.53	0.48

CPC	POD	0.76	0.84	0.88	0.77	0.82	0.78	0.73	0.72	0.83	0.71	0.70
	FAR	0.35	0.46	0.14	0.43	0.41	0.46	0.50	0.44	0.48	0.36	0.39
	CSI	0.54	0.49	0.77	0.49	0.52	0.47	0.42	0.46	0.47	0.51	0.49
SAOBS	POD	0.73	0.80	0.70	0.79	0.98	0.78	0.77	0.73	0.69	0.69	-
	FAR	0.36	0.36	0.33	0.37	0.18	0.41	0.53	0.42	0.48	0.42	-
	CSI	0.52	0.55	0.52	0.54	0.80	0.51	0.42	0.48	0.42	0.46	-
TRMM	POD	0.68	0.66	0.67	0.66	0.61	0.57	0.55	0.61	0.65	0.67	0.70
	FAR	0.31	0.35	0.31	0.34	0.36	0.40	0.44	0.44	0.38	0.29	0.38
	CSI	0.52	0.49	0.52	0.49	0.46	0.41	0.38	0.41	0.47	0.52	0.49

6 DISCUSSION

This study evaluated the eight GPPs: five gauge-based products (APHRODITE, CPC, CRU, GPCC and SAOBS), one satellite-based product (TRMM) and two reanalyzed products (CMORPH and CHIRPS) for the two sub-basins (NRB and VMD) of LMRB. The larger differences in the performance of GPPs were observed for these basins. The performance differences between the GPPs across SEA is also reported by Alexander et al. (2020). APHRODITE performed well for the NRB while TRMM outweighed others in VMD. The performance of APHRODITE outperforming other dataset for the NRB is consistent with the findings of Tian et al., (2021) and Tang et al., (2019). The better performance of APHRODITE in the NRB could be the outcome of the better interpolation technique addressing the topographic variation (Yi Yang et al., 2017) and was developed for Monsoon Asia by taking observed gauge-based precipitation products from within the region (Yatagai et al., 2012). Saying that, the APHRODITE failed to capture the EIs in many instances for both the sub-basins. For example, the APHRODITE overestimated(underestimated) CWD(CDD). The higher CWD is the reflection of spatial average of GPPs over the grid resolution (Hussain et al., 2018; Satgé et al., 2016). In contrast, the performance of GPPs is quite similar and discrepancies are not large for VMD as indicated by the statistical indices of GPPs except for SAOBS (Sun et al., 2018). Though the SAOBS was developed particularly for SEA with data obtained from the SEA countries, it observed the poorest skill in estimating the precipitation across VMD. The gauge records might not have been made available during the production of SAOBS product.

In terms of representing the mean precipitation, gauge-based products (except GPCC for NRB and VND and CRU only for VND) and CHIRPS (reanalyzed product) mostly underpredicted for 75%. The underestimation by these products could be attributed to the limited number of in-situ stations used for developing gridded dataset and inadequate quality control of the real-time GTS datasets whereby sometimes missing values are replaced with 0 especially for APHRODITE (Yatagai et al., 2012). The underprediction of precipitation by CPC over Myanmar and neighboring regions is also reported by Kim et al., (2019). In contrast, the GPCC overestimated (though close to observed) the mean monthly precipitation. The GPCC at the monthly scale out performs in terms of capturing the mean monthly precipitation attributed its increased number of stations and improved quality controlled data and the change in interpolation technique from kriging to spheremap (Alexander et al., 2020; Schneider et al., 2014). Similarly, the overestimation of precipitation of TRMM can be linked to the ignorance of altitudinal variations of surface in the algorithm, IR sensor estimating precipitation from non-raining cirrus cloud (Scheel et al., 2011) and its bias correction technique that employs GPCC as reference dataset at monthly scale (Trinh-Tuan et al., 2019). Similarly, the higher negative bias of the CMOPRH can be linked to its inherent characteristics of underestimating the precipitation at higher altitude (Hobouchian et al., 2017) and the CPC (which is already underestimating precipitation) as the reference dataset for bias correction (Xie et al., 2017).

The CMORPH usually simulates light-rain events at daily scale and fewer heavy rain-events. This can be attributed to its gridding algorithm which is bilinear interpolation (Yu et al., 2009). It ranked last in terms of representing CDD and CWD for almost all the stations. It is also noteworthy to contemplate that the precipitation by the GPPs is the mean areal value of the grid boxes and the spatial resolution of the different GPPs are different which compromises the spatial representativeness of the station to the grid. This may differ significantly in terms of elevation as well. Hence, it is difficult for a station to represent the precipitation of different spatial resolution of different GPPs.

The gauge-based GPPs exhibited higher POD compared to satellite-based and reanalyzed GPPs. In contrast satellite-based and reanalyzed products were far skillful in minimizing FAR compared to the gauge-based GPPs (except for SAOBS). Similar findings were reported by Yi Yang et al., (2017). The lower POD and higher FAR for satellite and reanalyzed product can be attributed to the low ability to discriminate the drizzle and frozen precipitation during dry season (Wu et al., 2019). The higher FAR for the gauge-based product could be caused by the differences in grid location and gauge location.

7 CONCLUSIONS

An evaluation and ranking of eight state-of-art GPPs was carried out for the two contrasting sub-basins of the LMRB: i) NRB of Lao PDR with undulating terrain and ii) humid VMD characterized by flat terrain. The noticeable differences in the performance of GPPs were revealed for two sub-basins. Most of former studies attempted to evaluate and recommend a best GPP for the MRB or LMRB as a whole. However, this may not be always applicable as the study domain might only be the sub-basins of smaller areal coverage. Depending upon the area considered for the study and the gauge-station availability, a diverse performance can be expected for different GPP with in sub-basins of the same basin as well. This study also indicates that there is no-size-fits-all GPP for different sub-basins for application within the LMRB as APHRODITE outperformed other GPPs at daily scale for NRB while TRMM ranked first for VMD. Further, Alexander et al., (2020) also pointed out that the differences between the performances of GPPs across the SEA is prominent. The differences in the performances can be attributed to the sparse station density considered for developing the GPPs, station's locations, gridding algorithms, location of stations and grid point, etc.

This study employs the ECP, an automated multi-criteria decision-making approach for evaluation and ranking of the GPPs. This is also a first attempt to rank the dataset using compromise programming in these two sub-basins. This method calculates the weight based on the uncertainty with in the timeseries and rank them with reference to minimum distance (minimum error/uncertainty) from the observed dataset by limiting the interference of the researcher. Most of the studies (A. Chen et al., 2018; C.-J. Chen et al., 2017; Dandridge et al., 2019; Dang Dinh et al., 2020) that has been carried out to evaluate GPPs in the LMRB rely only on the statistical and categorical indices and the ranking is solely based on the skill of the researcher to weigh these indices. As different statistical indices may favor different GPP resulting in a conflicting choice and it is entirely dependent on skill of researcher to choose the best one. This limitation can be overcome by employing the ECP which weighs the uncertainties in statistical indices and rank GPP with no influence from the researcher. However, the performance might be affected by the number of criteria being considered and the weight obtained from entropy gets redistributed on addition or removal of evaluation indices influencing the GPP selection. Hence care should be taken in limiting the number of statistical indices to be used. Saying that, the ECP can be a suitable choice in ranking and evaluating a

large suite of GPPs and when a researcher has hard time in selecting a suitable choice based on statistical indices only.

Saying that, the ranked GPP from this study can be used from different hydro-meteorological application such as water resources planning, estimating potential for hydropower potential, etc. The GPPs are the gateways to fill in the data gaps and spatial coverage for several hydrometeorological studies(Morales-Moraga et al., 2019; Prajapati et al., 2021). However, it should also be noted that the choice of the GPP should be considered based upon the application or purpose of the study as the error in the daily precipitation frequencies and intensities of GPPs significantly impact the output of hydrologic simulations (Luo et al., 2019). For instance, though APHRODITE was ranked best for NRB, its skill to reflect the EI for some instances (CWD, CDD) were poor. Hence, in case of extreme analysis, GPP that captures the EI well or an ensemble of the GPPs addressing the large uncertainty among the dataset shall be considered.

Data availability statement

The datasets generated during and/or analyzed during the current study are available upon reasonable request from the corresponding author.

Funding

This work was funded by Stockholm Environment Institute (SEI) under the SUMERNET 4 All Programme.

Conflict of interest/Competing interests

The authors declare no conflict of interest.

Author Contribution

SD: Conceptualization, data curation, formal analysis, investigation, methodology, visualization and validation, drafting original manuscript. SS: PI, overall supervision, validation, review and editing. SK: Data curation, review and editing, TPV: Data curation, review and editing, ADG: Review and editing, TPLN: Review and editing.

Ethics Approval

All authors have read and approved this manuscript.

Consent to participate

The authors have provided their consent to submit this manuscript to TAAC.

Consent for publication

The authors give permission to publish this manuscript.

8 REFERENCES

Ahmed, K., Shahid, S., Wang, X., Nawaz, N., & Khan, N. (2019). Evaluation of Gridded Precipitation Datasets over Arid Regions of Pakistan. In *Water* (Vol. 11, Issue 2). https://doi.org/10.3390/w11020210

Alexander, L. V, Bador, M., Roca, R., Contractor, S., Donat, M. G., & Nguyen, P. L. (2020). Intercomparison of annual precipitation indices and extremes over global land areas from in situ, space-based and reanalysis products. *Environmental Research Letters*, *15*(5), 55002. https://doi.org/10.1088/1748-9326/ab79e2

Aliyar, Q., Dhungana, S., & Shrestha, S. (2021). Spatio-temporal trend mapping of precipitation and its extremes across Afghanistan (1951–2010). *Theoretical and Applied Climatology*. https://doi.org/10.1007/s00704-021-03851-2

Arshad, M., Ma, X., Yin, J., Ullah, W., Liu, M., & Ullah, I. (2021). Performance evaluation of ERA-5, JRA-55, MERRA-2, and CFS-2 reanalysis datasets, over diverse climate regions of Pakistan. *Weather and Climate Extremes*, *33*, 100373. https://doi.org/https://doi.org/10.1016/j.wace.2021.100373

Awange, J. L., Ferreira, V. G., Forootan, E., Khandu, Andam-Akorful, S. A., Agutu, N. O., & He, X. F. (2016). Uncertainties in remotely sensed precipitation data over Africa. *International Journal of Climatology*, *36*(1), 303–323. https://doi.org/https://doi.org/10.1002/joc.4346

Brans, J. P., Vincke, P., & Mareschal, B. (1986). How to select and how to rank projects: The Promethee method. *European Journal of Operational Research*, *24*(2), 228–238. https://doi.org/https://doi.org/10.1016/0377-2217(86)90044-5

Camici, S., Ciabatta, L., Massari, C., & Brocca, L. (2018). How reliable are satellite precipitation estimates for driving hydrological models: A verification study over the Mediterranean area. *Journal of Hydrology*, *563*, 950–961. https://doi.org/https://doi.org/10.1016/j.jhydrol.2018.06.067

Chen, A., Chen, D., & Azorin-Molina, C. (2018). Assessing reliability of precipitation data over the Mekong River Basin: A comparison of ground-based, satellite, and reanalysis datasets. *International Journal of Climatology*, *38*(11), 4314–4334. https://doi.org/https://doi.org/10.1002/joc.5670

Chen, C.-J., Senarath, S. U. S., Dima-West, I. M., & Marcella, M. P. (2017). Evaluation and restructuring of gridded precipitation data over the Greater Mekong Subregion. *International Journal of Climatology*, *37*(1), 180–196. https://doi.org/https://doi.org/10.1002/joc.4696

Dandridge, C., Lakshmi, V., Bolten, J., & Srinivasan, R. (2019). Evaluation of Satellite-Based Rainfall Estimates in the Lower Mekong River Basin (Southeast Asia). In *Remote Sensing* (Vol. 11, Issue 22). https://doi.org/10.3390/rs11222709

Dang Dinh, K., Ngoc Anh, T., Nguyen, N., Bui, D., & Srinivasan, R. (2020). Evaluation of Grid-Based Rainfall Products and Water Balances over the Mekong River Basin. *Remote Sensing*, *12*, 21–32. https://doi.org/10.3390/rs12111858

Darand, M., & Khandu, K. (2020). Statistical evaluation of gridded precipitation datasets using rain gauge observations over Iran. *Journal of Arid Environments*, *178*, 104172. https://doi.org/https://doi.org/10.1016/j.jaridenv.2020.104172

Duan, Z., Liu, J., Tuo, Y., Chiogna, G., & Disse, M. (2016). Evaluation of eight high spatial resolution gridded precipitation products in Adige Basin (Italy) at multiple temporal and spatial scales. *Science of The Total Environment*, *573*, 1536–1553. https://doi.org/https://doi.org/10.1016/j.scitotenv.2016.08.213

Duy, N. Le, Nguyen, T. V. K., Nguyen, D. V., Tran, A. T., Nguyen, H. T., Heidbüchel, I., Merz, B., & Apel, H. (2021). Groundwater dynamics in the Vietnamese Mekong Delta: Trends, memory effects, and response times. *Journal of Hydrology: Regional Studies*, *33*, 100746. https://doi.org/https://doi.org/10.1016/j.ejrh.2020.100746

Ebert, E. E., Janowiak, J. E., & Kidd, C. (2007). Comparison of Near-Real-Time Precipitation Estimates from Satellite Observations and Numerical Models. *Bulletin of the American Meteorological Society*, *88*(1), 47–64. https://doi.org/10.1175/BAMS-88-1-47

Fallah, A., Rakhshandehroo, G. R., Berg, P., O, S., & Orth, R. (2020). Evaluation of precipitation datasets against local observations in southwestern Iran. *International Journal of Climatology*, *40*(9), 4102–4116. https://doi.org/https://doi.org/10.1002/joc.6445

Funk, C., Peterson, P., Landsfeld, M., Pedreros, D., Verdin, J., Shukla, S., Husak, G., Rowland, J., Harrison, L., Hoell, A., & Michaelsen, J. (2015). The climate hazards infrared precipitation with stations—a new environmental record for monitoring extremes. *Scientific Data*, *2*(1), 150066. https://doi.org/10.1038/sdata.2015.66

Gershon, M., & Duckstein, L. (1983). Multiobjective Approaches to River Basin Planning. *Journal of Water Resources Planning and Management-Asce - J WATER RESOUR PLAN MAN-ASCE*, *109*. https://doi.org/10.1061/(ASCE)0733-9496(1983)109:1(13)

Harris, I, Jones, P. D., Osborn, T. J., & Lister, D. H. (2014). Updated high-resolution grids of monthly climatic observations – the CRU TS3.10 Dataset. *International Journal of Climatology*, *34*(3), 623–642. https://doi.org/https://doi.org/10.1002/joc.3711

Harris, Ian, Osborn, T. J., Jones, P., & Lister, D. (2020). Version 4 of the CRU TS monthly high-resolution gridded multivariate climate dataset. *Scientific Data*, *7*(1), 109. https://doi.org/10.1038/s41597-020-0453-3

Hobeichi, S., Abramowitz, G., Contractor, S., & Evans, J. (2020). Evaluating Precipitation Datasets Using Surface Water and Energy Budget Closure. *Journal of Hydrometeorology*, *21*(5), 989–1009. https://doi.org/10.1175/JHM-D-19-0255.1

Hobouchian, M. P., Salio, P., García Skabar, Y., Vila, D., & Garreaud, R. (2017). Assessment of satellite precipitation estimates over the slopes of the subtropical Andes. *Atmospheric Research*, *190*, 43–54. https://doi.org/https://doi.org/10.1016/j.atmosres.2017.02.006

Hu, Z., Zhou, Q., Chen, X., Li, J., Li, Q., Chen, D., Liu, W., & Yin, G. (2018). Evaluation of three global gridded precipitation data sets in central Asia based on rain gauge observations. *International Journal of Climatology*, *38*(9), 3475–3493. https://doi.org/https://doi.org/10.1002/joc.5510

Huffman, G. J., & Bolvin, D. T. (2018). *26 April 2018 TRMM 3B42_3B43_doc 1. November 2013*, 1–48.

Hussain, Y., Satgé, F., Hussain, M. B., Martinez-Carvajal, H., Bonnet, M.-P., Cárdenas-Soto, M., Roig, H. L., & Akhter, G. (2018). Performance of CMORPH, TMPA, and PERSIANN rainfall datasets over plain, mountainous, and glacial regions of Pakistan. *Theoretical and Applied Climatology*, *131*(3), 1119–1132. https://doi.org/10.1007/s00704-016-2027-z

Kim, I.-W., Oh, J., Woo, S., & Kripalani, R. H. (2019). Evaluation of precipitation extremes over the Asian domain: observation and modelling studies. *Climate Dynamics*, *52*(3), 1317–1342. https://doi.org/10.1007/s00382-018-4193-4

Komaragiri, S. R., & Kumar, D. N. (2014). Ranking of global climate models for India using multicriterion analysis. *Climate Research*, *60*, 103–117. https://doi.org/10.3354/cr01222

Le, P. V. V, Pham, H. V, Bui, L. K., Tran, A. N., Pham, C. V, Nguyen, G. V, & Tran, P. A. (2021). Responses of groundwater to precipitation variability and ENSO in the Vietnamese Mekong Delta. *Hydrology Research*, *52*(6), 1280–1293. https://doi.org/10.2166/nh.2021.024

Lee, G. W. (2006). Sources of Errors in Rainfall Measurements by Polarimetric Radar: Variability of Drop Size Distributions, Observational Noise, and Variation of Relationships between R and Polarimetric Parameters. *Journal of Atmospheric and Oceanic Technology*, *23*(8), 1005–1028. https://doi.org/10.1175/JTECH1899.1

Luo, X., Wu, W., He, D., Li, Y., & Ji, X. (2019). Hydrological Simulation Using TRMM and CHIRPS Precipitation Estimates in the Lower Lancang-Mekong River Basin. *Chinese Geographical Science*, *29*(1), 13–25. https://doi.org/10.1007/s11769-019-1014-6

Meema, T., Tachikawa, Y., Ichikawa, Y., & Yorozu, K. (2021). Uncertainty assessment of water resources and long-term hydropower generation using a large ensemble of future climate projections for the Nam Ngum River in the Mekong Basin. *Journal of Hydrology: Regional Studies*, *36*, 100856. https://doi.org/https://doi.org/10.1016/j.ejrh.2021.100856

Morales-Moraga, D., Meza, F. J., Miranda, M., & Gironás, J. (2019). Spatio-temporal estimation of climatic variables for gap filling and record extension using Reanalysis data. *Theoretical and Applied Climatology*, *137*(1), 1089–1104. https://doi.org/10.1007/s00704-018-2653-8

Opricovic, S., & Tzeng, G.-H. (2004). Compromise solution by MCDM methods: a comparative analysis of VIKOR and TOPSIS. *European Journal of Operational Research*, *156*, 445–455. https://doi.org/10.1016/S0377-2217(03)00020-1

Prajapati, R., Talchabhadel, R., Silwal, P., Upadhyay, S., Ertis, B., Thapa, B., & Davids, J. (2021). Less rain and rainy days—lessons from 45 years of rainfall data (1971–2015) in the Kathmandu Valley, Nepal. *Theoretical and Applied Climatology*, *145*. https://doi.org/10.1007/s00704-021-03706-w

Prakash, S., Mitra, A. K., Rajagopal, E. N., & Pai, D. S. (2016). Assessment of TRMM-based TMPA-3B42 and GSMaP precipitation products over India for the peak southwest monsoon season. *International Journal of Climatology*, *36*(4), 1614–1631. https://doi.org/https://doi.org/10.1002/joc.4446

Satgé, F., Bonnet, M.-P., Gosset, M., Molina, J., Hernan Yuque Lima, W., Pillco Zolá, R., Timouk, F., & Garnier, J. (2016). Assessment of satellite rainfall products over the Andean plateau. *Atmospheric Research*, *167*, 1–14. https://doi.org/https://doi.org/10.1016/j.atmosres.2015.07.012

Satgé, F., Defrance, D., Sultan, B., Bonnet, M. P., Seyler, F., Rouché, N., Pierron, F., & Paturel, J. E. (2020). Evaluation of 23 gridded precipitation datasets across West Africa. *Journal of Hydrology*, *581*(November 2019). https://doi.org/10.1016/j.jhydrol.2019.124412

Scheel, M. L. M., Rohrer, M., Huggel, C., Santos Villar, D., Silvestre, E., & Huffman, G. J. (2011). Evaluation of TRMM Multi-satellite Precipitation Analysis (TMPA) performance in the Central Andes region and its dependency on spatial and temporal resolution. *Hydrology and Earth System Sciences*, *15*(8), 2649–2663. https://doi.org/10.5194/hess-15-2649-2011

Schneider, U., Becker, A., Finger, P., Meyer-Christoffer, A., Ziese, M., & Rudolf, B. (2014). GPCC's new land surface precipitation climatology based on quality-controlled in situ data and its role in quantifying the global water cycle. *Theoretical and Applied Climatology*, *115*(1), 15–40. https://doi.org/10.1007/s00704-013-0860-x

Sebesvari, Z., Le, H. T. T., Van Toan, P., Arnold, U., & Renaud, F. G. (2012). *Agriculture and Water Quality in the Vietnamese Mekong Delta BT - The Mekong Delta System: Interdisciplinary Analyses of a River Delta* (F. G. Renaud & C. Kuenzer (eds.); pp. 331–361). Springer Netherlands. https://doi.org/10.1007/978-94-007-3962-8_13

Shen, Z., Yong, B., Gourley, J. J., Qi, W., Lu, D., Liu, J., Ren, L., Hong, Y., & Zhang, J. (2020). Recent global performance of the Climate Hazards group Infrared Precipitation (CHIRP) with Stations (CHIRPS). *Journal of Hydrology*, *591*, 125284. https://doi.org/https://doi.org/10.1016/j.jhydrol.2020.125284

Sun, Q., Miao, C., Duan, Q., Ashouri, H., Sorooshian, S., & Hsu, K.-L. (2018). A Review of Global Precipitation Data Sets: Data Sources, Estimation, and Intercomparisons. *Reviews of Geophysics*, *56*(1), 79–107. https://doi.org/https://doi.org/10.1002/2017RG000574

Tang, X., Zhang, J., Wang, G., Ruben, G. B., Bao, Z., Liu, Y., Liu, C., & Jin, J. (2021). Error Correction of Multi-Source Weighted-Ensemble Precipitation (MSWEP) over the Lancang-Mekong River Basin. In *Remote Sensing* (Vol. 13, Issue 2). https://doi.org/10.3390/rs13020312

Tang, X., Zhang, J., Wang, G., Yang, Q., Yang, Y., Guan, T., Liu, C., Jin, J., Liu, Y., & Bao, Z. (2019). Evaluating Suitability of Multiple Precipitation Products for the Lancang River

Basin. *Chinese Geographical Science*, *29*(1), 37–57. https://doi.org/10.1007/s11769-019-1015-5

Tarek, M., Brissette, F., & Arsenault, R. (2021). Uncertainty of gridded precipitation and temperature reference datasets in climate change impact studies. *Hydrology and Earth System Sciences*, *25*(6), 3331–3350. https://doi.org/10.5194/hess-25-3331-2021

Taylor, K. E. (2001). Summarizing multiple aspects of model performance in a single diagram. *Journal of Geophysical Research: Atmospheres*, *106*(D7), 7183–7192. https://doi.org/https://doi.org/10.1029/2000JD900719

Tian, W., Liu, X., Wang, K., Bai, P., Liang, K., & Liu, C. (2021). Evaluation of six precipitation products in the Mekong River Basin. *Atmospheric Research*, *255*, 105539. https://doi.org/https://doi.org/10.1016/j.atmosres.2021.105539

Trinh-Tuan, L., Matsumoto, J., Ngo-Duc, T., Nodzu, M. I., & Inoue, T. (2019). Evaluation of satellite precipitation products over Central Vietnam. *Progress in Earth and Planetary Science*, *6*(1), 54. https://doi.org/10.1186/s40645-019-0297-7

Try, S., Tanaka, S., Tanaka, K., Sayama, T., Oeurng, C., Uk, S., Takara, K., Hu, M., & Han, D. (2020). Comparison of gridded precipitation datasets for rainfall-runoff and inundation modeling in the Mekong River Basin. *PloS One*, *15*(1), e0226814–e0226814. https://doi.org/10.1371/journal.pone.0226814

van den Besselaar, E. J. M., van der Schrier, G., Cornes, R. C., Iqbal, A. S., & Klein Tank, A. M. G. (2017). SA-OBS: A Daily Gridded Surface Temperature and Precipitation Dataset for Southeast Asia. *Journal of Climate*, *30*(14), 5151–5165. https://doi.org/10.1175/JCLI-D-16-0575.1

Wu, W., Li, Y., Luo, X., Zhang, Y., Ji, X., & Li, X. (2019). Performance evaluation of the CHIRPS precipitation dataset and its utility in drought monitoring over Yunnan Province, China. *Geomatics, Natural Hazards and Risk*, *10*(1), 2145–2162. https://doi.org/10.1080/19475705.2019.1683082

Xie, P., Chen, M., Yang, S., Yatagai, A., Hayasaka, T., Fukushima, Y., & Liu, C. (2007). A Gauge-Based Analysis of Daily Precipitation over East Asia. *Journal of Hydrometeorology*, *8*(3), 607–626. https://doi.org/10.1175/JHM583.1

Xie, P., Joyce, R., Wu, S., Yoo, S.-H., Yarosh, Y., Sun, F., & Lin, R. (2017). Reprocessed, Bias-Corrected CMORPH Global High-Resolution Precipitation Estimates from 1998. *Journal of Hydrometeorology*, *18*(6), 1617–1641. https://doi.org/10.1175/JHM-D-16-0168.1

Yang, Yan, Wang, G., Wang, L., Yu, J., & Xu, Z. (2014). Evaluation of Gridded Precipitation Data for Driving SWAT Model in Area Upstream of Three Gorges Reservoir. *PLOS ONE*, *9*(11), e112725.

Yang, Yi, Tang, J., Xiong, Z., & Dong, X. (2017). Evaluation of High-Resolution Gridded Precipitation Data in Arid and Semiarid Regions. *Journal of Hydrometeorology*, *18*(12), 3075–3101.

Yatagai, A., Kamiguchi, K., Arakawa, O., Hamada, A., Yasutomi, N., & Kitoh, A. (2012). APHRODITE: Constructing a Long-Term Daily Gridded Precipitation Dataset for Asia Based on a Dense Network of Rain Gauges. *Bulletin of the American Meteorological Society*, *93*(9), 1401–1415. https://doi.org/10.1175/BAMS-D-11-00122.1

Yong, B., Liu, D., Gourley, J. J., Tian, Y., Huffman, G. J., Ren, L., & Hong, Y. (2015). Global view of real-time TRMM multisatellite precipitation analysis: Implications for its successor global precipitation measurement mission. *Bulletin of the American Meteorological Society*, *96*(2), 283–296. https://doi.org/10.1175/BAMS-D-14-00017.1

Yu, Z., Yu, H., Chen, P., Qian, C., & Yue, C. (2009). Verification of Tropical Cyclone–Related Satellite Precipitation Estimates in Mainland China. *Journal of Applied Meteorology and Climatology*, *48*(11), 2227–2241. https://doi.org/10.1175/2009JAMC2143.1

Zandler, H., Haag, I., & Samimi, C. (2019). Evaluation needs and temporal performance differences of gridded precipitation products in peripheral mountain regions. *Scientific*

Reports, *9*(1), 15118. https://doi.org/10.1038/s41598-019-51666-z

Zeleny, M. (1973). "Compromise programming" Multiple criteria decision making. *Compromise Programming in Multiple Criteria Decision Making*, 262–301.

Zhang, X., Alexander, L., Hegerl, G. C., Jones, P., Tank, A. K., Peterson, T. C., Trewin, B., & Zwiers, F. W. (2011). Indices for monitoring changes in extremes based on daily temperature and precipitation data. *WIREs Climate Change*, *2*(6), 851–870. https://doi.org/https://doi.org/10.1002/wcc.147

Acknowledgements

Authors would like to extend their sincere thanks to the "Strengthening Groundwater Governance in Rapidly Urbanising Areas of the Lower Mekong Region (GIRA)" project funded by Stockholm Environment Institute (SEI) under the SUMERNET 4 All Programme which is funded by the Swedish International Development Cooperation Agency (Sida).

Annex I

Table 1: Statistical Indices of GPPs for different stations

		bias	rmsd	r	ss
APHRODITE	**BacLieu**	-17.86	86.31	0.84	0.69
	BaTri	-14.68	62.23	0.87	0.73
	CaMau	-23.48	49.03	0.98	0.91
	CangLong	-9.95	65.55	0.84	0.70
	CanTho	0.78	53.42	0.87	0.76
	CaoLanh	-5.72	66.22	0.81	0.66
	ChauDoc	-9.76	55.80	0.84	0.69
	MocHoa	-7.94	77.39	0.78	0.61
	MyTho	0.87	60.74	0.85	0.72
	SocTrang	-28.51	81.52	0.85	0.68
	RachGia	-55.55	103.81	0.85	0.55
CMORPH	**BacLieu**	-39.72	94.15	0.84	0.63
	BaTri	-28.67	70.60	0.84	0.65
	CaMau	-53.12	91.79	0.90	0.69
	CangLong	-23.00	68.78	0.84	0.67
	CanTho	-29.16	70.82	0.81	0.58
	CaoLanh	-37.13	80.11	0.78	0.50
	ChauDoc	-24.51	74.59	0.71	0.45
	MocHoa	-20.96	95.63	0.68	0.41
	MyTho	-18.71	65.44	0.84	0.67
	SocTrang	-35.04	85.21	0.84	0.65
	RachGia	-22.40	74.92	0.89	0.77
CHIRPS	**BacLieu**	-12.73	81.62	0.86	0.72
	BaTri	-12.51	61.77	0.86	0.73
	CaMau	-10.05	71.01	0.91	0.82
	CangLong	2.70	65.25	0.84	0.70
	CanTho	5.07	59.63	0.85	0.71
	CaoLanh	-0.66	62.18	0.84	0.70
	ChauDoc	5.33	63.62	0.78	0.60
	MocHoa	5.25	86.51	0.73	0.52
	MyTho	8.31	65.43	0.83	0.67
	SocTrang	-3.10	73.69	0.86	0.73
	RachGia	-8.86	78.44	0.86	0.74
CPC	**BacLieu**	-11.47	86.92	0.83	0.69
	BaTri	3.97	70.02	0.81	0.65
	CaMau	-27.78	46.20	0.98	0.92

	CangLong	4.80	77.19	0.79	0.59
	CanTho	-42.01	82.96	0.76	0.43
	CaoLanh	-41.68	87.74	0.73	0.40
	ChauDoc	-28.99	85.14	0.62	0.28
	MocHoa	-15.69	89.46	0.72	0.48
	MyTho	-2.19	72.70	0.78	0.60
	SocTrang	-39.60	95.61	0.79	0.55
	RachGia	-82.98	132.68	0.76	0.27
CRU	**BacLieu**	13.76	110.99	0.71	0.49
	BaTri	40.14	82.76	0.81	0.51
	CaMau	-7.12	119.69	0.69	0.47
	CangLong	39.42	87.28	0.77	0.47
	CanTho	38.22	83.09	0.77	0.43
	CaoLanh	38.55	92.76	0.71	0.33
	ChauDoc	44.39	110.51	0.58	-0.21
	MocHoa	23.35	99.96	0.67	0.35
	MyTho	46.07	91.29	0.76	0.36
	SocTrang	17.14	101.24	0.72	0.50
	RachGia	4.55	130.03	0.62	0.30
GPCC	**BacLieu**	-19.00	82.40	0.86	0.72
	BaTri	-11.40	72.13	0.80	0.63
	CaMau	-2.54	24.35	0.99	0.98
	CangLong	-4.60	70.95	0.82	0.65
	CanTho	4.14	63.78	0.85	0.66
	CaoLanh	-7.04	71.93	0.79	0.60
	ChauDoc	5.61	58.91	0.83	0.66
	MocHoa	-8.72	79.28	0.78	0.59
	MyTho	-4.59	79.56	0.74	0.52
	SocTrang	-13.01	66.03	0.89	0.79
	RachGia	-22.32	76.95	0.88	0.75
SAOBS	**BacLieu**	-153.69	220.32	0.16	-1.01
	BaTri	-107.77	162.15	0.25	-0.87
	CaMau	-186.02	244.60	0.27	-1.19
	CangLong	-113.80	167.77	0.24	-0.96
	CanTho	-109.69	151.74	0.38	-0.91
	CaoLanh	-104.85	155.64	0.30	-0.88
	ChauDoc	12.42	151.80	0.42	-1.28
	MocHoa	-112.44	172.31	0.21	-0.92
	MyTho	-99.52	154.47	0.25	-0.82
	SocTrang	-143.26	201.32	0.25	-0.98
	RachGia	-184.29	240.58		-1.41
TRMM	**BacLieu**	-1.96	76.83	0.87	0.76
	BaTri	-2.48	59.40	0.87	0.75
	CaMau	-17.02	55.97	0.95	0.89
	CangLong	2.17	59.22	0.88	0.76
	CanTho	8.53	56.32	0.88	0.74
	CaoLanh	1.18	59.93	0.85	0.72

	ChauDoc	8.04	60.54	0.82	0.64
	MocHoa	4.80	82.57	0.77	0.56
	MyTho	8.62	66.07	0.84	0.67
	SocTrang	-2.59	62.09	0.90	0.81
	RachGia	-16.05	70.40	0.90	0.79