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Evaluation of PERSIANN-CCS Satellite Derived Rainfall Product with Raingauge Data over Kelani River Basin, Sri Lanka

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Abstract: Satellite rainfall estimates (SREs) are high in spatial and temporal resolution and particularly important for regions with sparse raingauges. However, SREs are required to evaluate with gauged rainfall data before applying for hydrological studies. In this research, the accuracy of Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks Cloud Classification System (PERSIANN-CCS) product was evaluated at daily, monthly, yearly, and seasonal scale upon the raingauge data of the Kelani River basin of Sri Lanka for the period 2004 to 2010. The performance of the SREs was evaluated using both continuous and categorical verification statistics. PERSIANN-CCS rainfall estimates follow the bi-modal rainfall pattern and showed greater underestimation in South West Monsoon (SWM) season (May-Sep.) and overestimation in Inter-Monsoon 1 (IM1) period (March-April). PERSIANN-CCS is more capable of recognizing conventional and depressional rains than monsoonal rains. On the other hand, it produces low false alarms in the high rainy season than in the low rainy season. The daily categorical statistics show above average scores (Accuracy>0.69; POD>0.65; FAR<0.34; 0.76>FBias<1.11), however, estimations were with low CC (<0.53) and high bias (<24 & >-64%). Bias corrected PERSIANN-CCS may be a high-resolution rainfall source for flood forecasting applications in the Kelani River basin.

Keywords: Satellite rainfall product, PERSIANN-CCS, Kelani River basin, Raingauge data, Continuous verification, Categorical verification

1. Introduction

Precipitation is an important component in the climate system and the water cycle. It is the primary driver of hydrological processes and thereby a major input to the hydrological models. Representation of spatial and temporal variability of precipitation is a key issue in hydrological modelling due to the scarcity of precipitation data. Thereby, model complexity has to be balanced with the available precipitation data to represent its temporal and spatial variability leading to less accurate models [1]. Recently, several authors investigated the effect of spatial and temporal variability of precipitation on hydrological model performance [2]-[5]. Especially, in urban catchments, the hydrological response is highly sensitive to small-scale rainfall variability [4]. High-resolution satellite derived rainfall products attract the interest of researchers in the absence of precipitation data at appropriate temporal and/or spatial resolution.

Satellite Rainfall Estimates (SREs) are potentially useful for climate change studies and real time applications [6]. Many SREs are currently available, Tropical Rainfall Measuring Mission (TRMM), the Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks (PERSIANN), Climate Prediction Center (CPC) morphing technique (CMORPH), to name a few. Despite the availability of many satellite data products, it is required to evaluate their estimations with observed rainfall data before applying them to any research study. Most of the comparison studies applied continuous verification statistics. However, accuracy of amount of rainfall as well as detection of rainfall occurrence are more important especially for real time applications. Comparison of SRE products has also evidenced that their accuracy depends on hydroclimatic region [7]-[9].

To the best of authors' knowledge, the accuracy of SRE products has not been evaluated for Sri Lanka to date. In this research, SRE product

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evaluation was carried out at basin scale and the Kelani River basin was selected as the case study. It is frequently flooded due to its topographical and geographical setting. The most recent major flood in May 2016 led to 150 deaths and 59,000 damaged houses affecting 500,000 people [10]. Flood risk assessment in the Kelani River is therefore important as it flows through highly populated districts, Colombo and Gampaha, triggering high socio-economic loss. Flood forecasting research studies carried out by Sugeeswara & Jayawardena [11] and Basnayake [12] highlight the need for more refined data for greater accuracy in flood forecasts and long lead time. Out of the available SRE products, PERSIANN-CCS data resolution (1h, 0.01°x 0.01°) is matched with the spatial extent and the catchment concentration time of the Kelani River basin. Therefore, this research study aims to evaluate the performance of the widely used PERSIANN- CCS SRE product over the Kelani River basin of Sri Lanka. The ability of SRE product to capture occurrence and non-occurrence of rainfall was also evaluated on a daily basis.

This paper is organized as follows. The section on 'Methodology' describes the study area rainfall data sources, followed by a description of continuous and categorical verification statistics. The next section discusses the ability of PERSIANN-CCS in estimating the rainfall amount and in detecting the occurrence of rainfall. Finally, a summary is provided with the main conclusions of the research.

2. Methodology

2.1 Study Area

Kelani River originates from the central hills of Sri Lanka at about 2,300 m above mean sea level and travels 150 km to the west. Its catchment is mainly located in the west of the country in between Northern latitudes of 6° 45' to 7° 15' and Eastern longitudes of 79° 52' to 80° 50' (Figure 1). It is the second largest river basin, draining an area of 2292 km^2 [13]. The upper catchment is mountainous which occupies approximately two-thirds of the entire catchment and the lower basin below Hanwella has plain features. It is located in the wet zone of Sri Lanka receiving a high amount of rainfall. The annual rainfall in the basin varies within 2,700 mm ~ 5,000 mm with an average of 3,450 mm.

In this study, we considered PERSIANN-CCS data and raingauge data over the Kelani River basin in the common period of 2004 ~ 2010.

2.2 Rainfall Data

Observed daily rainfall of 13 raingauges from 2004 to 2010 was obtained from the Meteorological Department of Sri Lanka and was used to compare the quality of SRE data. The gauges are located unevenly in the basin as shown in Figure 1. Collected data was assessed for quality, using commonly applied techniques for testing outliers, missing rainfall imputation and homogeneity checks.

The PERSIANN method uses an artificial neural network approach to derive relationships between cloud-top temperature, measured by long-wave infrared sensors on

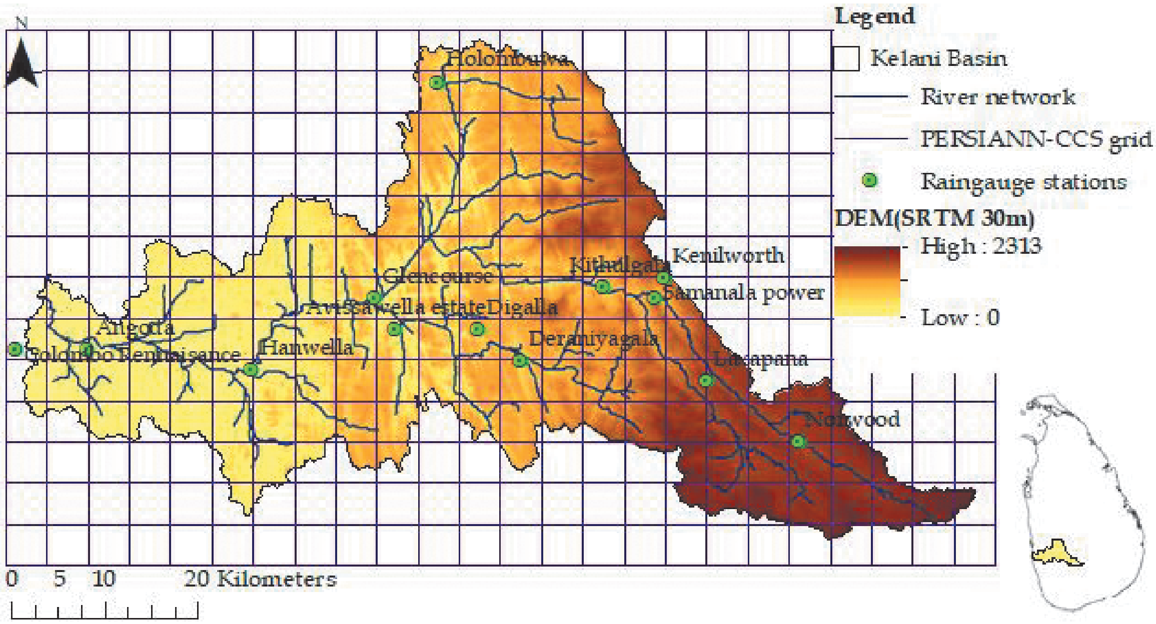

Figure 1 – Study Area and Distribution of Raingauges

geostationary satellites, and rainfall rates, with bias correction from passive microwave readings measured by low Earth-orbiting satellites [14]. PERSIANN-CCS provides high-resolution rainfall data (1h, 0.01°x 0.01°). It is an improvement to the PERSIANN method. It extracts informative features from cloud patches and classifies them into a number of patch groups based on the similarity of selected features, such as the patch size and texture instead of direct pixel-to-pixel fitting of infrared cloud images to the rain rate. Rainfall mapping for each classified cloud cluster has been achieved by using histogram matching and exponential function fitting [15]. PERSIANN-CCS data were downloaded from the Center for Hydrometeorology and Remote Sensing (CHRS) data portal in NetCDF format (http://chrs.web.uci.edu). This study evaluates the widely applied PERSIANN-CCS SRE product.

2.3 Evaluation Method

PERSIANN-CCS SRE product was compared with the raingauge data at annual, monthly, daily, and seasonal scale over the basin and on pixel to point. In addition, SRE's ability in detecting the amount and occurrences of rainfall in main climatic seasons, North East Monsoon (NEM) (Dec. to Feb.), First Inter Monsoon (IM1) (March-April), South West Monsoon (SWM) (May-Sep.), and Second Inter Monsoon (IM2) (Oct.-Nov.), were considered.

Continuous verification statistics, Relative Percentage bias (Pbias), Normalized Root Mean Square Error (NRMSE), and Correlation Coefficient (CC) were used to measure the accuracy of SREs (Equations 1 to 3). The bias (mean error) provides the average difference between the SREs and the raingauge data while CC measures the degree of linear correspondence between the SRE and gauge rainfall distributions. NRMSE provides the relative actual difference between the SRE and raingauge data.

$$Pbias = \frac{\sum_{i=1}^{n}\left(R_{s_i} - R_{g_i}\right)}{\sum_{i=1}^{n} R_{g_i}} \times 100\% \quad \ldots(1)$$

$$NRMSE = \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(R_{s_i} - R_{g_i}\right)^2}}{\max\left(R_g\right) - \min\left(R_g\right)} \quad \ldots(2)$$

$$CC = \frac{\sum_{i=1}^{n}\left(R_{s_i} - \overline{R_s}\right)\left(R_{g_i} - \overline{R_g}\right)}{\sqrt{\sum_{i=1}^{n}\left(R_{s_i} - \overline{R_s}\right)^2}\sqrt{\sum_{i=1}^{n}\left(R_{g_i} - \overline{R_g}\right)^2}} \quad \ldots(3)$$

Where R_s indicates the SRE value and R_g indicates raingauge values, $\overline{R_s}$ and $\overline{R_g}$ are mean gauge and SREs, respectively, and n is the number of samples. A correlation coefficient greater than 0.7 is usually considered to be as acceptable. The performance based on Pbias was characterized into three basic types: underestimation (Pbias < -10%), overestimation (Pbias >10%), and approximately equal (Pbias range from -10% to 10%, which is the acceptable range) [9].

Categorical verification statistics are based on the dichotomous forecasts, which say "yes" if an event occurs and "no" if an event does not happen. Figure 2 shows the contingency table of yes/no events indicating the four combinations of SREs and observed rainfalls [6].

		Observed	
		Yes	**No**
Estimated	**Yes**	Hits	False alarms
	No	Misses	Correct negatives

Figure 2 - Contingency Table [6]

Categorical verification statistics, accuracy, Frequency Bias (FBias), Probability of Detection (POD), and False Alarm Ratio (FAR) were applied to measure the correspondence between the SREs and raingauge data. Perfect matching of SREs with gauge rainfall data produces hits and correct negatives and not misses or false alarms. Accuracy measure provides what fraction of the SREs are correct. FBias is the ratio of the frequency of SRE events to the frequency of observed events. FBias greater than 1 infers overestimation of events while less than 1 implies underestimation of events. The POD or the hit rate provides the fraction of gauge rainfall occurrences that were correctly identified. The FAR gives the fraction of detected events that were non-events. The accuracy, FBias, POD, and FAR can be presented based on the contingency table as follows.

$$Accuracy = \frac{hits + correct\ negatives}{Total} \quad \ldots(4)$$

$$FBias = \frac{hits + false\ alarms}{hits + misses} \quad \ldots(5)$$

$$POD = \frac{hits}{hits + misses} \quad \ldots(6)$$

$$FAR = \frac{false\ alarms}{hits + false\ alarms} \qquad \ldots (7)$$

Perfect values for the accuracy, FBias, and POD measures are 1 while it is 0 for FAR measure.

3. Results and Discussion

3.1 Comparison at Catchment Scale

Figure 3(a) shows the annual average total rainfall variation over the Kelani River basin and it varies from 2649 mm to 6025 mm with an average of 3426 mm. However, that of PERSIANN-CCS varies from 1983 mm to 3047 mm. Figures 3(a) and 3(b) illustrate that PERSIANN-CCS properly estimates the annual total rainfall in the downstream region and underestimates in the upstream mountainous areas. Further, according to gauge data, high rainfall is centred on Kenilworth and it gradually decreases towards the sea and Norwood. On the contrary, PERSIANN-CCS records high rainfall closer to the outlet and it decreases towards the central hills.

Figure 4 illustrates the catchment averaged monthly total rainfall variation of gauge and SREs. The basin receives heavy rainfall at the beginning of the SWM and during the IM2 period. Additionally, a considerable amount of rainfall is received during the IM1. NEM gives comparatively less rainfall to the basin. January is the driest month and receives less than 200 mm rainfall for most parts of the basin. PERSIANN-CCS also captures the bimodal rainfall distribution pattern. Catchment receives the first peak rainfall in May while it is in April for PERSIANN-CCS. The second peak rainfall is received in October whereas it appears to be in November for PERSIANN-CCS. The mean monthly total rainfall of PERSIANN-CCS exceeds the gauge data only in the months of January and April, while it tends to underestimate the reference data in the other months.

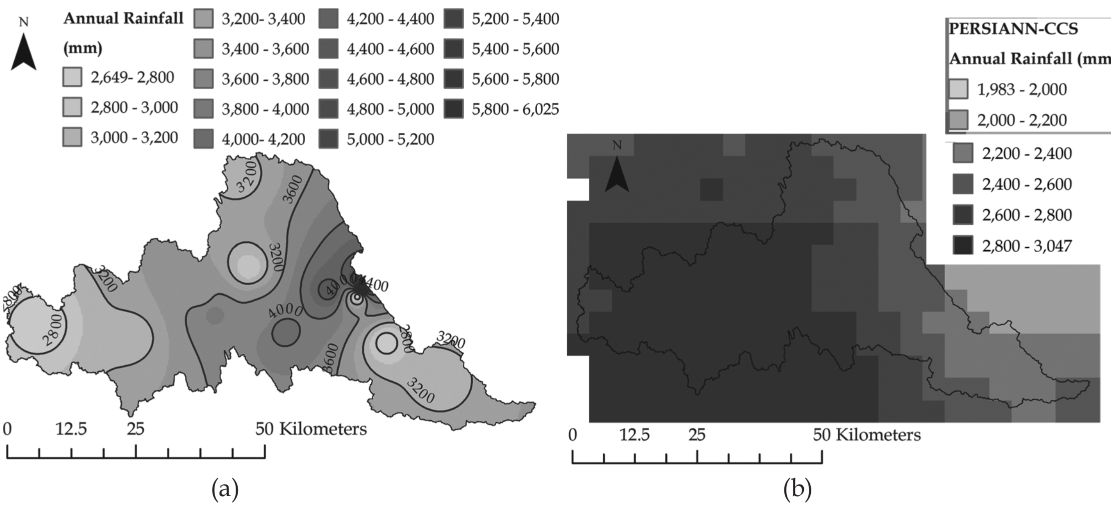

Figure 3 - Spatial Distribution of Annual Average Rainfall over Kelani River Basin (a) RainGauge Data; (b) PERSIANN-CCS Rainfall Data

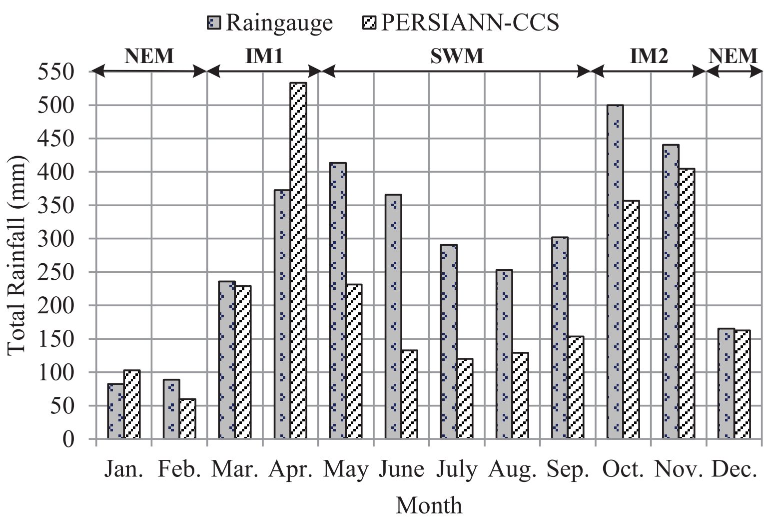

Figure 4 - Catchment Average Monthly Total Rainfall Variation of Gauge and PERSIANN-CCS

Comparison of seasonal rainfall contribution to the total rainfall showed that 46%, 27%, 17% and 10% of the rainfall is brought by SWM, IM2, IM1 and NEM, respectively. PERSIANN-CCS rainfall estimates provided the least share (12%) in the NEM, which is in agreement with gauge data. However, the remaining percentage is equally shared by SWM, IM2, and IM1. PERSIANN-CCS's IM2 share (29%) closely matches with that of raingauge. However, lesser share and higher share of PERSIANN-CCS rainfall in SWM and IM1 compared to raingauge data might be attributed to the underestimation and overestimation of rainfall, respectively.

3.2 Comparison at Point to Pixel

A point-to-pixel evaluation was performed to compare daily time series at each raingauge station with the respective grid cell of satellite data. First, equivalence between SREs and gauge data was considered in terms of the amount and occurrence of rain using daily data for the entire period.

The CC between the PERSIANN-CCS estimates and raingauge data was in the range of 0.23~0.53 indicating low linear correspondence (Figure 5a). It is 0.53 at Duneidin and declines towards the outlet and upstream, recording the lowest at Kenilworth. Percentage bias is -25%±23%, marking a significant spatial variation. Closer to the river mouth, slight overestimation can be observed, which then turns into proper estimation up to just above Hanwella, and beyond that rainfall is underestimated with the highest of 61% around Kenilworth (Figure 5b). Variation in NRMSE (4.0±1.1) is not considerably high, however, a slight increase can be observed towards the mountainous region (Figure 5c). Based on the above descriptive statistics, we can conclude that PERSIANN-CCS rainfall estimate accuracy drops with the magnitude of the rainfall.

Figure 6 presents the spatial variation of categorical statistics of daily data for the entire period. Accuracy (Mean±std.) measure shows that 71%±2% of PERSIANN-CCS estimates are correct. Mean±std values of POD and FAR of daily PERSIANN-CCS rainfall estimates were 0.69±0.02 and 0.27±0.08, respectively. These estimates signpost that 69% of the observed rain events ("yes" events) are correctly detected and 27% of the "yes" events are false alarms. Bias score (Mean±std.) was 96%±11% indicating rain frequency is slightly underestimated. Spatial variation of accuracy and POD measures for the entire period is insignificant. On the other hand, a high number of "no rain" events have been detected as "rain" events and bias frequency is closer to 1 where it receives high rainfall.

The above discussion on statistical indices of daily data for the entire period indicates a dependency on the amount of rainfall.

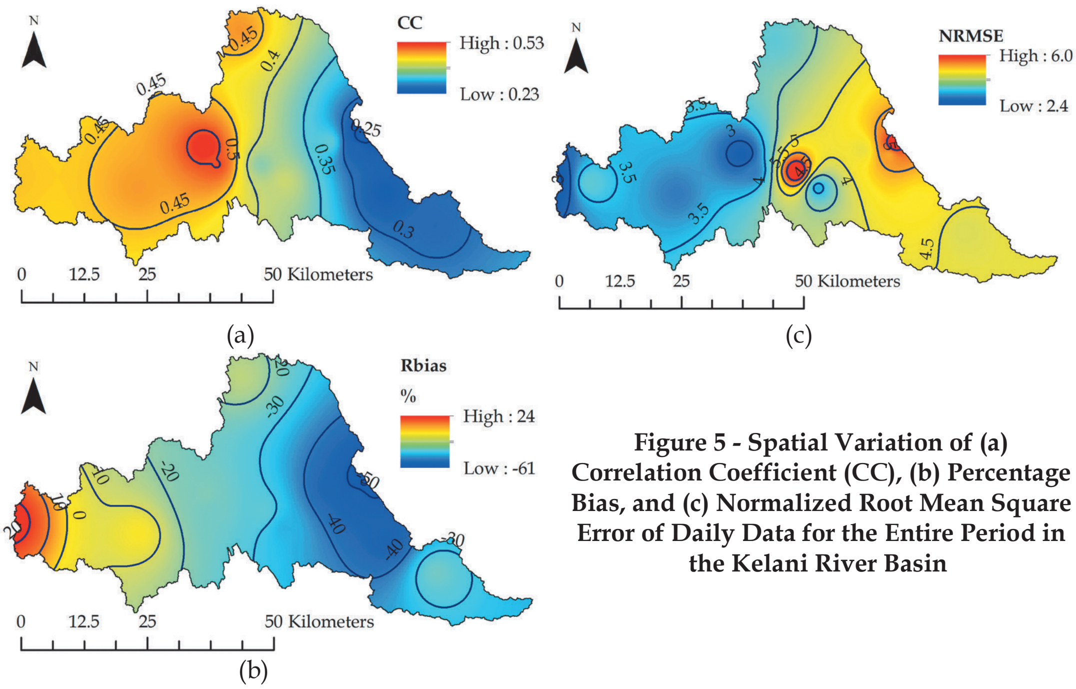

Figure 5 - Spatial Variation of (a) Correlation Coefficient (CC), (b) Percentage Bias, and (c) Normalized Root Mean Square Error of Daily Data for the Entire Period in the Kelani River Basin

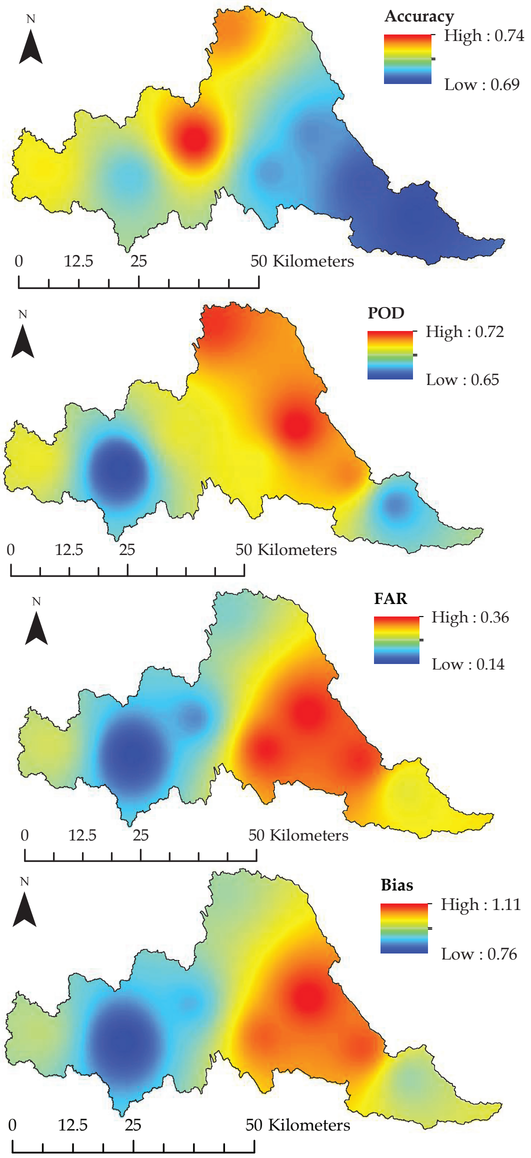

Figure 6 - Spatial Variation of Categorical Statistics, Accuracy, Probability of Detection (POD), False Alarm Ratio (FAR), and Frequency Bias (FBias) of Daily Data for the Entire Period in the Kelani River Basin.

Figure 7 shows the Pbias variation over the catchment in climate seasons. Pbias of PERSIANN-CCS was in the range of -56%~17%, - 27%~53%, -75%~30%, and -50%~3% in NEM, IM1, SWM, and IM2, respectively. Pbias in the SWM period recorded the highest underestimation during which period basin received a large amount of rainfall. During NEM, IM2, and SWM periods, Pbias of PERSIANN-CCS data are at the acceptable range closer to the sea, and it is in the underestimated range in other regions increasing towards the NE direction. On the contrary, Pbias of PERSIANN-CCS rainfall data in the IM1 period is at the acceptable range in the high rainfall region above Glencourse and it is overestimated in other regions having the highest overestimation at Hanwella.

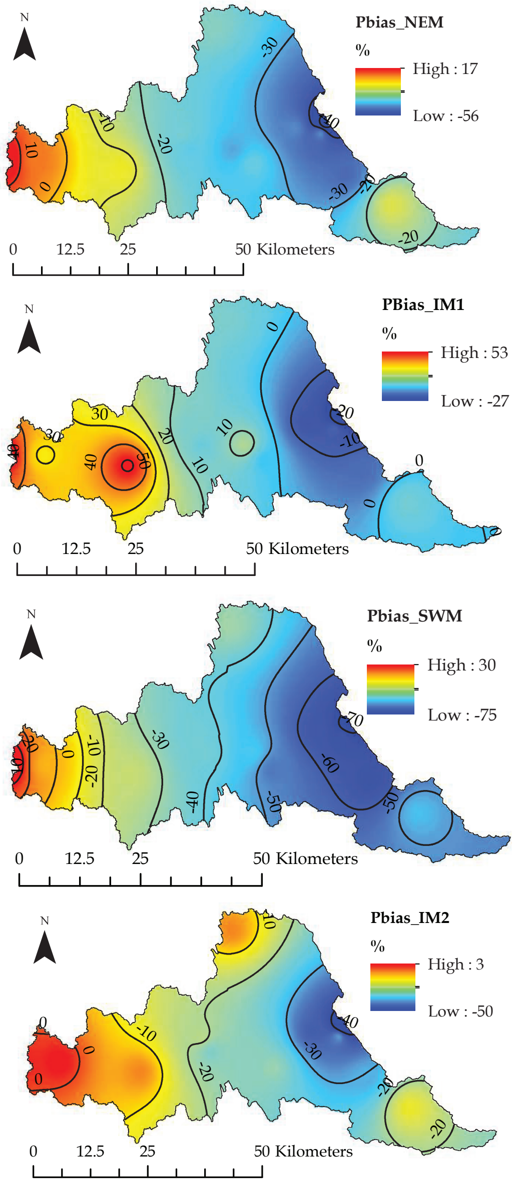

Figure 7 – Seasonal Pbias Variation.

Mean±std values of CCs of PERSIANN-CCS were 0.42±0.09, 0.44±0.11, 0.36±0.12, and 0.38±0.16 in NEM, IM1, SWM, and IM2, respectively (Figure 8). The highest recorded CC was 0.69. Concerning CCs, SREs show poor agreement with the gauge rainfall data. In NEM, SWM and IM2 seasons, CC tends to be high downstream while high CCs are evident in mid-catchment around Deraniyagala in IM1.

Similar to Pbias and CC, the spatial pattern of NRMSE also shows that PERSIANN-CCS estimates are comparatively accurate in low-lying areas during NEM, SWM, and IM2.

NRMSE appeared to be very high below Glencourse in the IM1 (Figure 9).

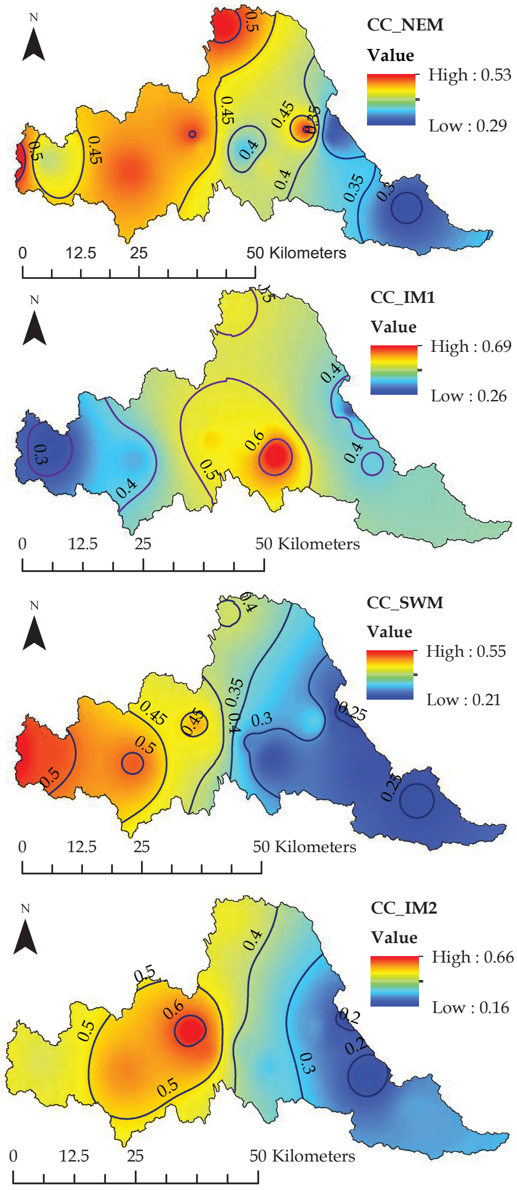

Figure 8 – Seasonal CC Variation

Table 1 summarizes the seasonal descriptive statistics. Both NEM and IM2 have comparable accuracy in PERSIANN-CCS rainfall estimates. SWM provided the lowest accuracy in terms of CC and NRMSE and its rainfall was highly underestimated. IM1 rainfall showed the highest overestimation.

Table 1- Seasonal Descriptive Statistics

Statistic (%)	NEM	IM1	SWM	IM2
Pbias	-21±18	9±23	-39±28	-19±15
CC	0.42 ±0.09	0.44 ±0.11	0.36 ±0.12	0.38 ±0.16
NRMSE	2.8±0.6	2.8±1.0	3.1±0.8	2.7±0.8

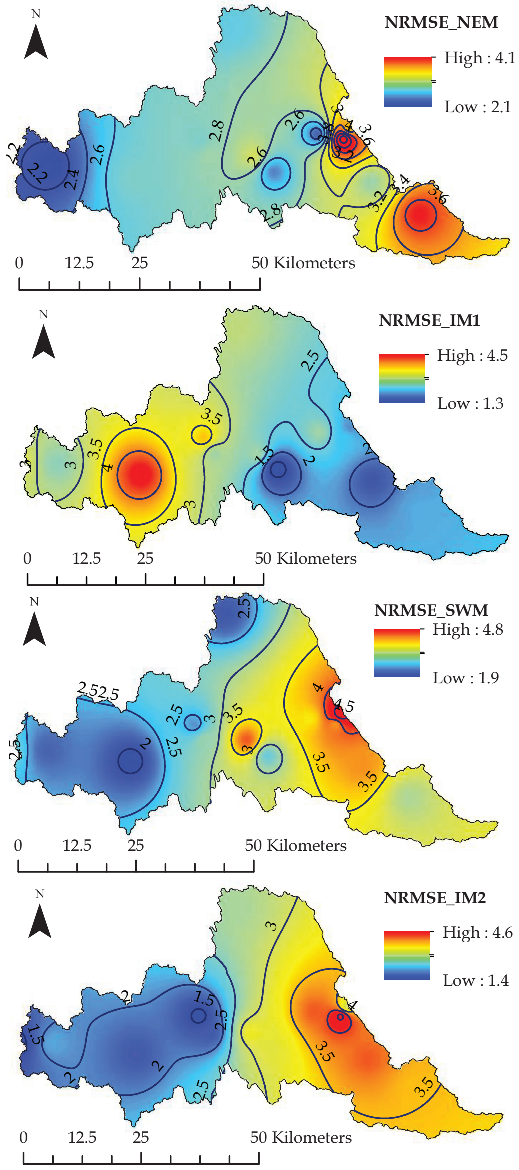

Figure 9 – Seasonal NRMSE Variation

Figure 10 presents the seasonal categorical verification statistics. The highest accuracy (83%±3%) is achieved in February. This means that 83%±3% of rain events and no rain events are correctly identified in February. This may be a result of the presence of a high number of dry days. However, rain events are more accurately identified by the peak rainfall months of April and November, providing 90%±3% of POD (Figure 3). The lowest accuracy (60%±6%) and POD (55%±7%) appeared in July. FAR is inversely proportional to monthly rainfall variation (Figure 3). The minimum number of false alarms (23%±4%) occurred in November while the greatest number of false alarms (57%±7%) are recorded in January. Rain frequency is slightly underestimated in June, July and September whereas it is slightly overestimated in January to April, and November to December. The highest overestimation in rain frequency appeared in January. Rain frequency is properly estimated in May and October.

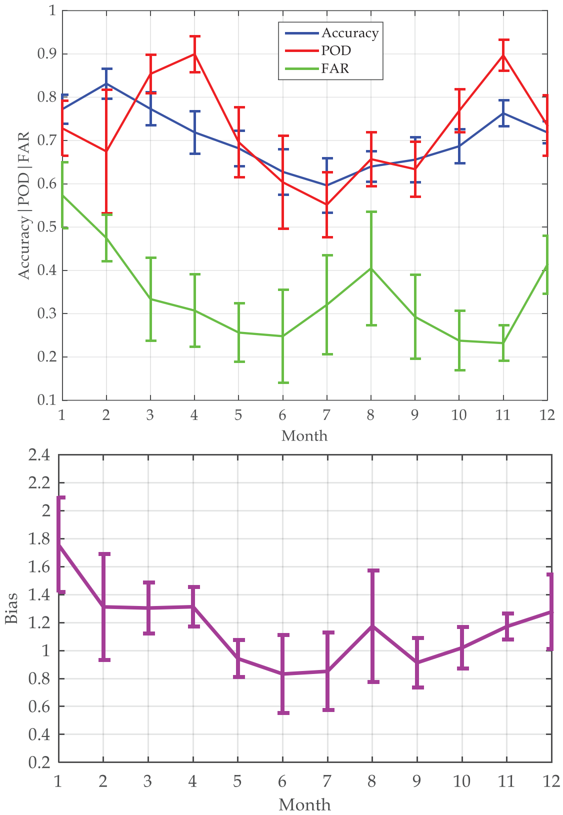

Figure 10 - Monthly Variation of Categorical Statistics

Seasonal categorical statistics are summarized in Table 2. Accuracy measure is observed to be low in the upstream where it receives high rainfall. The accuracy measure of PERSIANN-CCS was in the order of NEM, IM1, IM2 and SWM for the reason that it is biased towards the correct negatives (Table 2).

Table 2 - Seasonal Categorical Statistics

Statistic (%)	NEM	IM1	SWM	IM2
Accuracy	77±2	75±4	64±3	72±3
POD	71±7	88±4	63±7	83±7
FAR	48±4	32±8	30±8	23±5
Bias	138±19	130±14	93±21	109±11

The spatial pattern of POD statistics uncovers that "rain" events are accurately detected downstream than upstream in NEM and SWM. Spatial variation of POD is insignificant in IM1 and IM2 while it varies largely in monsoonal periods (Figure 11). Moreover, the PODs of PERSIANN-CCS provided the highest values in IM1 and IM2, followed by NEM and SWM (Table 2). Seasonal variation of POD with FAR also confirms that PERSIANN-CCS detects convectional and depressional rain events than monsoonal rain events (Figure 12).

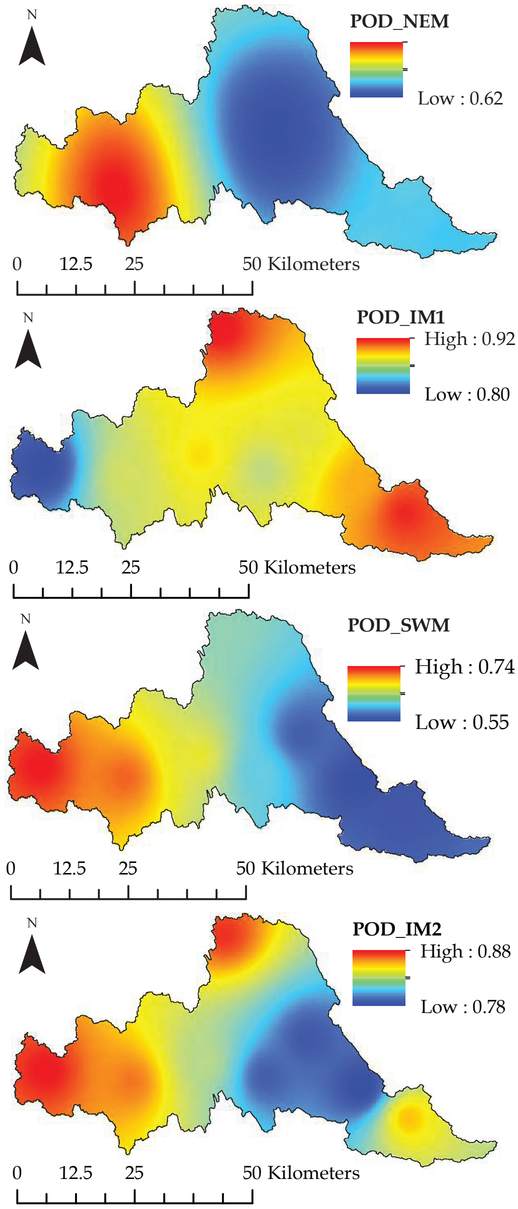

Figure 11 – Spatial Variation of Seasonal POD

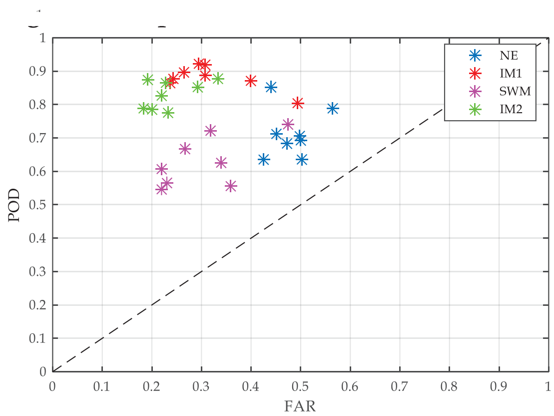

Figure 12 - Seasonal Variation of POD with FAR

On average, FAR is low and rain frequency is closer to proper estimation in high rainy seasons IM2 and SWM (Table 2), whereas NEM recorded the highest false alarms and rain frequency is overestimated by low rainy seasons. Both FAR and FBias variations showed dependency with the altitude irrespective of the season and were low in the high altitude (Figures 13 & 14).

Further, PERSIANN-CCS's ability in detecting different rainfall intensities was evaluated and the contingency table was rearranged to consider different rainfall intensities as: no rain (<1 mm/day); light (1-10 mm/day); moderate (10-30 mm/day); heavy (>30 mm/day). On average, POD was 0.69, 0.33, 0.24, and 0.23 for no rain, light, moderate and heavy rains, respectively. This indicates a decline in

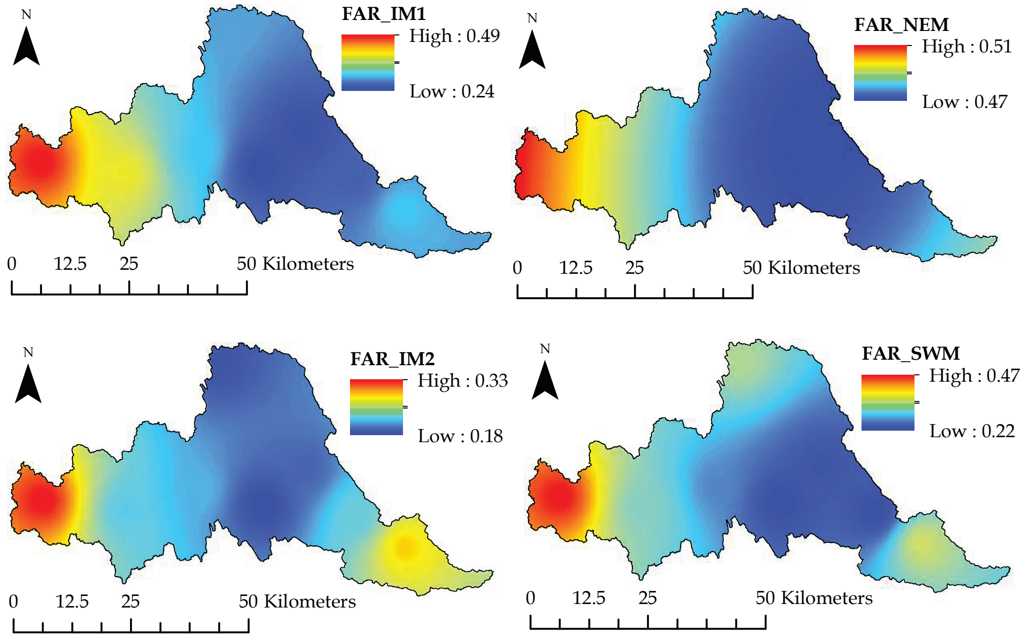

Figure 13 - Seasonal Variation of FAR.

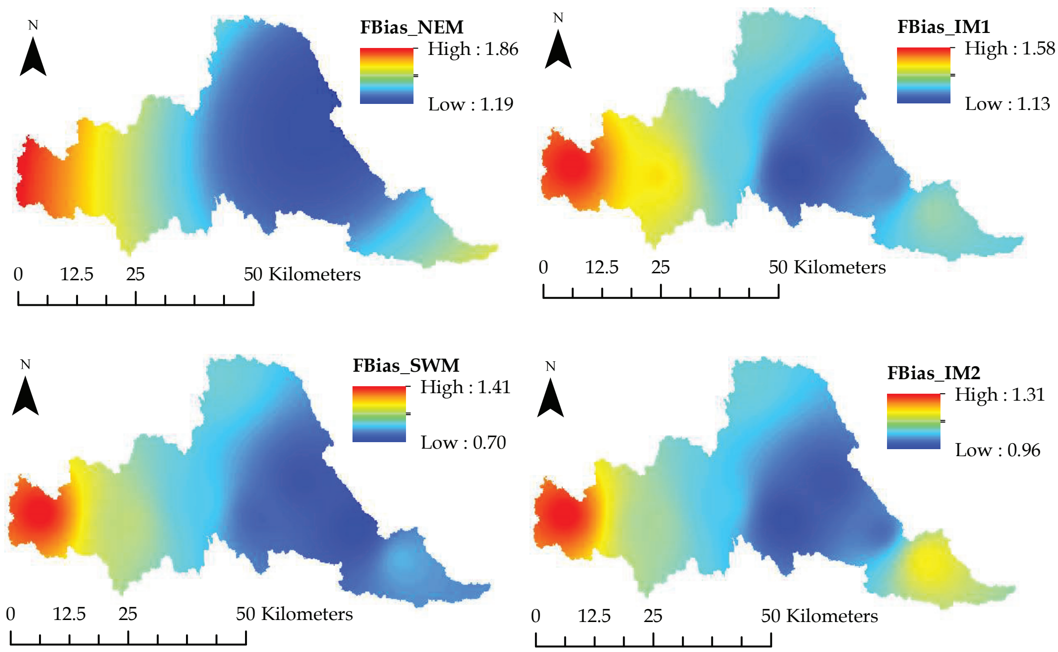

Figure 14 - Seasonal Variation of FBias

detectability in rainfall with increase in intensity. Further, FAR is very high for light, moderate and heavy rains. This might be due to the low reliability in the timing of the events.

Table 3 - Summary of Categorical Statistics for different Rainfall Intensities: No Rain (<1 mm/day); Light (1-10 mm/day); Moderate (10-30 mm/day); Heavy (>30 mm/day)

Statistic (%)	No rain	Light	Moderate	Heavy
Accuracy	0.71 ±0.02	0.67 ±0.01	0.76 ±0.03	0.88 ±0.02
POD	0.69 ±0.02	0.33 ±0.02	0.24 ±0.03	0.23 ±0.01
FAR	0.27 ±0.07	0.74 ±0.03	0.75 ±0.02	0.64 ±0.08
Fbias	0.95 ±0.12	1.28 ±0.15	0.99 ±0.21	0.62 ±0.19

4. Summary and Conclusions

The PERSIANN-CCS product was assessed upon 13 raingauges in estimating daily rainfall of the Kelani River basin of Sri Lanka from 2004 to 2010. The evaluation was performed using both descriptive and categorical statistics.

Monthly comparison of data showed that PERSIANN-CCS could capture the seasonal rainfall pattern with considerable overestimation and underestimation in rainfall in IM1 and SWM season months, respectively. On average, 71% of "rain" and "no rain" events are accurately detected and Frequency bias was 96%. Further, 69% of rain events are correctly detected while 27% were false alarms. PERCIANN-CCS product has fair-to-middling ability in detecting rainfall occurrences over Kelani Basin of Sri Lanka. However, correlation coefficient was less than 0.53 in all stations and bias varies remarkably from 24% to -61% indicating the necessity of bias correction prior to the modelling applications. It was found that PERSIANN-CCS detects conventional and depression rain events better than the monsoonal rain. It also gives more false alarms in the low rainy season, NEM. Comparison of detection ability of different rain intensities of PERSIANN-CCS showed that it is in good agreement for the rain or no-rain events and not for different rain rates. Based on the results, it can be concluded that bias adjusted form of PERSIANN-CCS may be applicable for flood forecasting applications in the Kelani River basin.

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