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Selection of Observed Gridded Rainfall Data for different Analysis Purposes in Cambodia

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Abstract: *For Hydrological and Meteorological research over Cambodia with sparsed rainfall gauges, reliable rainfall is essential. In this study,12 gridded rainfall datasets with a reasonable spatial resolution including Asian Precipitation Highly Resolved Observational Data Integration Towards Evaluation (APHRODITE), Gridded rainfall Observational Dataset for precipitation and temperature Southeast Asia (SA-OBS), Integrated Multi-gridded rainfall Retrieval for the global precipitation mission (GPM-IMERG), Tropical Rainfall Measuring Mission Project (TRMM), Climate Hazards Group Infrared Precipitation with Station data (CHIRPS-V2), Bias-Corrected Climate Prediction Center (CPC) Morphing Technique (CMORPH), JAXA Global Gridded rainfall Mapping Precipitation (GSMaP), Precipitation Estimation Remotely Sensed Information Artificial Neural Network (PERSIANN), PERSIANN Dynamic Infrared Rain Rate Near Real-Time (PERSIANN-PDIRNOW), PERSIANN Cloud Classification System (PERSIANN-CCS), PERSIANN Climate Data Record (PERSIANN-CDR), and Multi-Source Weighted-Ensemble Precipitation (MSWEP), were properly evaluated during 2000-2014 by using statistical metric and categorical metrics and comparing with 58 local rainfall station data. At the same time, this study also set out to find which product could detect historical extreme rainfall events. The result shows that APHRODITE and GPM-IMERG are the better rainfall product reflecting the local rainfall in Cambodia. For the overall performance, APHRODITE is seen to be underestimated but has the highest correlation with station data. Meanwhile, GPM-IMERG shows a lower correlation than APHRODITE, but lower biases in variation magnitude. Well-known extreme indices, namely Consecutive Dry Day (CDD) and Consecutive Wet Day (CWD) of the Expert Team on Climate Change Detection and Indices (ETCCDI) were investigated as a showcase of extreme event detection. GPM-IMERG with an average bias of 29.87, and APHRODITE with an average bias of 31.85, in comparison to rainfall station data which indicates that GPM-IMERG is good at detecting extreme rainfall events compared to APHRODITE. Observabally, the following conclusions can be drawn from the analysis 1) APHRODITE product can be utilized for gauged rainfall estimations in some sort of relative analysis application, like rainfall index transformation. 2) GPM-IMERG is recommended for the study of extreme rainfall since it is capable of detecting light and heavy rainfall event magnitude.*

Keywords: Cambodia; Gridded data; Statistical metrics; Categorical metric; ENSO

1. INTRODUCTION

An extreme event is generally defined as the abnormal phenomena of weather or climate when its value is above or below a threshold. As climate differs from location to location, thus the definition of extreme events also depends on location. In addition, precipitation is one of the most common variables used in climatic extreme research [1]. On top of that, El Niño and La Niña phenomena are well-known as one of the root causes of extreme events. The study of Gershunov and Bernett [2] mentioned that El Niño and La Niña influenced extreme rainfall in United State spatially. Also, the widespread flooding over the east coast of Peninsular Malaysia in December-January-February is increasing during Moderate La Niña events [3].

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More than that, the study of ESCAP et al. [4] found that the 2015-2016 El Niño event was one of the strongest and most significant on record where a large part of Asia and the Pacific experienced many extreme weather events. As well as, 1998-2000 there was the presence of a strong La Niña [5].

At the same time, analysis of such an extreme event above mentioned would be particularly problematic because lacking high-quality daily data observation which means there is a small amount of station data with a short length of available data and transcriptional errors that occur mostly when data is recorded or written incorrectly. Thus, gridded rainfall data were used in the study to fulfill and enhance the quality of the station data for accurate analysis and investigate the trends, or record any changes for as long as possible in a period. In addition, gridded rainfall data have their deficiency since they are not a direct estimate of rainfall station data, meaning that improvement and advancement of gridded rainfall products are needed. Keeping the product updated is the only way to fulfill the shortcoming. For instance, the APHRODITE project tries to keep their product updated to ensure they can complete their inadequacy [6].

In recent times there are so many gridded rainfall products that can access freely on the internet. However, not every product is fit for every location or region, so evaluating before choosing the product is crucial. Therefore, this study aims to investigate both the performance of each gridded rainfall product that would be suitable to be used in Cambodia and the ability to detect extreme rainfall events that have happened in the past.

2. METHODOLOGY

2.1 Dataset

In this study, rain gauge data were obtained from the Mekong River Commission (MRC), and station Observation of the Department of Meteorology of the Ministry of Water Resource and Meteorology (MOWRAM) of Cambodia. There are 108 stations in total (Fig. 1), owning the fact that some stations are too close to each other and some are only recorded in short periods and even contain a lot of missing data. Since the study requires good-quality rain gauge data well distribute over Cambodia, quality checks on rain gauge stations are essential. Simultaneously, the period of the evaluation is from 2000-2014.

According to geographical characteristics and topography, Cambodia's territories are classified into three main natural regional classifications: plains, coastal, and mountainous. Hence, this evaluation is divided into three regions, including coastal, plateau and mountainous, and plain regions, respectively. Moreover, the combination of all stations from each region is required to see which product is generally fit to use in the whole country besides the specific regions. So the remains station for this study is 58 stations.

Table 1 List of the 12 Gridded Datasets, S indicated Satellite-Based, G indicated Gauge-Based, R indicated Reanalysis

Dataset	Res.	Data Source	Source
Asian Precipitation-Highly-Resolved Observational Data Integration Toward Evaluation of Extreme Event (APHRODITE)	0.25	G	[7]
Gridded rainfall observational dataset for precipitation and temperature Southeast Asia (SA-OBS)	0.25	G	[8]
Integrated Multi-gridded rainfall Retrievals for the Global Precipitation Mission (GPM-IMERG)	0.1.	S	[9]
Tropical Rainfall Measuring Mission Project (TRMM)	0.25	S	[10]
Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS)	0.05	S,G	[8]
Bias-Corrected Climate Prediction Center (CPC) Morphing technique (CMORPH)	0.25	S	[11]
JAXA Global Gridded rainfall Mapping of Precipitation (GSMap)	0.1	S	[12]
Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks (PERSIANN)	0.25	S	[13]
PERSIANN - Dynamic Infrared Rain Rate near real-time (PDIR-Now)	0.04	S	[14]
PERSIANN-Cloud Classification System (PERSIANN-CCS)	0.04	S	[15]
PERSIAN-Climate Data Record (PERSIAN-CDR)	0.25	S	[16]
Multi-Source Weighted-Ensemble Precipitation (MSWEP)	0.1	S, G, R	[17]

2.2 Evaluation method using gauge observation data

Statistical and categorical metrics were employed for this evaluation to measure the performance of 12 gridded rainfall products. The gridded rainfall was evaluated in daily and monthly time series based on the user's needs or different fields.

The statistical metrics include Root Mean Square Error (RMSE), Correlation coefficient (R), and Standard Deviation (SD).

Categorical data (ordinal or nominal) are data that can only ever fall into certain categories categorical metric was determined using a 2 by 2 contingency (Table 1).

The possible form of the categorical metric [18] is the Possibility of Detection (POD), and False Alarm Ratio (FAR) [19]. The FAR specifies how often the gridded rainfall data detected rainfall when rain does not actually fall to the ground.

Table 2 Contingency table to determine the possible conditions for detecting rainfall from gridded rainfall product and ground measurement

Possible Combinations of Rain Detection	Gridded rainfall Product	Gauge data
Hit (H)	Yes	Yes
False (F)	Yes	No
Miss (M)	No	Yes
Null (X)	No	No

Where H is hit (i.e., number of pixels that both of gridded rainfall and gauge data simultaneously detected the rainfall at the same location), F stands for false alarm (i.e., number of pixels that are recorded by gridded rainfall product as rainfall but not by the in-situ gauge), M is missed (i.e., number of pixels that are reported as rainfall by the ground gauge but not by the gridded rainfall sensor), and X refer to null or correct negatives (i.e., the number of pixels that are not recognized as rainfall for both gridded rainfall and ground-gauge).

Graphical representation of data might reduce the cognitive load of measurement analysis compared to the only numerical representation of data. Thus scatter plot, Taylor Diagram [20], and violin plot were chosen to be the graphical representation for the study.

2.3 Extreme Rainfall Indice

All selected gridded rainfall datasets are re-evaluated for the extreme rainfall event to ensure the ability to detect. Based on a subset of the Expert Team on Climate Change Detection and Indices (ETCCDI), extreme rainfall characteristics are included with intensity, frequency, and duration. At the same time, Consecutive Wet Days (CWD) and Consecutive Dry Days (CDD) were much more strong indices in terms of inconsistencies within the duration of extremes.

CWD and CDD represent the number of consecutive wet days and consecutive dry days, respectively. For both indices, the precipitation threshold is 1 mm and the number of dry or wet periods exceeds 5 days. [21, 22] These two extreme precipitation indices were calculated using Climate Data Operators (CDO) software. (https://code.mpimet.mpg.de/projects/cdo/).

At the same time, CDD and CWD calculations were also performed both on the station data and gridded dataset. After obtaining the result of CWD and CDD from station data and gridded data, RSME is the statistical metric were used to evaluate the average difference of CDD and CWD between rainfall station data and gridded data, The RMSE values are then used for comparison, to find gridded data suitable for analysis of extreme rainfall in Cambodia.

3. RESULTS AND DISCUSSION

3.1 Evaluation of gridded rainfall data

The purpose of the study is to investigate the gridded product's performance, which adds up to the ability to detect extreme rainfall events over Cambodia, thus the combination of each station data from 3 divided regions is significant. After the quality check, there are 3, 9, and 46 gauge station data for coastal, plateau, mountainous, and plain areas, respectively, meaning that there are 58 stations after the combination.

12 gridded data were extracted into calculatable data, this implies that from gridded data to excel data, after all, station data and gridded data obtained are in the form of excel so statistical metrics and categorical metrics can be calculated.

Taylor diagram shows the evaluation of gridded rainfall data through correlation, standard deviation, and RMSE between rainfall station data (Fig. 2). The diagram shows the ability of gridded rainfall datasets in estimating the rain gauge station data. The dissimilarity between gridded rainfall data and observation data is shown in Fig. 2. In terms of higher-ranking efficiency in correlation and RMSE, ensemble-based and gauge-based gridded rainfall dataset (MSWEP and APHRODITE) is remarkably high.

Among all gridded rainfall datasets, APHRODITE has the highest correlation (> 0.7) and is closer to the lower RMSE. Also, the gauge-based dataset (MSWEP) is ranked after APHRODITE with a correlation of 0.4 and closer to lower RMSE. On top of that, the satellite-based rainfall dataset (GPM-IMERG) shows a correlation of 0.4 as well with a reasonable RMSE value (1<RMSE<1.5).

Since standard deviation provides variation magnitude of a time series (a fluctuation around the mean value), gauge-based and ensemble-based rainfall dataset (APHRODITE and MSWEP) is more likely to underestimate the observed magnitude compared to GPM-IMERG (Fig. 2).

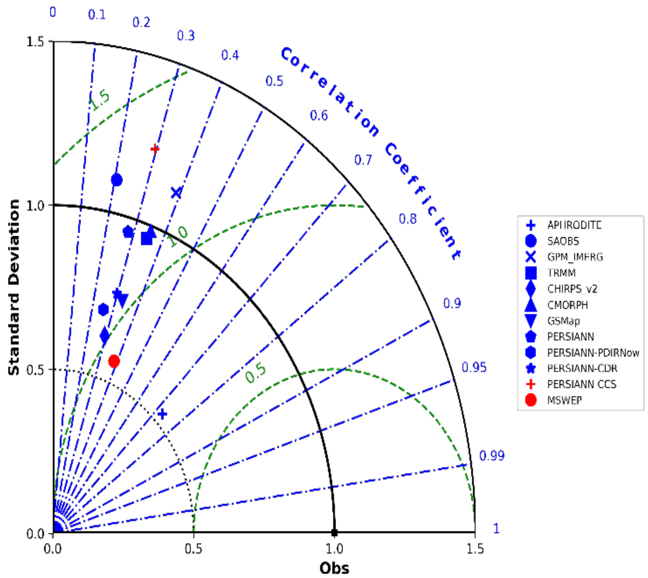

Fig. 2. Taylor diagram of the median for all stations. The green contours indicate the RSME value which shows the difference between the gridded datasets and station data corresponding to the distance of the x-axis.

Violin plot is a method of plotting numeric data showing the data distribution that can convey the information provided by box plot (median, mean, interquartile range) and probability density of the data into one plot.

In terms of categorical metrics for this evaluation, a rainfall event occurred if the amount of rainfall is more than or equal to 1 mm. See [19, 23] for the detailed description and application of this metric in model evaluation. Additionally, Hit Rate is a categorical metric, that conveys information about the ability of the dataset or model in detecting rainfall events defined by a specific threshold (1 mm in this current study).

Fig. 3 shows the violin plot of hit rate for all the stations used in this evaluation.

The plot indicates that the gauge-based and ensemble-based gridded dataset (APHRODITE, MSWEP) perform better in this metric, while PERSIANN-PDIRNow and PERSIANN-CDR are ranked after, followed by GPM-IMERG.

In summary, a gauge-based dataset, an ensemble-based dataset, and a satellite-based dataset are considered to be suitable for Cambodia, namely APHRODITE, MSWEP, and GPM-IMERG.

In terms of correlation coefficient and hit rate, APHRODITE is ranked first among the other datasets, followed by MSWEP. However, these two gridded datasets underestimate the observed variation magnitude (lower standard deviation), which could be problematic in detecting the magnitude of the extreme rainfall event. Meanwhile, GPM-IMERG shows a better estimation of the observed variation magnitude, even though its correlation is lower than the above two datasets.

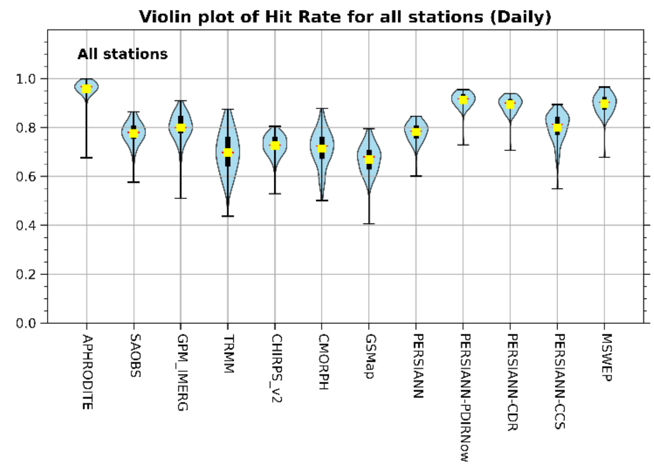

Fig. 3. Violin plot of the Hit Rate for all stations

3.2 Application for extreme rainfall analysis

Ensuring the ability to detect extreme rainfall events of the gridded dataset is crucial. So, to compare the detecting skill of the gridded data, RMSE is used to evaluate the bias of the gridded dataset compared to rainfall station data where the smaller the RMSE score is the better for detecting extreme events with regards to CDD and CWD.

The overall average difference of CDD and CWD of gridded rainfall data was calculated under the condition of perceiving the suitable gridded dataset for extreme rainfall analysis over Cambodia.

For the biases of CDD, among 58 stations, there are 46 stations where APHRODITE is better than GPM-IMERG in RMSE (Fig. 4), and the average RMSE of GPM-IMERG and APHRODITE are 45.549 and 41.209 respectively, Hence, APHRODITE works well for CDD index, while GPM-IMERG seems to have a hard time detecting.

In Fig. 5, there are 51 stations where GPM-IMERG is better than APHRODITE in detecting CWD. The average RMSE score of APHRODITE and GPM-IMERG are 22.497 and 14.193, respectively. In other words, GPM-IMERG detects CWD well with lower RMSE scores compared to APHRODITE.

Between APHRODITE and GPM-IMERG, to get only the best-gridded product for extreme rainfall analysis, so the average RMSE among CDD and CWD results was calculated in each dataset. The average calculation indicates that GPM-IMERG contains an overall bias of 29.87, while APHRODITE contains overall bias of 31.85. Thus, GPM-IMERG can capture the CDD and CWD with lower overall bias than APHRODITE..

After the above investigation, we further check the performance of both datasets in capturing CDD and CWD during specific drought and flood years. The results of this analysis are shown in Figs. 6-9 and Figs. 10 and 11.

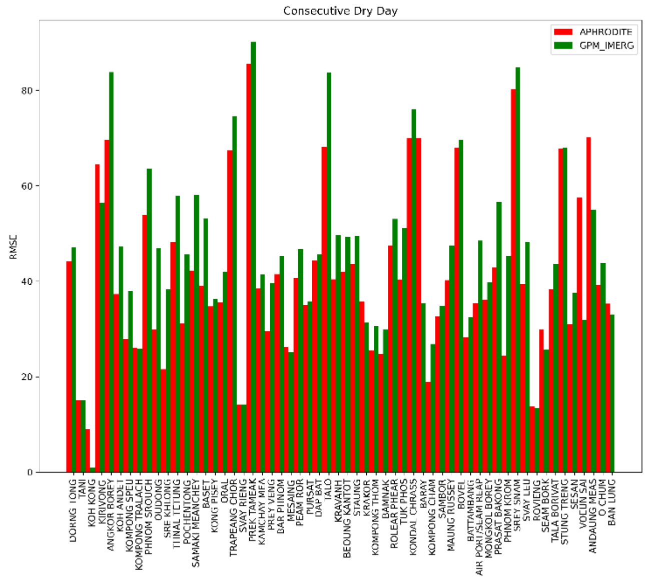

Fig. 4. RMSE of consecutive dry days for each rainfall station.

The study by Guo et al. [24] mentioned that Lower Mekong River Basin (LMB) experienced four severe droughts during the last three decades with the driest one in 2015-2016 with drought-affected areas up to 75.6%, meanwhile, Cambodia is one among LMB countries. More than that, the El Niño that began in 2015 hit hard, causing a two-year drought (2015-2016) that danger health, food security, and finance of millions of people [25, 26]. So the CDD is calculated in the year 2015 for both gridded rainfall products (APHRODITE and GPM-IMERG) to investigate which one is capable to capture this extreme event.

Fig. 6 and Fig. 7, are the map of CDD in 2015 for APHRODITE and GPM-IMERG, respectively. The result shows that the minimum dry day and maximum dry days of APHRODITE are 15 and 68 days, respectively. While the minimum and maximum dry days of GPM-IMERG are 4 and 128 days, respectively. If compared station data (Fig. 10), only GPM-IMERG can capture the CDD of value more than 80 days (yellow color scale) as in station data. Thus, GPM-IMERG was better at detecting light rain than APHRODITE in case of dry spell in 2015. This is because GPM-IMERG uses a wider range of microwave frequencies, which makes it more sensitive to light rain. Additionally, GPM-IMERG has a higher spatial resolution than APHRODITE, which allows it to better resolve small-scale rainfall events.

In late September 2011 considered one of the highest floods in a decade and over 1.64 million people were affected by the flood. In the first week of October, the Royal Government of Cambodia declared that the heavy flood affected 18 out of 24 provinces.In addition, [27] mentioned that the 2010-2011 La Niña was one of the most intense, and the flood affected millions of people.

As a direct consequence, CWD is calculated in the year 2011, to see which gridded product is capable to capture this extreme event. Figure 8 and Figure 9 show the result of CWD in 2011 for APHRODITE and GPM-IMERG, respectively. APHRODITE (Fig. 8) shows higher CWD values (more than 60 days) from central to the northeastern parts of the country, while GPM-IMERG shows lower values (less than 40 days). If we check with station data (Fig. 11), GPM-IMERG shows closer values of CWD to station data then APHRODITE. This indicates the better performance of GPM-IMERG in capturing the CWD in 2011.

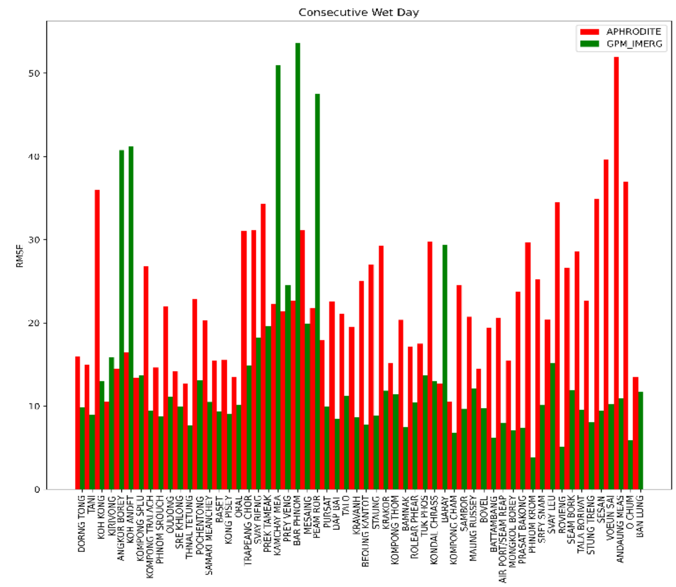

Fig. 5. RMSE of consecutive wet days for each rainfall station.

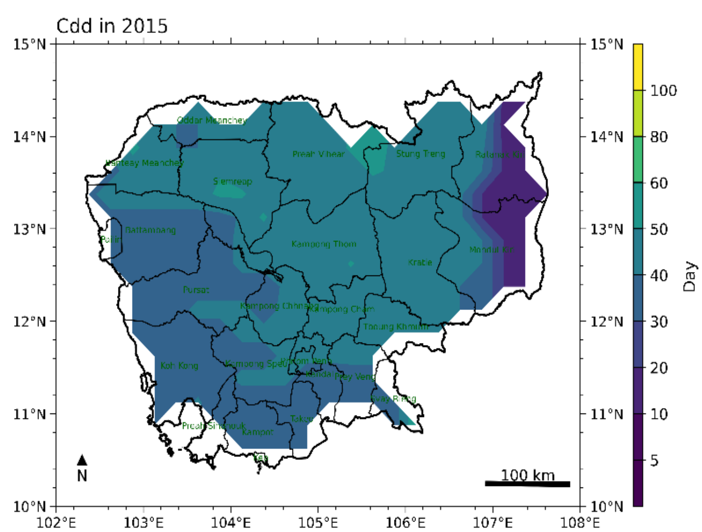

Fig. 6. Consecutive dry days for APHRODITE product.

The study by Sunilkumar et al. [28] stated that between GPM-IMERG and APHRODITE, there is a close interaction at rainfall intensity but GPM-IMERG seems to be improved in detecting light/heavy rainfall event magnitude.

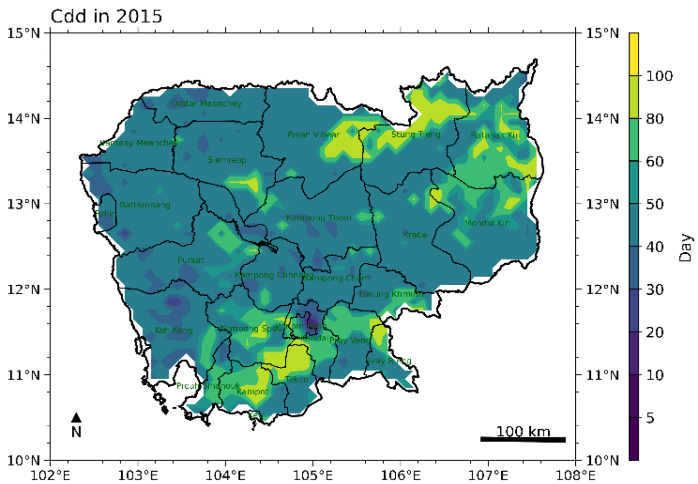

Fig. 7. Consecutive dry days for GPM-IMERG product.

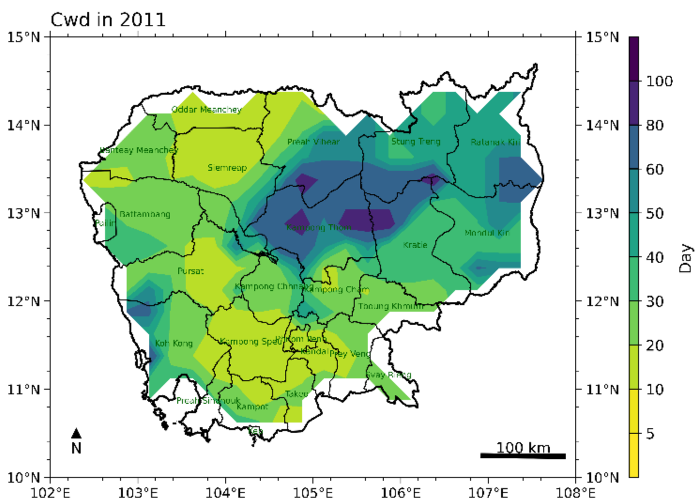

Fig. 8. Consecutive wet days for APHRODITE product.

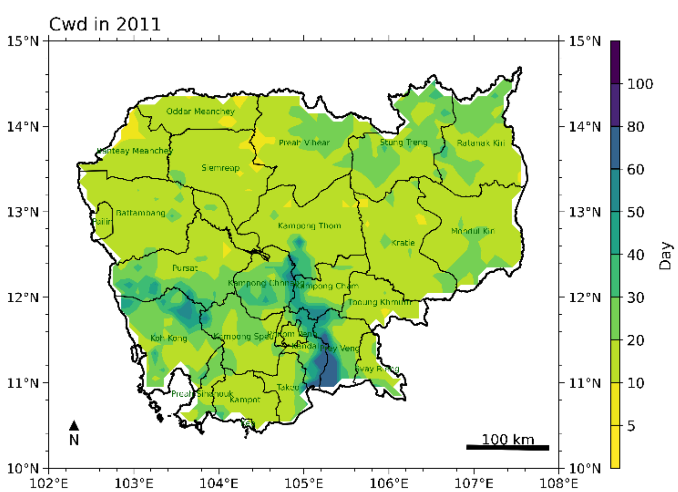

Fig. 9. Consecutive wet days for GPM-IMERG product.

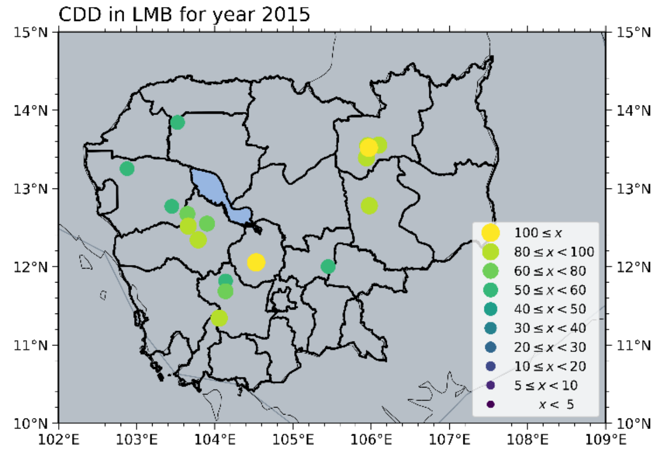

Fig. 10. Number of consecutive dry days, X indicated the number of dry days.

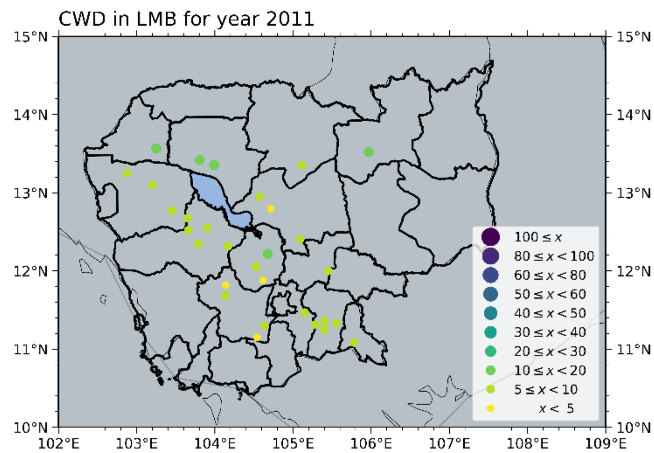

Fig. 11. Number of consecutive wet days, X indicated the number of wet days.

4. CONCLUSIONS

Under the influence of climate change, it is believed that both the frequency and intensity of extreme rainfall would rise globally. Cambodia has been experiencing extreme rainfall which has led to floods and drought, like many other countries of the world. Likewise, extreme rainfall assessment is imperative to maintain the prevention and mitigation of any kind of disaster that happens in the future. This task requires suitable observed rainfall dataset so that the extreme rainfall event can be captured on the local scale.

In this study, 12 gridded rainfall datasets were properly evaluated. As a result, APHRODITE and GPM-IMERG are the best rainfall products for Cambodia, with APHRODITE having the highest correlation with station data despite being underestimated, and GPM-IMERG having lower biases in variation magnitude despite a lower correlation than APHRODITE.

Well-known extremes, namely Consecutive Dry Days (CDDs) and Consecutive Wet Days (CWDs) from ETCCDI have been studied as a demonstration. The detection of extreme events. Computationally, GPM-IMERG has an average bias of 29.87 and APHRODITE has an average bias of 31.85, compared with rain gauge data, indicating that GPM-IMERG is effective in detecting extreme rainfall events compared to APHRODITE.

In general, APHRODITE is used for rainfall analysis, like index transformation. GPM-IMERG is ideal for studying extreme rainfall as it detects light and heavy rainfall well.

The short length of the time series of this study from 2001-2015 is considered a short period for extreme analysis and it is recommended to have at least 30 years of time series for this extreme rainfall study. Besides that, for a trustworthy and accurate evaluation, the division between gauge-based products and satellite-based products should be considered for future study.

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