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Comparison of GPM IMERG and PERSIANN-CDR satellite-derived precipitation estimate products over Trinidad

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ABSTRACT. A quantitative assessment of two satellite-derived precipitation estimate (SPE) products - the Integrated Multi-satellitE Retrievals for Global Precipitation Measurement (IMERG) V06, and Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks-Climate Data Record (PERSIANN-CDR) - was conducted in the Caribbean Island of Trinidad. Using a point to pixel evaluation method, SPE products were compared to rain gauge records at daily, monthly, seasonal, and annual scales over a ten-year period, 2006-2015. Continuous statistical metrics provided information on the level of agreement between SPE and rain gauge data, while categorical statistical metrics were used to determine the precipitation detection capabilities of SPE products. IMERG generally has weak correlations at all temporal scales assessed, while PERSIANN-CDR, has stronger correlations at the monthly ($r = 0.62$) and dry season ($r = 0.59$) scales. Both SPE products show spatial variability across the island, with generally larger underestimations of rainfall experienced in the wetter north-east region of the island, and overestimations occurring towards the west. Over the entire time period, PERSIANN-CDR has a higher POD (0.57), lower FAR (0.47), and higher CSI (0.38) than IMERG (POD = 0.30; FAR = 0.58; CSI = 0.21). PERSIANN-CDR provides a better representation of seasons based on mean monthly rainfall and can be utilised for long-term assessments of monthly rainfall over the island. Both SPE products appear to have limitations in detecting the largest intensity rainfall events (> 20 mm/day), particularly in the wet seasons. Further calibration of both products is recommended to provide more improved rainfall estimation over Trinidad.

Keywords: Climate, Precipitation, Remote Sensing, Trinidad.

1. INTRODUCTION

Precipitation is a major component of the energy and hydrological cycle and influences the global climate (**Kidd et al., 2017**). It is a primary source of drinking water (**Michaelides et al., 2009**) and is critical for the social and economic welfare of people, particularly in regions dependent on rain-fed agriculture (**Gamble et al., 2010**). Rainfall influences extreme events such as droughts, floods, and storms which have devastating impacts on humans and the environment. It is therefore important to have long-term historical records of precipitation in order to develop better understanding of its variability and dynamics, and to improve the capacity and resilience of societies to respond and adapt to these climate extremes (**Nguyen et al., 2018**). Furthermore, it is essential to have reliable rainfall measurements which are capable of representing the high spatial and temporal variability of rainfall (**Barrett, 2001**). Consequently, the provision of accurate estimates of rainfall, would enable an improved understanding of climate and water resources for societies to create resilient communities (**Kidd and Huffman, 2011**).

Rainfall data can be obtained from a variety of sources, including ground-based (rain gauges, disdrometers and radars) and satellite-derived measurements. Ground-based measurements are most commonly made with rain gauges at point-based locations (**New et al., 2001**). Since rainfall has high spatial variability, the use of point-based rain gauge measurements may not always give an accurate representation of rainfall conditions over a given area. This is true in many regions of the world, particularly in developing countries, where rain gauge networks are sparse (**Hughes, 2006**) and rainfall events occurring in areas between rain gauges may not be accounted for. The establishment of dense networks of operational rain gauges to capture the spatial variability of rainfall is not always possible due to limitations such as economic and political issues (**Su et al., 2008**). To overcome these problems, satellite-derived precipitation estimate (SPE) products can be utilised for monitoring rainfall conditions (**Ayugi et al., 2019**). The use of satellites allows for an economical and effective means of determining areal rainfall estimates (**Artan et al., 2007**).

SPE products are based on various precipitation retrieval methods which can be categorised as Vis/IR methods, Passive Microwave Methods (PMW), Active Microwave Methods and Muti-sensor techniques (**Kidd and Levizzani, 2011**). Examples of operational SPE products include PERSIANN (**Hsu et al., 1997**), the Climate Prediction Center MORPHing Technique (CMORPH) analysis (**Joyce et al., 2004**), Global Satellite Mapping of Precipitation (GSMaP) (**Kubota et al., 2007**), Tropical Rainfall Measuring Mission (TRMM) Multi-Satellite Precipitation Analysis (TMPA) (**Huffman et al., 2007**), and Global Precipitation Measurement (GPM) mission (**Hou et al., 2014**). SPE products can be utilised in applications such as water resource management (**Filho et al., 2010**), hydrological modelling (**Tramblay et al., 2016**), drought and flood monitoring (**Toté et al., 2015**), landslide modelling (**Rossi et al., 2017**) and climate-related studies (**Miao et al., 2015**). However, their utility must first be assessed through comparison to ground-based rainfall measurements to validate their accuracy and reliability.

Rain gauges have frequently been used as ‘ground truth’ for the validation of SPE products (e.g., **Dinku et al., 2007**). Validation studies have been conducted under various climatic conditions, such as within the tropics (**Tan and Santo, 2018**) and in arid environments (**Katiraie-Boroujerdy et al., 2013**), and over regions with variable topographic conditions (**Derin et al., 2016**). SPE products may show varying results under different environmental conditions. As such, **Feidas** (**2010**) asserts that for any satellite precipitation product to be successful, its performance must be quantitatively assessed in different regions and under seasonal variations. These assessments are critical to facilitate the development of satellite sensors and to improve the algorithms used to generate these products (**Tan and Santo, 2018**). Many studies have focused on assessment of SPE products on continental regions, while a few have been conducted on island environments (e.g., **Huang et al., 2018**; **Caracciolo et al., 2018**).

Many islands within the Caribbean are classified as Small Island Developing States (SIDS) and are extremely vulnerable to natural disasters and the impacts of climatic change (**Gheuens et al. 2019**). They are faced with issues such as limited water resources (**Falkland, 1999**), droughts (e.g., in Jamaica - **Campbell et al., 2011**) and floods (e.g., in Trinidad - **Ramlal and Baban, 2008**), hence it is critical to have a comprehensive understanding of the spatial and temporal variability of rainfall in SIDS. **Gamble and Curtis** (**2008**) have highlighted the importance of utilising satellite data for providing an improved understanding of rainfall regimes across the Caribbean. Furthermore, few SIDS have extensive temporal and spatial hydrometeorological records (**Staub et al., 2014**). As such, an assessment of SPE products in SIDS will offer an alternative to using rain gauge records, and potentially offer a more complete picture of the spatio-temporal variability of rainfall across islands. Having this knowledge will ultimately allow these islands to better manage and mitigate water-related issues.

This paper focuses on the Caribbean island of Trinidad; part of the twin-island Republic of Trinidad and Tobago – a Small Island Developing State. In Trinidad, there has been only one published study on the assessment of satellite rainfall data with rain gauge measurements (**Tambie et al., 2012**). In that study, TRMM 3B42 data were compared to rain gauge measurements at two stations found within a single satellite grid. The major findings of that study highlighted that the relationship between TRMM 3B42 and rain gauge data varied across temporal scales, with weaker correlations on daily and annual scales, and stronger correlations during the dry seasons. The authors of that paper also found that TRMM 3B42 underestimated rainfall measurements made by rain gauges at all temporal scales investigated. When that study was undertaken, rain gauge data for other parts of the island were not readily available to the researchers, hence an assessment on the spatial variability of rainfall was limited. At present, with the availability of rainfall data from more rain gauges, the utility of SPE products for Trinidad can now be assessed, taking into consideration the spatial and temporal variability of rainfall over different parts of the island.

For this study, two daily SPE products (areal estimates of rainfall), the GPM IMERG V06 and PERSIANN-CDR were chosen for assessment with rain gauge data (point-based rainfall measurements) to determine their potential for use in hydrological and climatological research in Trinidad. The products were selected because they are easily accessible (in the public domain) on the Internet and have a relatively long time series. This latest version of IMERG has been available since March 2019 with records dating back to June 2000. PERSIANN-CDR was released in 2014 and covers a longer temporal range, with data from 1983. The finer resolution GPM IMERG has the potential for use in hydrological applications (e.g., **Zubieta et al., 2017**), while the coarser resolution PERSIANN-CDR can be utilised for long-term climate-based research (e.g., **Arvor et al., 2017**).

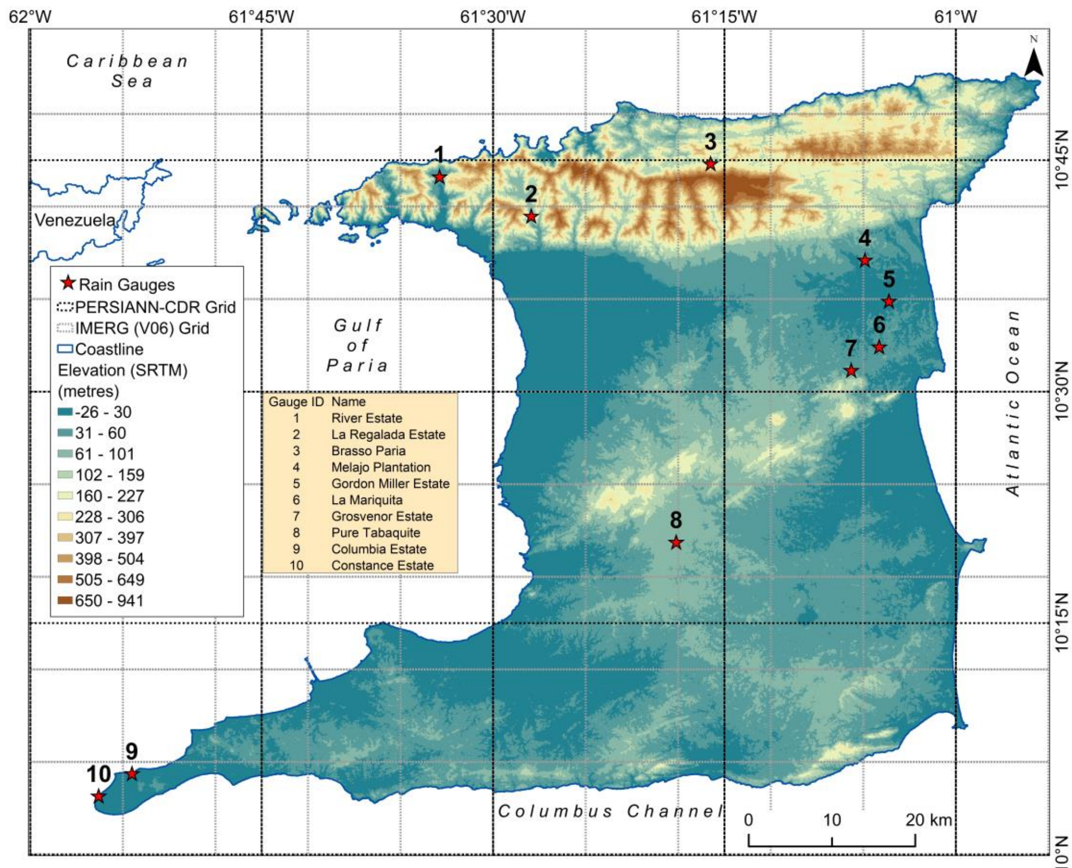

Figure 1: Study site showing locations of rain gauges and satellite data footprints.

The purpose of this research is to provide a quantitative assessment of two SPE products, GPM IMERG and PERSIANN-CDR. The performance of these products is assessed in relation to rain gauge data from ten stations over a ten-year period from 2006-2015, using statistical metrics. The main objectives are (1) to determine the level of agreement between SPE and rain gauge data at various temporal aggregations (daily, monthly, seasonal and annual) by utilising continuous statistical metrics, (2) to determine the precipitation detection capabilities of each SPE product by utilising categorical statistical metrics, and (3) to examine how the performance of each SPE product varies spatially at specific sites across the island. This study seeks to provide a better understanding of the spatial and temporal variability of rainfall over the tropical island of Trinidad, as well as generating information on the potential of utilising remotely sensed rainfall estimates for hydrological and climatological research in small island territories, where reliable ground-based measurements may be sparse. The outcomes of this research can also provide useful information that could assist other researchers in the development of future versions of both SPE product algorithms.

2. Study Site

Trinidad is the larger of two islands which comprise the Republic of Trinidad and Tobago. It is the southernmost island of the Caribbean and covers an area of 4,768 km^2. The terrain of Trinidad consists of mountainous regions to the north, central and southern parts of the island, with plains and undulating land found in the remaining areas. The island experiences a dry season from January to May characterised as a tropical maritime climate, and a wet season from June to December that represents a modified moist equatorial climate (**Trinidad and Tobago Meteorological Service, 2019**). In the wet season, a short (2–3 weeks) dry spell known as the 'Petit Careme' occurs around mid-September to mid-October (**Anderson et al., 2012**). The dominant winds are the Northeast Trades which bring moisture from over the Atlantic Ocean.

Table 1. Characteristics at rain gauge stations

ID	Name	Lon	Lat	Elevation (m)	Mean Annual Rainfall (mm)	Mean Dry Season Rainfall (mm)	Mean Wet Season Rainfall (mm)	Missing Data (%)
1	River Estate	-61.56	10.73	42	1584.79	270.84	1313.95	0.03
2	La Regalada Estate	-61.46	10.69	71	1520.86	273.20	1247.66	0
3	Brasso Paria	-61.26	10.75	156	2460.71	634.98	1825.73	0
4	Melajo Plantation	-61.1	10.64	58	2957.79	736.12	2221.67	0
5	Gordon Miller Estate	-61.07	10.6	21	2360.41	560.99	1799.42	0
6	La Mariquita	-61.08	10.55	43	2595.08	660.27	1934.81	0
7	Grosvenor Estate	-61.11	10.52	65	2716.41	719.68	1996.73	0
8	Pure Tabaquite	-61.3	10.34	70	2130.29	508.47	1621.82	0.03
9	Columbia Estate	-61.89	10.09	11	1569.41	451.67	1117.74	0.05
10	Constance Estate	-61.93	10.06	8	1237.60	363.90	873.70	0

3. DATA

3.1. Rain Gauge Data

Daily rainfall data from pot (Casella) rain gauges were obtained from the Water Resources Agency [WRA], Trinidad and Tobago. Initially, to ensure continuity of records, gauges having more than two consecutive days of missing data were excluded (e.g., **Liu et al., 2011**). A total of 10 pot gauges were eventually selected for use (**Figure 1**) over the ten-year period from 2006–2015.

Further quality control was performed on the data from the 10 rain gauges through examination for outliers and any possible erroneous values. This was done through spatial and temporal checks (e.g., **Dinku et al., 2018**) to ensure the reliability of the data. It must be noted, however that the data may still contain errors even though quality control checks have been conducted. **Table 1** provides some characteristics of the rain gauge stations used in this study.

3.2. Satellite Data

Two SPE products are assessed in this paper. The GPM IMERG V06 and PERSIANN-CDR are described below. The spatial extent of gridded data from both SPE products over Trinidad are shown in **Figure 1**.

GPM IMERG V06. The Global Precipitation Measurement [GPM] mission is a network of satellites that provide global observations of precipitation (**NASA, 2019**). Its core observatory was launched on February 27th 2014, and it builds upon the work of the Tropical Rainfall Measuring Mission [TRMM]. Further details of the GPM mission can be found in **Hou et al.** (**2014**). In this study, the Integrated Multi-satellite Retrievals for GPM (IMERG) V06 (**Huffman et al., 2019**) product was assessed. It was downloaded in netCDF4 format through the Goddard Earth Sciences Data and Information Services Center [GES DISC] at https://disc.gsfc.nasa.gov/datasets/GPM_3IMERGDF_06/summary. This product is found at a spatial resolution of 10 km × 10 km (0.1° × 0.1°) and at a daily temporal resolution.

PERSIANN-CDR (Version 1, Revision 1). Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks [PERSIANN] was developed by researchers from the University of Arizona in 1997 (**Nguyen et al., 2019**). In this study, PERSIANN-CDR (Version 1, Revision 1) was assessed. This daily product is found at a spatial resolution of 0.25° × 0.25° (**NCAR, 2019**). Further details can be obtained from (**Hsu et al., 1997**). Data are provided in netCDF format and can be downloaded directly from a public server: https://www.ncei.noaa.gov/data/precipitation-persiann/access/ at the National Centers for Environmental Information [NCEI], National Oceanic and Atmospheric Administration [NOAA].

4. METHOD

A point to pixel evaluation method (e.g., **Dembélé and Zwart, 2016**) was undertaken in which data from each rain gauge were compared to the data values of the corresponding grid cell of the GPM IMERG V06 (IMERG, hereafter) or PERSIANN-CDR precipitation product. The authors chose not to interpolate the point-based observations since only ten gauges are being used and they are sparsely distributed across the study site. It must be noted that some systematic differences are expected between observations at point-based locations, and pixel-based estimates (Toté et al., 2015). Comparisons between gauge and satellite data were undertaken at daily, monthly, seasonal, and annual temporal scales over the period 2006–2015. Daily data from each precipitation source were aggregated to provide monthly, seasonal, and annual totals.

Continuous and categorical statistical metrics were employed to assess the performance of the SPE products. Further details on these metrics can be derived from previous literature (e.g., Tan and Santo, 2018; Xu et al., 2019). A threshold of 1 mm/day was selected for distinguishing between days with no rain (< 1 mm/day) and rainy days (≥ 1 mm/day) (e.g., Xu et al., 2019).

The capability of SPE products to detect varying rainfall intensity events was also assessed. Rainfall intensities were categorised based on the World Meteorological Organisation and adaptations from other studies (Xu et al., 2019) (**Table 2**).

Table 2. Precipitation classes

Precipitation Classes	Range (mm/day)
Trace	0 – 0.1
Tiny	0.1 – 1
Light	1 – 2
Low moderate	2 – 5
High moderate	5 – 10
Low heavy	10 – 20
High heavy	20 – 50
Violent	>50

5. Results

5.1. Daily and Monthly Scale

The relationships between rain gauge data and satellite estimates at daily and monthly aggregations over the ten-year period are illustrated in **Figure 2**. All correlations are positive, except between rain gauge data and IMERG estimates at the daily temporal scale (**Figure 2a**), where a weak negative correlation exists ($r = -0.01$). Overall, the correlations between rain gauge data and PERSIANN-CDR are stronger (having significant relationships: $p < 0.05$) than those between rain gauge data and IMERG (having no significant relationships: $p > 0.05$) at both daily and monthly aggregations. Both SPE products generally underestimate daily and monthly rainfall totals (overall negative relative biases). Furthermore, larger root mean square error [RMSE] values occur between rain gauge and IMERG estimates than between rain gauge and PERSIANN-CDR estimates at both daily and monthly temporal scales.

Spatial variations in continuous statistics (only daily continuous statistics are visualised for reference in this paper) revealed that positive relative biases occurred at two locations (Columbia Estate and Constance Estate) in the southwestern peninsula of the island, where the PERSIANN-CDR overestimated rain gauge measurements (**Figure 3b, 3e and 3h**). This was also found at the monthly temporal scale (not shown). In **Figure 3**, the x-axes representing longitude are reversed for presentation purposes and to depict the actual spatial variation across the island. The relative bias [RB] generally becomes more negative (**Figure 3h**), while the RMSE error tends to increase (**Figure 3i**) towards the eastern region of the island, for both SPE products.

The mean monthly rainfall totals over the ten-year period were also calculated for each rain gauge and its corresponding satellite product. PERSIANN-CDR appears to follow the general trend of mean monthly rainfall measurements from rain gauges better than IMERG (**Figure 4**). Rain gauges show a clear delineation of the dry (January to May) and wet season (June to December) in Trinidad, as well as the short dry spell ('Petit Careme') which typically occurs in September/October. PERSIANN-CDR clearly shows a decline in mean monthly rainfall values during the 'Petit Careme', while IMERG, on the other hand shows a 'spike' in mean monthly rainfall totals during this time. Furthermore, IMERG has higher mean monthly rainfall estimates during the dry season months in contrast to PERSIANN-CDR (**Figure 4**). Student t tests were calculated between the average monthly data from all rain gauges and each SPE product. Findings suggest that significant differences exist between average monthly rain gauge data and IMERG ($t = 2.62$, $df = 22$, $p > 0.95$), while no significant differences are found between average monthly rain gauge data and PERSIANN-CDR ($t = 1.70$, $df = 22$, $p < 0.95$). This suggests that PERSIANN-CDR is a better estimator of mean monthly rainfall and may be more suitable for delineating seasons in Trinidad.

5.2. Seasonal and Annual Scale

For each year, total rainfall in the dry season (January to May), and the total rainfall in the wet season (June to December) were calculated for rain gauges and SPE products, before calculating seasonal continuous statistical metrics. Generally, correlations between rain gauge totals and SPE estimates were weak and not significant ($p > 0.05$), except for the strong positive relationship ($r = 0.59$)

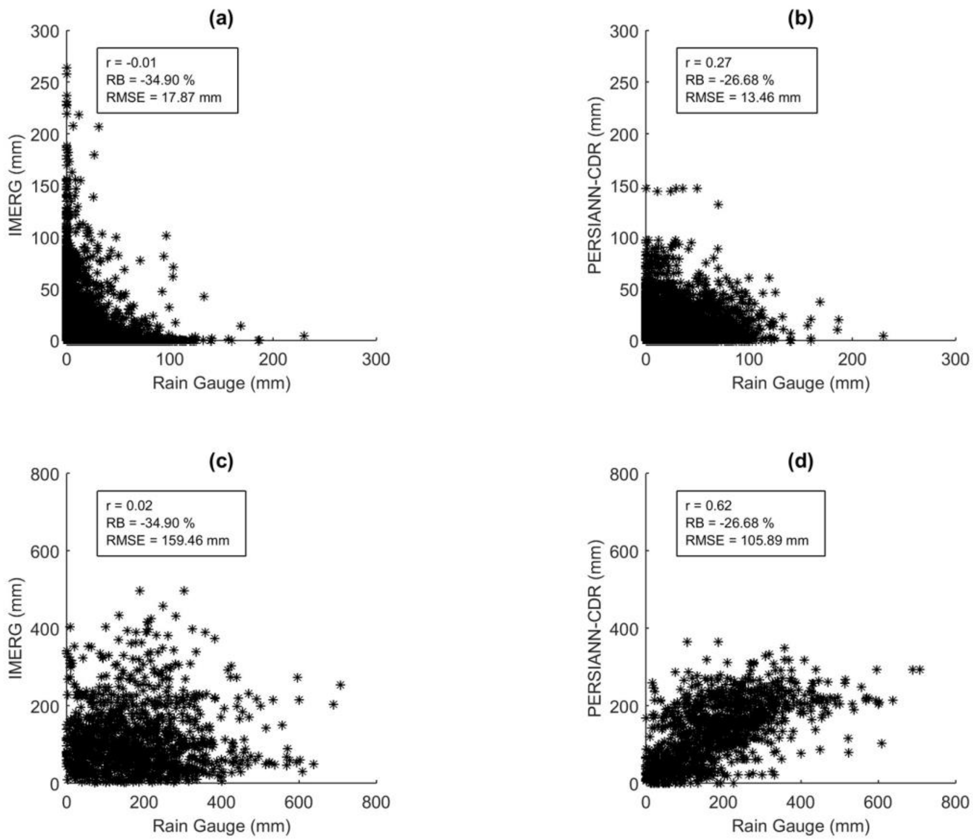

Figure 2. Scatterplots showing the relationships between rain gauge data and satellite estimates at daily: (a and b), and monthly (c and d) aggregations, over the period 2006–2015

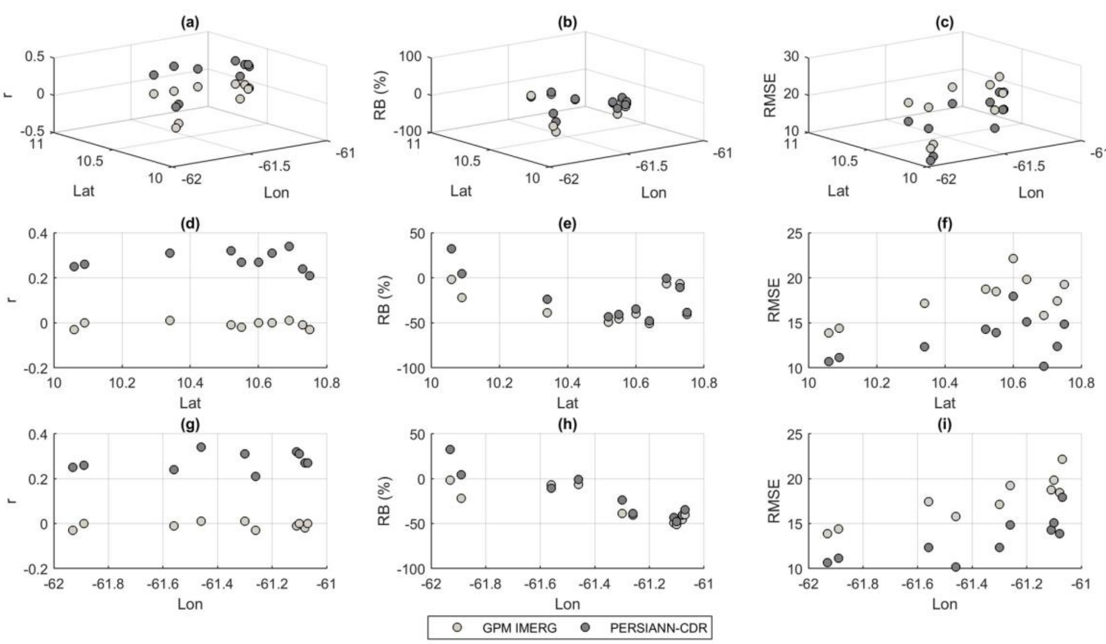

Figure 3. Spatial variations in daily continuous statistics

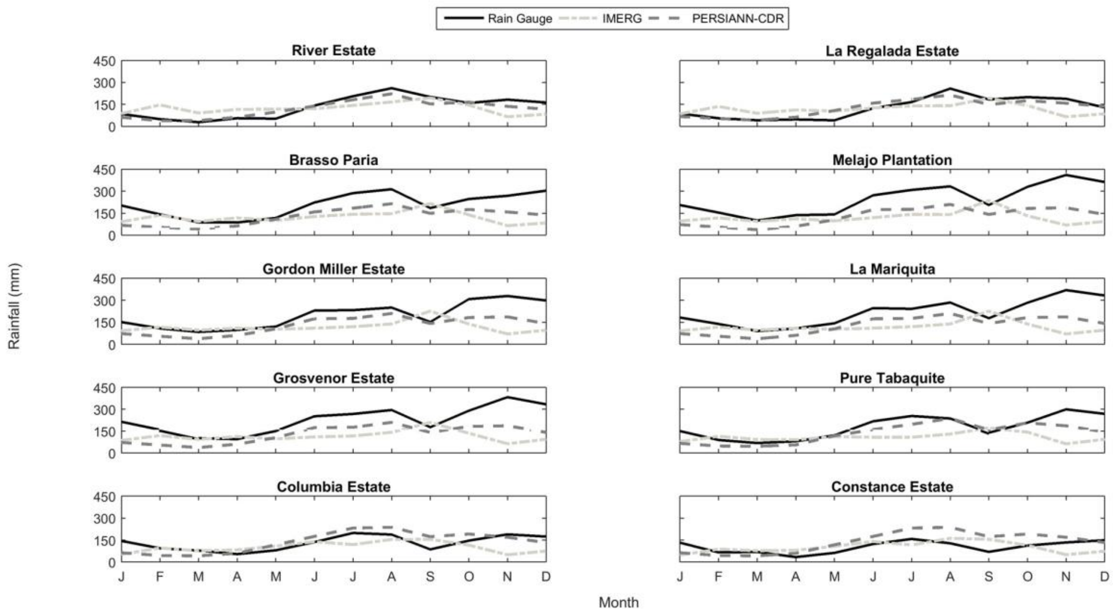

Figure 4. Mean monthly rainfall from 2006–2015 for rain gauges and SPE Products

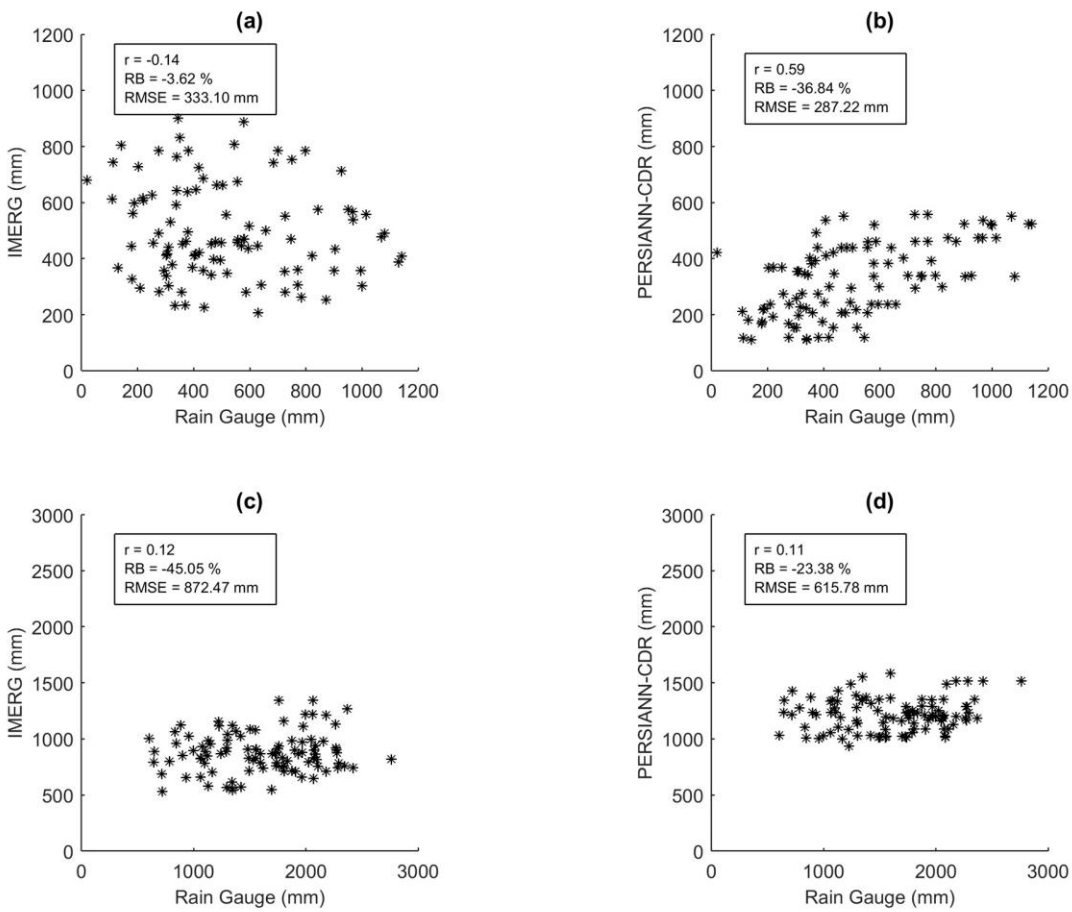

Figure 5. Scatterplots showing the relationships between rain gauge data and satellite estimates at dry season: (a and b), and wet season: (c and d) aggregations, over the period 2006–2015.

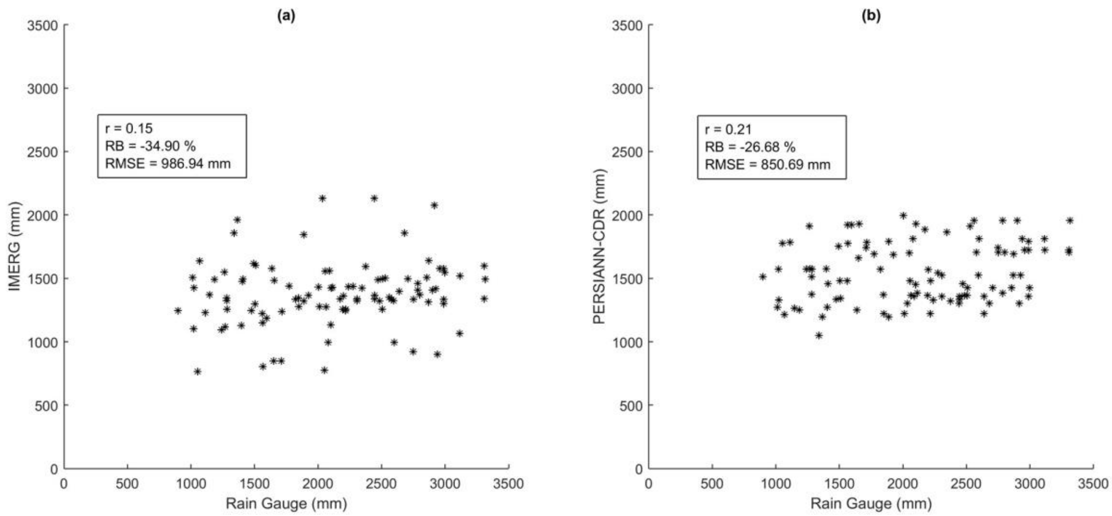

Figure 6. Scatterplots showing relationships between annual rainfall totals from all rain gauges and (a) IMERG, and (b) PERSIANN-CDR, over the period 2006–2015.

observed between dry season rain gauge totals and PERSIANN-CDR estimates (which was statistically significant: $p < 0.05$) (**Figure 5b**).

Dry season rainfall totals are underestimated more by PERSIANN-CDR (RB = -36.84%) than by IMERG (-3.62%). On the other hand, IMERG (RB = -45.05%) underestimates wet season rainfall totals more than PERSIANN-CDR (RB = -23.38%). RMSE values are larger for IMERG estimates than PERSIANN-CDR estimates for both dry and wet season rainfall totals.

Upon examination of RB values at individual stations, it was found that both SPE products overestimated dry season rainfall totals (positive RB values) at River Estate (RB (IMERG) = 106.34%; (RB (PERSIANN-CDR = 10.77%) and La Regalada Estate (RB (IMERG) = 92.85%; RB (PERSIANN-CDR) = 21.85%). IMERG also overestimated dry season rainfall totals at the Constance Estate, with an RB value of 10.48%. These overestimations all occurred in the western section (-61.4° W to -62.0° W) of the island, with larger overestimations made by IMERG. For wet season rainfall totals, positive relative biases were calculated for PERSIANN-CDR at two locations (Columbia Estate and Constance Estate) on the western side of the island which indicate overestimation of rainfall. No overestimations were made by IMERG for wet season rainfall totals at individual station locations.

Generally, both PERSIANN-CDR and IMERG appear to underestimate dry and wet season rainfall totals more towards the north and east of the island. These regions of the island also have larger RMSE values for both SPE products.

The correlations between annual rainfall totals of rain gauges and satellites are generally weak and positive (**Figure 6**) with no significant relationship between rain gauge data and IMERG estimates ($p > 0.05$) and a significant relationship ($p < 0.05$) between rain gauge data and PERSIANN-CDR. However, at station locations in the Northern Range (River Estate, La Regalada, and Brasso Paria), negative correlations exist between annual rainfall totals of IMERG and rain gauges. Both SPE products generally underestimate annual rainfall measurements made by rain gauges (negative RB values) (**Figure 6**), except at two locations in the southwestern peninsula of the island (Columbia Estate and Constance Estate) where PERSIANN-CDR overestimated annual rainfall totals. When considering spatial variability across the island, correlations for IMERG tend to be lower towards the north. For both SPE products, RB values generally decline towards the north and east, while RMSE values increase in these directions.

The mean seasonal and annual rainfall totals were also calculated for rain gauges and each SPE over the period 2006–2015 (**Figure 7**). In the dry seasons, the mean rainfall totals for IMERG always exceed those being estimated by PERSIANN-CDR at all station locations (**Figure 7a**). On the other hand, PERSIANN-CDR estimates always exceed IMERG estimates at all station locations in the wet seasons (**Figure 7b**).

The highest mean annual rainfall measured by rain gauges are found at locations in the northeastern region of the island. Lower mean annual rainfall measured by rain gauges are found at locations towards the northwest and southwest. At

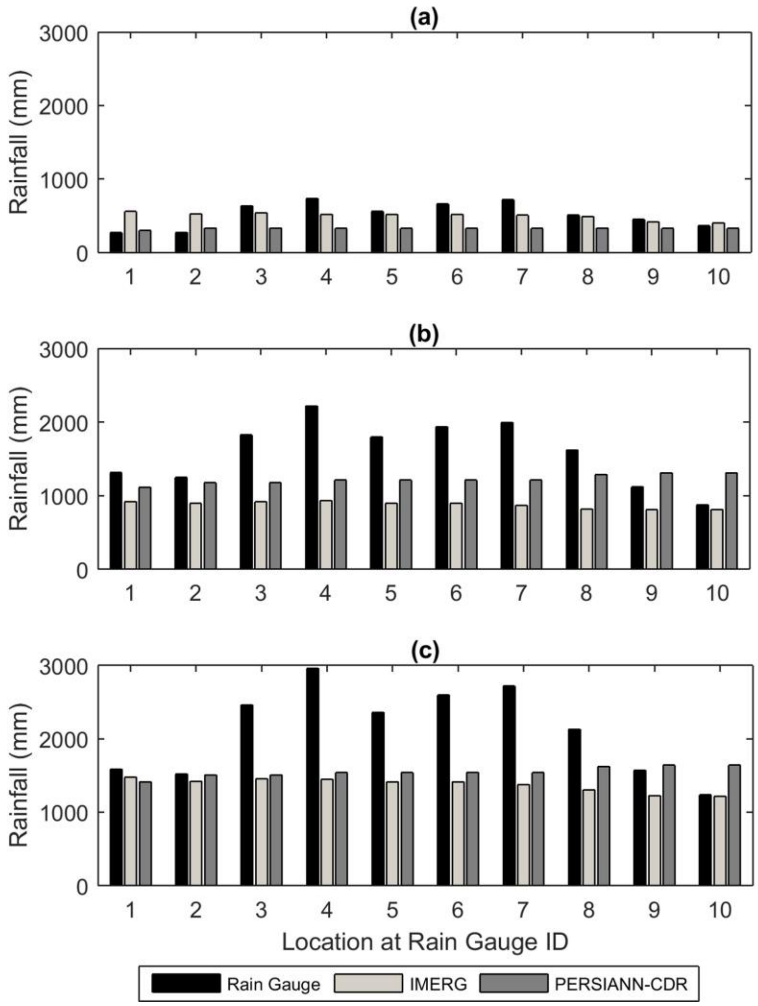

Figure 7. Mean (a) Dry Season, (b) Wet Season, and (c) Annual, rainfall totals from 2006–2015.

80% of the station sites, both SPE products underestimate the mean annual rainfall. Both SPE products appear to provide better mean annual rainfall estimates at stations measuring mean annual rainfall totals less than 2000 mm (**Figure 7c**).

5.3. Precipitation Detection

Categorical statistics were calculated to determine the precipitation detection capabilities of the two SPE products. These were determined for all days, all dry season days and all wet season days from 2006–2015. Overall categorical statistics calculated for all rain gauges over the time period are shown in **Figure 8**.

PERSIANN-CDR has a higher POD (Probability Of Detection) than IMERG, for the entire period, and for both seasons (**Figure 8a**). The larger difference in POD between the two SPE products occurs in the wet season, where the POD by PERSIANN-CDR is more than twice the POD by IMERG. During the dry seasons, both satellite precipitation products have POD values less than 0.5. Over the entire period and during both seasons, the FAR (False Alarm Rate) is higher for IMERG than PERSIANN-CDR. Lower FARs were calculated for both SPE products in the wet seasons. PERSIANN-CDR has the higher CSI (Critical Success Index) over the entire period and for both seasons. Both SPE products have higher CSIs during the wet seasons than in the dry seasons. When considering the spatial variability of categorical statistics at each station location, it was found that over the entire period, generally lower FARs occur at locations towards the east of the island.

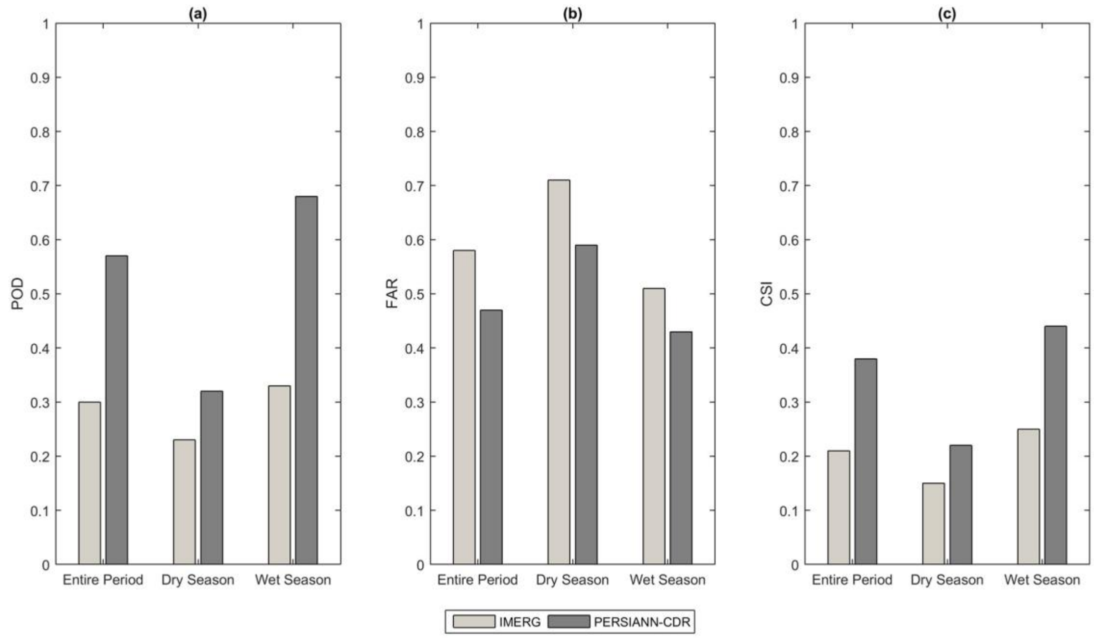

Figure 8. Overall Categorical Statistics.

Detection of various precipitation intensity classes

Overall, trace precipitation (0–0.1 mm/day) constitutes the largest percentages of rainfall intensities measured by rain gauges and estimated by SPE products (**Figure 9**). Tiny precipitation (0.1–1 mm/day) intensities are detected most frequently by IMERG for the entire period and for both seasons. For the entire period, rain gauges capture higher intensity precipitation, such as high heavy (20–50 mm/day) and violent (>50 mm/day) most frequently in comparison to IMERG and PERSIANN-CDR (**Figure 9a**).

In the dry seasons, PERSIANN-CDR detects the highest frequency (73.43%) of trace precipitation (**Figure 9b**), while IMERG detects trace precipitation most frequently (51.35%) in the wet seasons (**Figure 9c**). Rain gauges appear to capture the low moderate (2–5 mm/day), high moderate (5–10 mm/day) and low heavy (10–20 mm/day) events with the highest frequencies in the dry seasons, while in wet seasons, PERSIANN-CDR appears to capture these events with the highest frequencies.

6. Discussion

6.1. Temporal Variability

The overall correlation coefficients between IMERG and rain gauge measurements are weak (-0.5 ≤ r ≤0.5) at all temporal scales assessed. Daily correlations, in particular may be affected due to the calibration of the IMERG product with monthly gauge data, which may result in an inadequate representation of daily rainfall (**Tan and Santo, 2018**). Furthermore, weak daily correlations may also be attributed to the poor representation of coastal regions by the GPROF2014 that is utilised in IMERG products (**Tan and Duan, 2017**). In one study, **Caracciolo et al.** (**2018**) found lower correlations in coastal pixels as compared to inland pixels when assessing hourly IMERG and rain gauge data over two Mediterranean islands. Since most of the rain gauges used for the assessment in Trinidad are found within 1-2 IMERG pixels from the coast, correlations between ground-based data and IMERG estimates may have been affected. The performance of IMERG at the daily temporal scale shows varying relationships with rain gauge measurements in different regions of the world, for example, weaker correlation coefficients were found in the Southern Tibetan Plateau (0.46) (**Xu et al., 2017**), and Myanmar (0.224–0.316) (**Yuan et al., 2017**), while stronger correlations were found in the Huang-Huai-Hai Plain, China (0.76) (**Xu et al., 2019**), and in the Mishui basin, China (0.85) (**Jiang et al., 2018**).

PERSIANN-CDR exhibited overall positive correlations with rain gauge measurements at all temporal scales assessed. Stronger relationships (r >0.5) were found at the monthly scale and the dry season scale. In Trinidad, PERSIANN-CDR also provides a better estimation of mean monthly

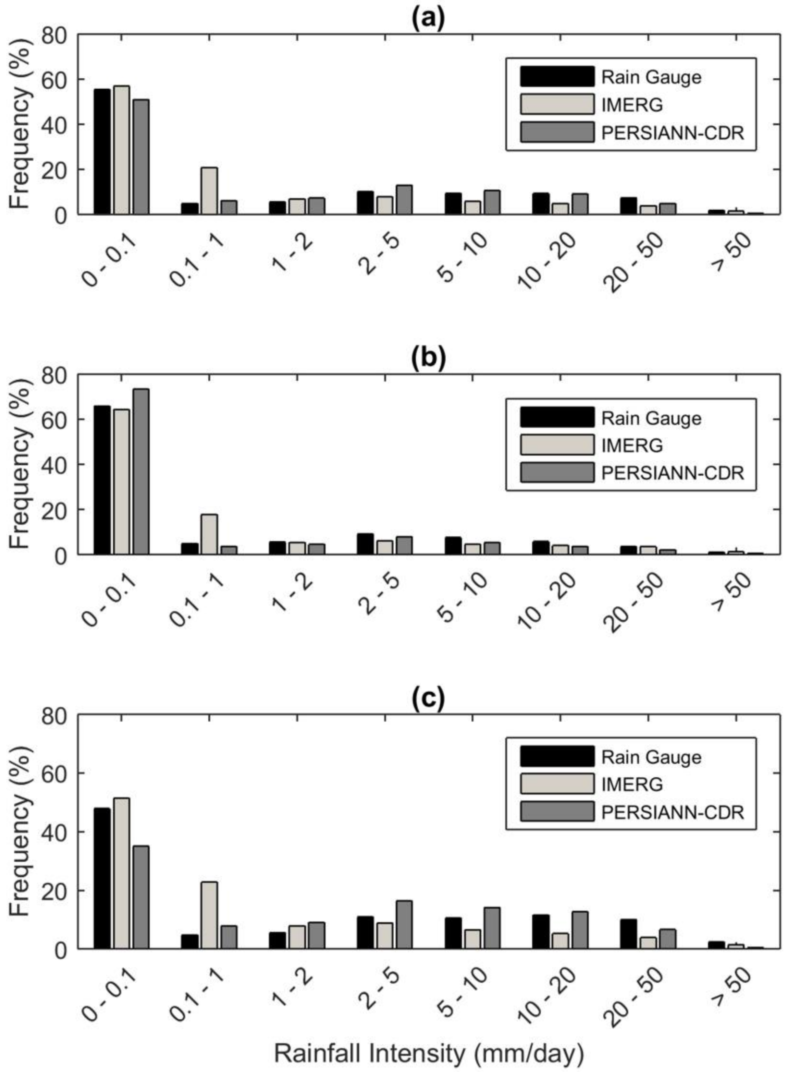

Figure 9. Frequency of daily rainfall intensities for (a) entire period (b) dry seasons and (c) wet seasons, from 2006–2015.

rainfall in comparison to IMERG. A study conducted by **Alijanian et al.** (**2017**) over Iran, also showed that PERSIANN-CDR had higher correlations at the monthly scale (r = 0.74) as compared to the daily scale (r = 0.33), as well as closely following the observed pattern of monthly rainfall. As such, potential exists for PERSIANN-CDR to be utilised for climate-based studies in Trinidad, such as drought monitoring.

A visual inspection of average monthly rainfall data revealed that IMERG generally overestimates rainfall during the dry season months and underestimates rainfall during the wet season months. An exception, however, was noted during the Petit Careme (the short dry spell which occurs during the wet season), when average monthly IMERG data overestimated ground-based rainfall. Research conducted in West Africa by **Maranan et al.** (**2020**) found that IMERG underestimates rainfall in the wet seasons and overestimates monthly rainfall during a short dry season (July–August), with overestimation being attributed to IMERG having issues with capturing weak convective rainfall (WCR). It appears that IMERG is sensitive to dry periods, which may be experiencing high evaporation rates.

At each temporal scale assessed, both IMERG and PERSIANN-CDR underestimate rainfall (overall negative relative biases). The largest difference in RB between IMERG and PERSIANN-CDR occurred at the dry season scale (difference in RB = 33.22%), where IMERG had a less negative

RB (-3.62%) than PERSIANN-CDR (-36.84%). This indicates that IMERG may be providing closer estimates of total dry season rainfall by underestimating less rainfall than PERSIANN-CDR. IMERG also generally overestimates mean monthly rainfall in the dry season, and this may have contributed to the overall low underestimation at the dry season scale.

6.2. Spatial Variability

In assessing spatial variability of continuous statistical metrics across the island, it was found that at most temporal scales (daily, monthly, wet season and annual) there were generally declines in RB (higher underestimation of rainfall) and increases in RMSE for both SPE products towards the northeast of the island. The northeast of Trinidad is the wettest region of the island and experiences mean annual rainfall totals over 2000 mm (**Table 1**). On the other hand, the western parts of the island (~61.4° W to 62° W) experience mean annual rainfall totals less than 1600 mm. Furthermore, all overestimations recorded at individual station locations for both SPE products were experienced in the northwestern and southwestern regions of the island. The spatial variations in overestimations by both SPE products, indicate that in drier regions (regions experiencing a lower mean annual rainfall) there is a greater chance that ground-based records are overestimated.

Mashingia, et al. (**2014**) suggest that overestimation of rainfall by SPE products under dry conditions may be due to the bases of convective clouds being generally higher than those of convective clouds which develop over moist conditions. As such, when rain falls from higher in the atmosphere, it has a greater chance of being evaporated before reaching the ground. The rain gauges would therefore measure a lower rainfall than what is being estimated by the satellite from the clouds. Those authors also found that in more humid regions, satellite products generally underestimated precipitation since rain gauges were able to better capture the local precipitation.

In other research, **Ayugi et al.** (**2019**) found that PERSIANN-CDR overestimates rainfall where there are large bodies of water and a humid climate. Those authors suggest that this may be attributed to the absorption of radiation over the coastal waters which may produce non-raining clouds that can be falsely detected as rainfall. In the south-western peninsula of Trinidad, the majority of the PERSIANN-CDR satellite grid cell covers water from the Gulf of Paria and the Columbus Channel. As such, this may have also attributed to the overestimation of rainfall by PERSIANN-CDR at stations located in this region of the island. This may also be true in the northwestern region, particularly over the River Estate station.

Table 3. Summary of relationships between SPE product data and rain gauge data

Relationships between SPE product data and rain gauge data		
Temporal Aggregation	**GPM IMERG**	**PERSIANN-CDR**
Daily	Weak Negative	Weak Positive*
Monthly	Weak Positive	Strong Positive*
Dry Season	Weak Negative	Strong Positive*
Wet Season	Weak Positive	Weak Positive
Annual	Weak Positive	Weak Positive*

Note: weak correlation: $-0.5 \leq r \leq 0.5$, strong correlation: $-0.5 > r > 0.5$, *statistically significant.

6.3. Precipitation Detection Capabilities

PERSIANN-CDR has a higher POD and CSI than IMERG across all days, and in both seasons. Overall, IMERG has a higher FAR which could be due to the rainfall threshold utilised to distinguish between rain/no rain days in this study. When considering all days within the study period, IMERG detected the highest frequencies of both trace and tiny precipitation, which both fall below the rainfall threshold. In regions experiencing more rainfall, both SPE products appear to generally have lower FARs, particularly PERSIANN-CDR. Lower FARs may be attributed to more rainfall events occurring within an SPE product grid at any given time, therefore having a higher probability of being detected by the satellite.

Over the entire period (2006–2015), IMERG was capable of capturing the largest frequencies of smaller intensity rainfall events (trace and tiny precipitation). IMERG appears to be less capable of estimating moderate and heavy intensity events, particularly in the wet seasons. This may explain why IMERG has an overall larger underestimation of rainfall in the wet seasons. In contrast, PERSIANN-CDR appears to capture larger frequencies of moderate and heavy intensity precipitation events in the wet season as compared to IMERG. Furthermore, it is clear that both SPE products fail to capture some of the largest intensity precipitation classes (high heavy and violent), particularly in the wet season. These may be more localised events which appear to be captured better by point-based rain gauges.

Table 3 provides a summary of the relationships between SPE products and rain gauge data at different temporal aggregations. The precipitation detection capabilities of both SPE products may have implications on potential applications. For example, PERSIANN-CDR may be more applicable for use in daily-scale hydrological modelling of river catchments in Trinidad, because of its ability to capture a larger frequency of moderate and heavy intensity rainfall events, which may contribute to larger surface runoff, than if IMERG were to be utilised.

7. CONCLUSIONS

The findings of this research have highlighted some differences in how two SPE products estimate rainfall over Trinidad and **Table 3** summarizes the relationships between SPE products and rain gauge data at different temporal aggregations. IMERG generally has weak correlations with rain gauge data at all temporal scales assessed, while PERSIANN-CDR has strong correlations at the monthly scale and dry season scale.

PERSIANN-CDR provides a better representation of mean monthly rainfall totals and can therefore be considered for use in long-term assessments of monthly rainfall over the island. For mean seasonal rainfall totals, IMERG underestimates less in the dry seasons, and more in the wet seasons. Both SPE products also show spatial variability, with larger underestimations occurring in the wetter northeast region of the island.

With regard to rainfall detection, PERSIANN-CDR generally has a higher probability of detection than IMERG. Both SPE products appear to also have limitations in capturing the largest intensity precipitation events. Further calibration of both SPE products may be required before they can be utilised as a proxy for rain gauge measurements in Trinidad. Future research can be conducted on an assessment of sub-daily satellite rainfall data, particularly IMERG, however sub-daily data must first become available for the rain gauges on the island.

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