An assessment of Tropical Cyclone Rainfall Characteristics within the Eastern Caribbean.

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Abstract

Precipitation generated by tropical cyclones contribute to major losses of property and life in the Caribbean. Owing to the sparse regional monitoring network, estimates of damage and loss and exposure to disaster risk often rely on rainfall estimates from satellite and reanalysis products but their accuracy remains uncertain. Precipitation intensities and amounts from the TRMM, PERSIANN and ERA-Interim products were compared against rain-gauge measurements from seven tropical cyclones between 2004 and 2010 using measures of central tendency, categorical statistics and correlation. Results show that satellite estimated intensities and reanalysis products can resolve the TCs precipitation reasonably well. However, precipitation products underestimated the rainfall depths relative to the gauges. All of the datasets were non-Gaussian with the low-intensity events being far more frequent than high-intensity events. ERA-I over-predicted the occurrence of light rain (0-2.5 mm/hr), PERSIANN was most accurate in matching the observed frequency, but TRMM produced the most accurate rates. PERSIANN over-predicted the occurrence of moderate rain (2.5-10 mm/hr) but produced the most accurate rates. None of the products detected heavy rain (10-50 mm/hr). More accurate rainfall estimates may be possible by weighting contributions of the various products according to the intensities to which they are most sensitive. In addition a generalized calibration for a given region shows some error but a significant improvement in accuracy for site-specific calibrations.

1. Introduction

Tropical Cyclones (TCs) are known to be highly destructive, particularly when impacting populated regions; where the loss of property, life and livelihood can be devastating. In the last 150 years, the Eastern Caribbean were struck by 38 major hurricanes (≥ Cat. 3) and hundreds of tropical storms (CHN, 2013). The typically small size of the island states exposes a large proportion of the total produced capital to the risk of hydrometeorological hazards like TCs (UNISDR, 2013). Therefore, it is no surprise a major impact of repeated TCs in the Caribbean over the decades has been “sluggish” economic growth (UNISDR, 2013). The annual direct and indirect losses is approximately 6% of the gross domestic product (GDP) in some countries. These losses are anticipated to increase owing to climate change (Cavallo and Noy, 2010; Ghesquiere and Mahul, 2010).

Records show that more people die from storm surge and rainfall-induced hazards like floods and landslides resulting from TCs than from the associated strong winds. Accurate precipitation estimates are therefore essential for forcing hydrological models (Bastola and Misra, 2013) and predicting damage and loss (CCRIF, 2012). However, in the Caribbean, sparse monitoring networks and typically low measurement frequencies created a data scarce environment. Remote sensing and reanalysis products, are alternative methods, which offer significant potential for supplementing measurements in data sparse areas.

While remote-sensing products provide independent, reliable, real-time data, they are not as accurate as ground-based measurements. Routine use of these data to make defensible decisions requires that relationships be established with ground-based data (Scott, 2011). In other regions, estimates of precipitation from satellite and reanalysis products have been validated on daily (Sapiano and Arkin, 2009, Almazroui, 2011), monthly (Yilmaz et al., 2005; Villarini and Krajewski, 2008; Almazroui, 2011) and seasonal (Almazroui, 2011) time scales. However, to the best of our knowledge, none have been performed nor reported for the Eastern Caribbean (Scott, 2011). The objective of this study was to validate precipitation estimates from satellite and reanalysis data for TCs in the Eastern Caribbean.

2. Data and Methods

a. Study Area

The study area is the Eastern Caribbean, which consists of approximately 50 islands forming a 1000-km arc at the eastern boundary of the Caribbean Sea. The island chain is in the hurricane-active zone of the North Atlantic basin. The precipitation regime is dominated by a summer wet season (Jun – Nov), which also coincides with a TC season that brings high winds and torrential rains.

b. Datasets

Archived rainfall data were obtained from 11 rain gauge stations on islands affected by the storms during the period 2004 to 2010 and used to validate satellite rainfall products and one reanalysis product. Data for this study were sourced from Hewanorra and George Charles in St. Lucia; Maurice Bishop in Grenada; E.T Joshua in St. Vincent and Crown Point in Tobago. Martinique provided data from gauges at Lamentin, Morne Rouge, Ste-Anne, Saint-Pierre, Trinte and Vauclin (Figure 1). Owing to their proximity (7.8 km), the Morne Rouge and Saint-Pierre data were combined and averaged. With the exception of Martinique, data were 6-hourly accumulations starting at 12:00 UTC and obtained from a single gauge. Data from Martinique were 1-hourly accumulations from 6 tipping bucket rain gauges. Given the higher spatial and temporal resolution of the Martinique dataset, these data are the focal point of this analysis.

Satellite data were sourced from the Tropical Rainfall Measuring Mission (TRMM) multi-sensor precipitation product (3B42) and the Precipitation Estimation from Remotely Sensed Information Using Artificial Neural Networks (PERSIANN) product. Reanalysis data were sourced from the European Centre for Medium-Range Weather Forecasts (ECMWF), ERA-

Interim (ERA-I). The TRMM is a joint USA–Japan satellite mission for monitoring tropical and subtropical precipitation. Instrumentation is described by Kummerow et al. (1998) but the principal precipitation measuring instruments are the TRMM Microwave Imager (TMI) and the Precipitation Radar (PR). Algorithm 3B42 produces precipitation and root-mean-square error (RMSE) estimates on a 0.25° (~25-km) grid every 3 hours (Huffman et al., 2004). PERSIANN is an automated system developed to estimate precipitation from remotely sensed infrared imagery (Sorooshian et al., 2000). PERSIANN data are also generated on a 0.25° (~25-km) grid every 3 hrs. The ERA-I is a global reanalysis of recorded climate observations for the period 1979 to present. Estimates of precipitation are available on a 0.75° (~75-km) grid from two forecasts which are produced every 3 hrs initialized at 0000UTC and 1200UTC (Dee et al. 2011).

c. Tropical Cyclones

A total of 116 TCs traversed the North Atlantic basin during the period 2004 to 2010. Seven of these either made landfall or near landfall within the Eastern Caribbean. The TCs of interest included Hurricane Tomas (2010), Tropical Storm Erika (2009), Hurricane Dean (2007), Tropical Storm Felix (2007), Hurricane Emily (2005), Tropical Storm Earl (2004), and Hurricane Ivan (2004). Remotely-sensed precipitation amounts and reanalysis data associated with these systems were compared with the gauge data.

d. Analytical Procedures

The analysis is based on direct comparisons of ground-based measurements at gauge stations with station-centred precipitation estimates extracted over a 20-km radius (TRMM and PERSIANN) products or a 47.5-km radius (ERA-I). The gauge situated at the centre of the extracted domain represented the observed amount corresponding to the precipitation estimates. Rainfall estimates were extracted from the precipitation products at 3-hr intervals and spatially averaged for comparison with rain-gauge data.

Different types of rainfall patterns can have significantly different statistical properties. The measures of central tendency were determined using histograms. The ordinary histogram is a function f_i that counts and graphs the number of observations occurring in discrete intervals as a representation of the probability distribution of a continuous variable. The histogram statistic was calculated as follows: the number of rainfall observations i = 1 to n, and k be the total number of bins. Then by definition, f_i must satisfy:

$$n=\sum_{i=1}^{k}(f_i) \tag{1}$$

The cumulative histogram, F_i, of histogram f_j, counts the cumulative number of observations in all of the bins up to some specified bin and is defined as:

$$F_i=\sum_{j=1}^{i}(f_j) \tag{2}$$

Ordinary and cumulative histograms were derived for rain gauge, TRMM, PERSIANN, and ERA-I data using 2-mm/hr bins. Precipitation estimates from TRMM, PERSIANN, and ERA-I were also regressed on observations and the coefficients of determination (R^2) determined for each gauge station. To quantify the performance, categorical statistics including threat score (TS), equitable threat score (ETS), and bias were calculated based on the contingencies in Table 1.

In Table 1, H is a hit, an event forecast to occur, that did occur. M is a miss, an event forecast not to occur, but did occur. F is a false alarm, an event forecast to occur, but did not occur. Z is a correct negative, an event forecast not to occur, that did not occur. In this context, an event is a threshold of interest. As an example, H would be the number of correct predictions of intensities above a specified threshold whereas Z would be the number of correct predictions of intensities below that threshold. Thresholds for light (0 – 2.5 mm/hr), moderate (2.5 – 10 mm/hr), heavy (10 -50 mm/hr), and violent (> 50 mm/hr) rainfall intensities (AMS, 2000) were used with Table 1 to evaluate skill in detecting storm types. The resulting tallies were used to calculate the treat score according to Stanski et al. (1989):

$$TS = \frac{H}{H + M + F} \tag{3}$$

The TS gives high scores for accurate (high skill) estimates. For a skilled estimator, H=1 and M=F=0 to yield a TS of 1. For an unskilled estimator, H = 0 to yield TS = 0. Owing to the sensitivity of the TS to the climatology of the events, it tends to give lower scores (low skill) for rare events. The equitable threat score (ETS) corrects for this tendency and is simply a modification of the threat score that accounts for correct forecasts due to chance (Stanski et al., 1989):

$$ETS = \frac{H - H_r}{H + M + F - H_r} \tag{4}$$

where H_r = hits due to random chance and is given by:

$$H_r = \frac{(H + M)\,(H + F)}{N} \tag{5}$$

and N is the sample size. The ETS ranges from -1/3 to 1, with 0 indicating no skill and 1 being skilled. The bias compares the forecast frequency of events to the observed frequency and is defined as:

$$\mathrm{BIAS} = \frac{H + F}{H + M} \tag{6}$$

BIAS ranges from 0 to ∞ and indicates whether the estimator has a tendency to under-forecast (BIAS<1) or over-forecast (BIAS>1) events. The root mean square error (RMSE) was used to quantify differences between estimates ($\hat{Y}_i$) and observations (Y_i), and was calculated as:

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\hat{Y}_i - Y_i)^2} \tag{7}$$

The RMSE is a good measure of accuracy; here it is used to compare forecasting errors of the precipitation products. It gives a relatively high weight to large errors so it is most useful when large errors are undesirable. The RMSE ranges from 0 to ∞, with a 0 being a perfect score.

3. Results and Discussion

a. Comparison of the 3-hr rainfall rates

The comparison of the intensities obtained from satellite and reanalysis products during hurricane Tomas (Tomas) are compared with gauge data from Lamentin in Martinique and are shown in Figure 2. The most striking observation is the difference in intensities. The gauge data show the highest rate (10.2 mm/hr), which is 1.4 times the rate recorded by the TRMM (7.07 mm/hr) and the PERSIANN (7.29 mm/hr) and 1.7 times the ERA-I rate (6.07 mm/hr). These differences are partly attributed to the differences in temporal resolution. While the rain gauge data were collected at 1-hr intervals, the products were reported every 3 hrs. At the finer temporal resolutions (Fig. 1a-c), the increase in maximum values is clear. This observation is consistent with the findings of Georgakakos et al. (1994) who reported a four-fold increase in intensity, from 30 mm/hr at a 10-min resolution to almost 120 mm/hr at 1-min and 10-sec resolutions.

Some of the discrepancies can also be attributed to differences in spatial resolution. Undoubtedly, averaging of the ERA-I estimates over a larger area (47.5-km radius) versus the satellite products (20-km radius) contributes to greater smoothing and thereby a smaller peak and smaller variance (smoother curve) for the ERA-I data (Fig. 1d). For mountainous regions of the tropics, the World Meteorological Organization (WMO) recommends 1 station for a 100 – 250 km^2 area whereas 1 station for a 250 – 1000 km^2 is considered acceptable. Even then, a WMO standard rain gauge provides a point measurement of the distribution of a storm over a given area from an inlet diameter of 15.95 cm or orifice area of 200 cm^2. The footprint for TRMM and PERSIANN footprint is 625 km^2 and around 5×10^3 km^2 for ERA-I. Spatial variability in rainfall rates, especially during convective precipitation, may therefore introduce uncertainty into estimates of spatially-averaged rainfall that cannot be easily quantified with the sparse monitoring networks.

Finally, some inherent errors may be due to data quality. Tipping-bucket rain gauges are known to be affected by wind blockage, eddies, and wetting losses, all of which could be important during a TC. Uncertainty in satellite-retrieved estimates related to spatial and temporal sampling have been discussed by other authors (e.g. Bell and Kundu, 2000; Steiner et al., 2003, Bowman, 2005). In the context of the Eastern Caribbean, the 25-km spatial resolution and the 3-hr temporal resolution are still relatively coarse and could also add to the uncertainty in TRMM and PERSIANN estimates. Possible sources of errors in the ERA-I data include faulty measurements that were assimilated into the model.

Intensity differences translate into different total accumulations over the 40-hr monitored period. A comparison of the mean total accumulations shows significant differences between the gauges (168.08 mm) and the estimation products. For the same period, TRMM estimates totalled to 82.66 mm compared to 116.20 mm for PERSIANN and 97.31 mm for ERA-I. Such large differences in rates and depths have implications for parameterizing models for loss projection and weather-related hazards. These discrepancies will invariably increase the uncertainty in timing the onset and duration of the rainfall events and the impact of rainfall-induced hazards.

To determine the significance of the observed differences, statistical methods were used to compare the intensities. First, an F-test was conducted to test the null hypothesis that the variances were different. The F-test showed that the variance of the observations (14.30) was not significantly different ($\alpha = 0.05$) from the variance of the TRMM (5.92). However, the variance of the PERSIANN (4.72) and ERA-I (4.02) were both different from the observations. The large variance in the observations is attributed to the higher temporal resolution. To determine the significance of differences in the means, a two sample t-test was conducted, assuming equal sample variances (gauge vs. TRMM) and unequal variances (gauge vs. ERA-I). The t-test shows that the observed mean intensity (4 mm/hr) is not statistically different from the TRMM (1.985 mm/hr), the PERSIANN (2.79 mm/hr), nor ERA-I (2.37 mm/hr).

b. Probability Distributions of 3-hr rainfall rates

Figure 3 shows ordinary and cumulative histograms of rainfall intensity at 2-mm intervals for the rain gauge and precipitation products for Tomas. These plots represent all of the data collected at the six gauge stations in Martinique (N = 70). The observations and estimates show very different distributions. It is known that different types of rainfall patterns can have significantly different statistical properties. The most striking observation is the non-Gaussian distribution for the 4 products. If the zero intensities are ignored in the rain-gauge data the ordinary histograms all show a truncated distribution with the peak near the origin at 2 mm/hr and a gentle trailing off to intensities over 10 mm/hr.

This is indicative of a process in which part of the distribution has been removed through screening. In this case, intensities at a temporal resolution less than 1-hr have been effectively screened out. In the literature, rates have been reported to increase by a factor of over 4 in going from a resolution of 10-min resolution to 1-min (Georgakakos et al., 1994). These distributions are not at all surprising as one of the main statistical features of intense rainfall fields at spatial scales between about 1 and 200 km and temporal scales between a few minutes and several hours is that they have a non-Gaussian probability distribution of intensity both in space and time (Rebora et al., 2006).

The choice of technique used for the measure of the central tendency, to estimate missing data, or for downscaling are all influenced by the probability distribution as all of these procedures must be able to reproduce the observed statistical properties. It is now known that techniques developed for mid-latitude precipitation may not be applicable to the topics (Rebora et al., 2006). Therefore an essential step in the interpretation and use of rainfall in tropical latitudes is identification of the most appropriate probability distribution. These data show a clear dependence of the distribution on sampling resolution.

Figure 4 compares the 1-hr observations from Martinique during Tomas with the TRMM, PERSIANN, and ERA-I estimates at 2-mm/hr intervals. All of the products follow an approximate exponential distribution, with the lower intensity events being far more frequent than higher intensity. The ERA-I data, which was most Gaussian in distribution, shows a monotonic decrease. All of the products, except the PERSIANN, show a mode of 2 mm/hr; the mode of the PERSIANN occurred at 4 mm/hr. Figure 4 also shows that the TRMM and ERA-I overestimate the occurrence of the lowest-intensity (2 mm/hr) events. However, the frequency of the rain gauge and PERSIANN estimate are essentially the same. There is no significant difference between the number of 4-mm/hr occurrences detected by the rain gauge and the TRMM but they are overestimated by both the PERSIANN and ERA-I. The 6-mm/hr occurrences are over-estimated by PERSIANN and underestimated by the TRMM. The estimates show similar skill at 8 and 10 mm/hr. These data show that heavy rainfall events (10-50 mm/hr) were very rare, occurring only twice with the rain gauge and once with the TRMM.

c. Performance of Estimates

The estimates were assessed using categorical statistics according to Table 1 and the results are summarized in Table 2. ERA-I scored the most hits (56%) during light rainfall, with the TRMM the second most (53%) and the PERSIANN the lowest (39%). Based on threat scores, ERA-I was the more skilled in detecting light rain (TS=0.81) and extreme events (ETS=0.57), than TRMM (TS=0.76) and PERSIAN (TS=0.64). However, the ERA bias was highest (1.18) suggesting a tendency to over-forecast light rain relative to TRMM (1.15) and PERSIANN (0.73). The low PERSIANN bias is consistent with Fig. 3, which showed identical occurrences for PERSIANN and rain gauges. The TRMM estimates showed the lowest error (RMSE=0.69) and PERSIANN the highest (0.76) so although TRMM tends to over-forecast the number of occurrences relative to PERSIANN the estimated intensities are more accurate.

During moderate rainfall, PERSIANN scored the most hits (37%) and TRMM the lowest (27%) but ERA-I show the highest threat score (TS=0.70). The higher PERSIANN hits in the 2.5

– 10 mm/hr range is due to its over-forecasting in the 4 – 6 mm/hr range (Fig. 3). This is reflected in the higher bias (1.46). Both ERA-I and TRMM showed the same amount of bias (0.82). The lowest RMSE was for PERSIANN (2.52 mm/hr) when compared to ERA-I (2.86 mm/hr) and TRMM (2.66 mm/hr). These results suggest that PERSIANN estimates of intensity would be the most accurate in this range. A skilled estimator would have RMSE = 0 so a value of 2.52 is quite large. Table 2 shows that none of the products detected rainfall in the heavy (10 – 50 mm/hr) category. Although TRMM reported a rate of 11.12 mm/hr, it was not recorded as a hit but as a false alarm. Therefore, for all the products H=0 and TS=0. As a result, BIAS and RMSE were incalculable.

To further characterize the relationship between the estimates and observations, a simple regression was performed (Scott, 2011). The correlation between two normal random variables is considered statistically significant if the sample correlation coefficient, r, is greater than $r^* = 2/\sqrt{N}$. Correlation of the estimates for all TCs against the entire rain gauge network across all the islands (N=143, r^*=0.167) resulted in r values of 0.518 (TRMM), 0.571 (PERSIANN), and 0.343 (ERA-I). When compared to r^*, all of the correlations are statically significant ($\alpha<0.05$). However, the high bias for TRMM (0.55), PERSIANN (0.78) and ERA-I(-1.48) as well as high RMSE of 4.24 mm/hr, 3.35 mm/hr, and 3.64 mm/hr for TRMM, PERSIANN, and ERA-I, respectively limits use of the relationship for correction or prediction.

In attempt to improve the accuracy of the estimates, data from individual storms were correlated and compared to the critical values. Although the correlations improved, the bias and RMSE scores were still quite high (Scott, 2011). Figure 5 shows cross plots and correlations of estimates and observations during Tomas regressed for Martinique only. The network mean r's were 0.62 for TRMM (Fig. 4a), 0.62 for PERSIANN (Fig. 4b), and 0.67 for ERA-I (Fig. 4c), which when compared to r^*=0.24, are all statistically significant (α = 0.05). Visual inspection shows that even though the correlation is significant, product accuracy is limited. This is supported by the high RMSE and non-zero bias. Values of RMSE were 2.69 mm/hr for TRMM, 2.48 mm/hr for PERSIANN, and 2.40 m/hr for ERA-I. Values of the bias were -0.56 for TRMM, -0.12 for PERSIANN, and -0.58 for ERA-I, suggesting that all of the products underestimated intensity.

When precipitation estimates were regressed on observations at individual gauges in Martinique during Tomas, the correlations were dramatically improved with r ranging from 0.45 to 0.83. With the r^* = 0.53, many of the correlations were significant but the best are shown in Fig. 4d-f. The most predictive relationship for the TRMM (r = 0.79) was derived from the Vauclin gauge (Fig. 4d). The gauge at Morne Rouge/Saint-Pierre provided the best relationship for the PERSIANN with r = 0.78 (Fig. 4e) and the ERA-I with r = 0.83 (Fig. 4f). For the TRMM the bias increased from -0.56 to 0.59, going from under-prediction to over-prediction at the local scale. For the PERSIANN, bias increased from -0.12 to 0.99, from a slight under-prediction to over-prediction, whereas for ERA-I, it increased from -0.58 to -0.41, an improvement but still an under-prediction.

In terms of the accuracy of the predictions, the RMSE for TRMM decreased from 2.69 mm/hr to 1.86 mm/hr; for the PERSIANN it remained essentially unchanged (2.45 mm/hr) whereas it decreased from 2.40 mm/hr to 1.51 mm/hr for ERA-I. Overall, ERA-I appears to be the most accurate with the lowest RMSE and smallest bias. These findings suggest that a generalized calibration for the region may have significant error but the error can be reduced through site-specific calibrations.

4. Conclusions

Knowledge of the amount and distribution of rainfall resulting from TCs is essential for quantifying and managing disaster risk. Owing to the sparse rainfall monitoring network in the Caribbean and infrequent data collection, satellite and reanalysis products offer potential to reduce uncertainty in rainfall estimates. However, routine use of products like TRMM, PERSIANN and ERA-I, especially for damage and loss models, require calibration against ground-based rain gauge data.

Rain gauge intensities were almost 2 times those estimated by the precipitation products and the spread about the mean was higher. Differences in rates resulted in accumulation ratios (products : gauge) ranging from 0.49 (TRMM) to 0.7 (PERSIANN) for the same period. The higher mean intensity and variance in the rain gauge data are attributed to the higher temporal resolution. These discrepancies are likely to increase the uncertainty in timing the initiation and duration of rainfall-induced hazards and ultimately loss projections for insurance products.

Probability distributions of intensity, which are essential for downscaling and the estimation of missing values, were also calculated. All of the datasets were non-Gaussian and followed an approximate exponential distribution, with the low-intensity events being far more frequent than high-intensity events. Based on threat scores, ERA-I was the more skilled in detecting light rain and extreme events, than TRMM and PERSIAN. However, the ERA bias was highest, suggesting a tendency to over-forecast light rain. The PERSIANN was most accurate in matching frequency of light rain detected by the rain gauges. Although TRMM tends to over-forecast the frequency of light rain relative to PERSIANN the estimated intensities are more accurate with the lowest RMSE. The PERSIANN over-forecasted moderate rainfall but it was the most accurate in matching the intensities. Heavy rainfall events were very rare, and when they did occur, were classified as false alarms. The accuracy of a rainfall estimate comprised of contributions from the different products, weighted according to intensity, may be worth evaluating.

Regression of precipitation estimates on rain-gauge data for the entire network for all the TCs show small, but statistically significant, correlations. However, the high bias and RMSE for the precipitation products limit use of the relationship for correction or prediction. Analysis of individual storms improved the correlations but the bias and RMSE scores remained high. Network mean correlations coefficients were calculated for Tomas over Martinique only. Although the correlations were statistically significant, model accuracy remained low with high RMSE and non-zero bias. In the final analysis, regression of precipitation estimates on observations at individual gauges in Martinique during Tomas produced the best correlations with statistically significant r values ranging from 0.45 to 0.83. The relationships with the lowest RMSE, least bias, and best correlations for TRMM ($r = 0.79$) came from the Vauclin gauge. The gauge at Morne Rouge/Saint-Pierre gave the best results for PERSIANN ($r = 0.78$) and ERA-I ($r = 0.83$). Overall, the ERA-I appears to be the most accurate with the lowest RMSE and smallest bias. While it appears that a generalized calibration for a region may have some error, the error can be reduced through site-specific calibrations.

Rainfall intensities estimated from satellite and reanalysis products can resolve tropical precipitation systems, such as TCs reasonably well. However, there are some fundamental issues that must be recognized when comparing the data sets. It is not unusual for satellite products to record rain over a region when it is not raining at the gauge. Similarly, it often rains at the gauge between satellite overpasses. It is essential that the data be properly averaged in space and time. Work is on-going to evaluate the effect of averaging periods on the accuracy of the relationships.

The sensitivity of relationships between satellite products and rain gauges to the local climatology and other factors has also been reported in the literature for other latitudes. The inter-island as well as intra-island dependence of the relationships raises questions on the validity of generalized calibration for TCs. Undoubtedly a general equation introduces additional uncertainty in the rainfall rates used to force models for predicting the initiation and duration of rainfall-induced hazards estimating damage and loss. These findings suggest that site-specific relationships may be more accurate.

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List of Figures

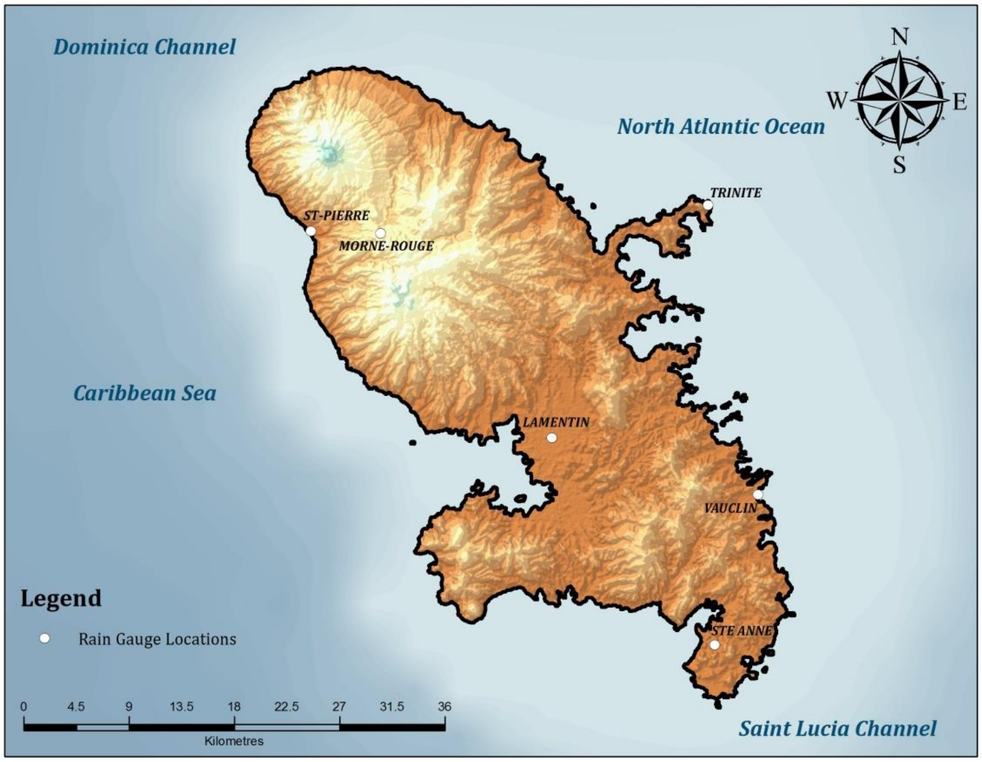

Figure 1. Map of Martinique showing the location of the ground-based monitoring stations.

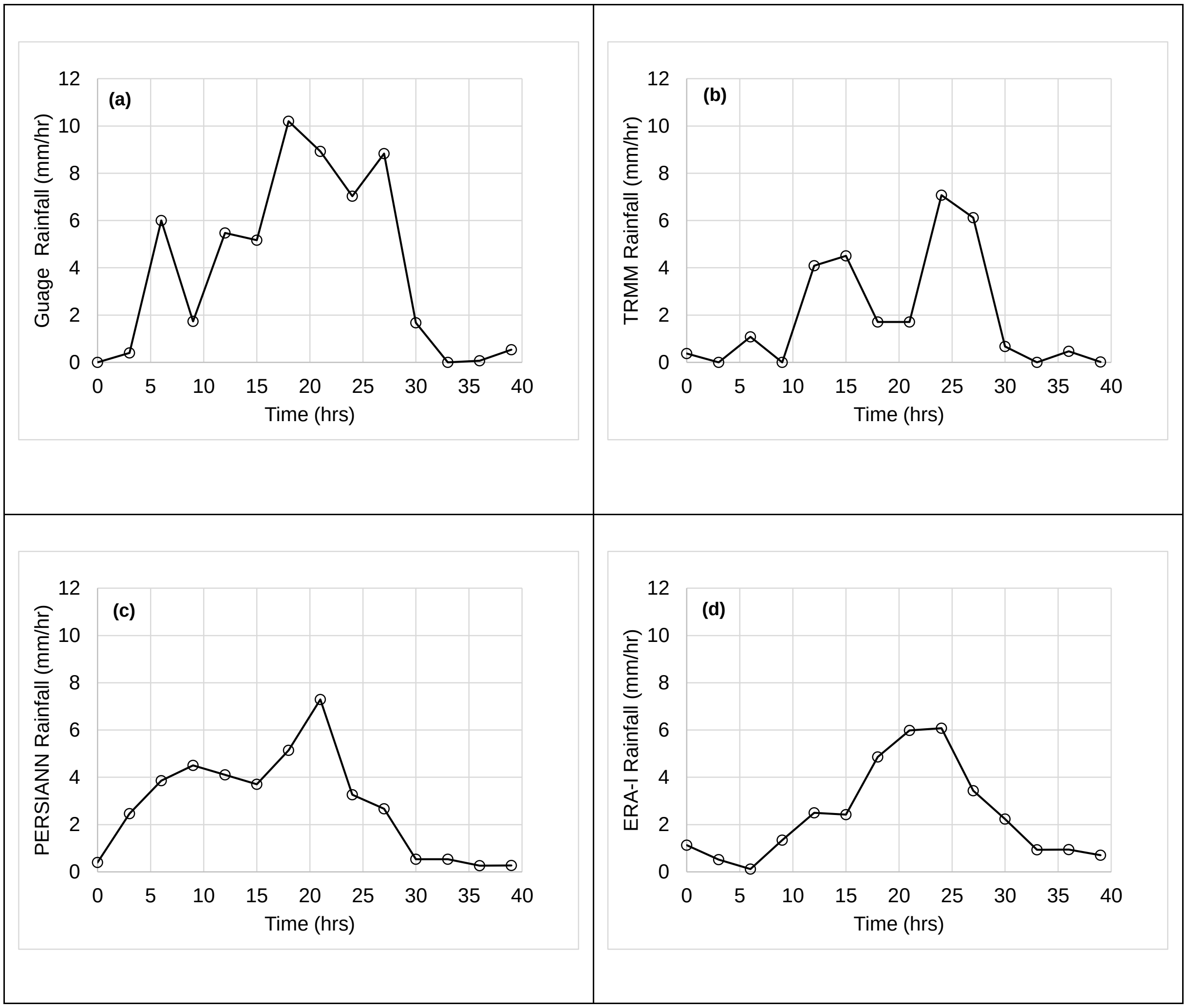

Figure 2. Temporal distribution of rainfall intensities during Tomas from: (a) rain gauge, (b) the TRMM, (c) the PERSIANN, and (d) ERA-Interim. Rainfall is averaged on a 3-hr interval.

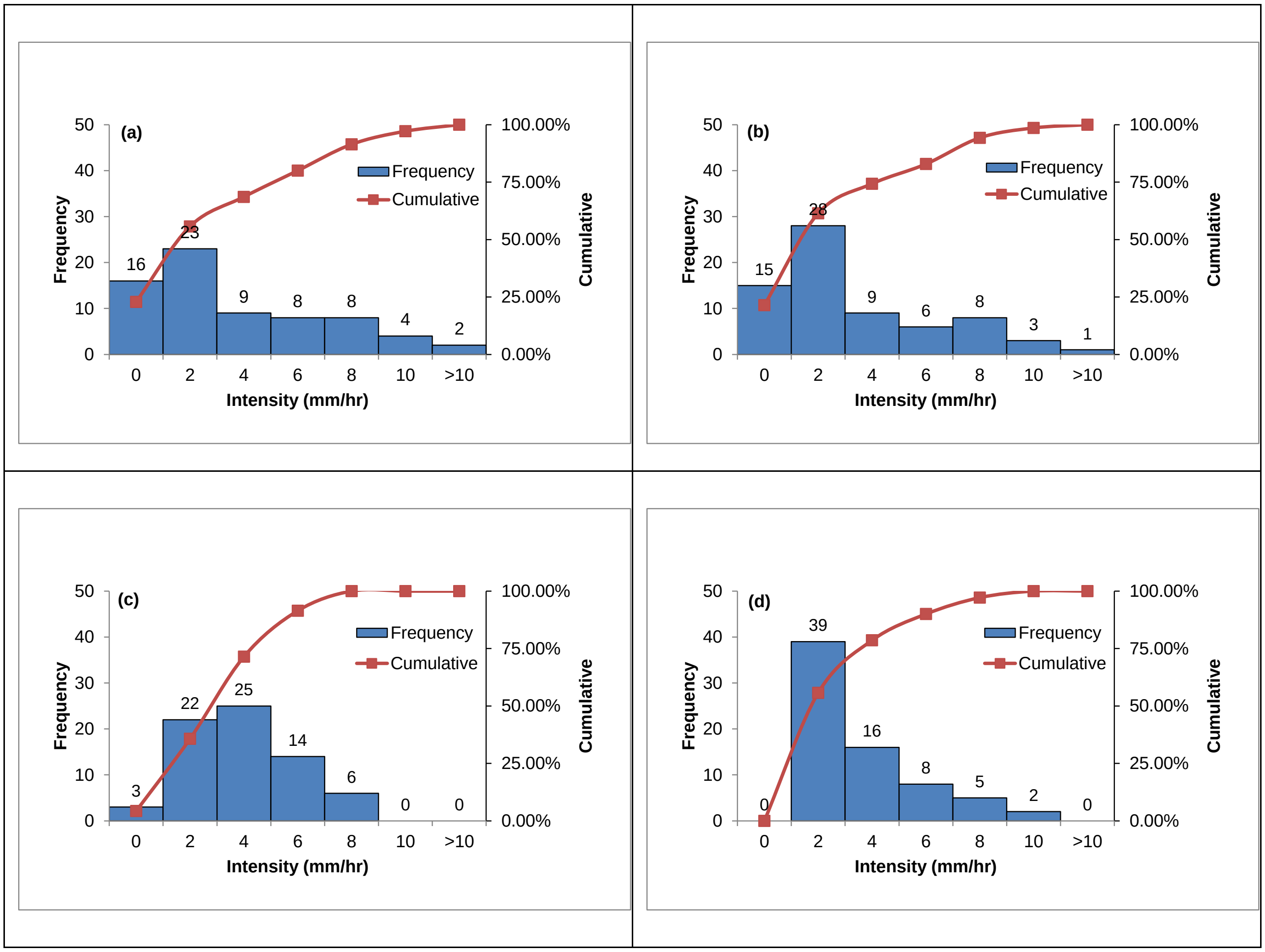

Figure 3. Histograms of rainfall intensity at 2-mm intervals: (a) rain gauge, (b) the TRMM, (c) the PERSIANN, and (d) ERA-I.

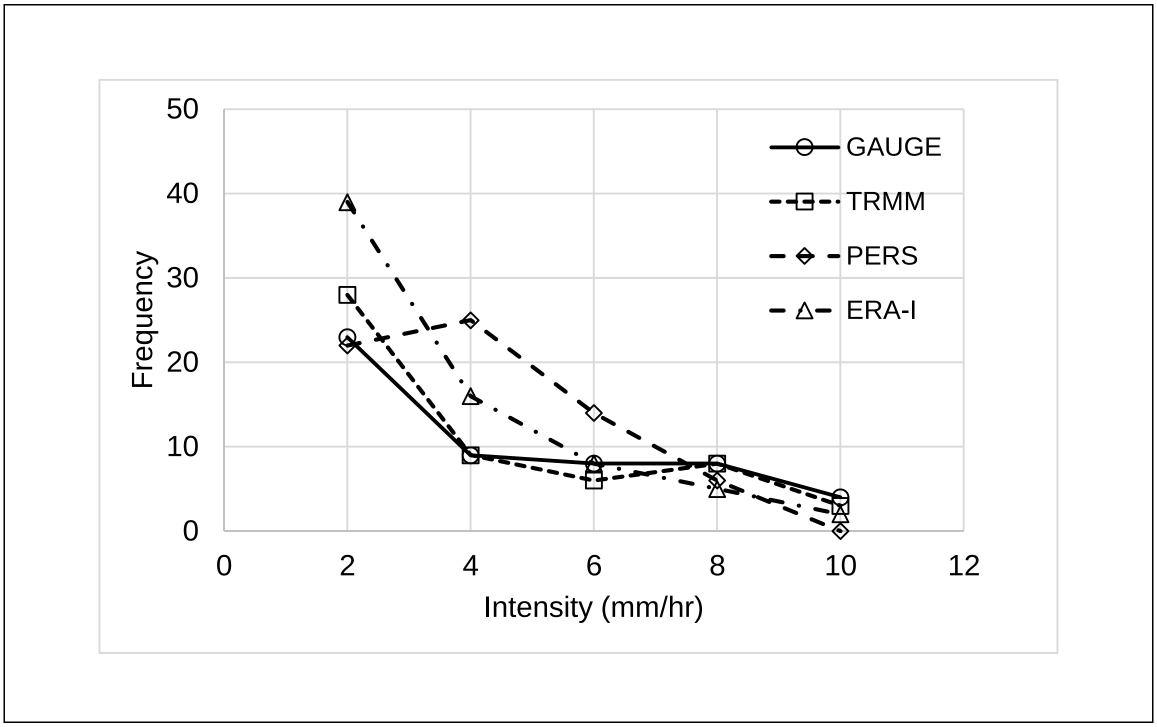

Figure 4. Comparison of gauge data with TRMM, PERSIANN, and ERA-I estimates at 2-mm/hr intervals.

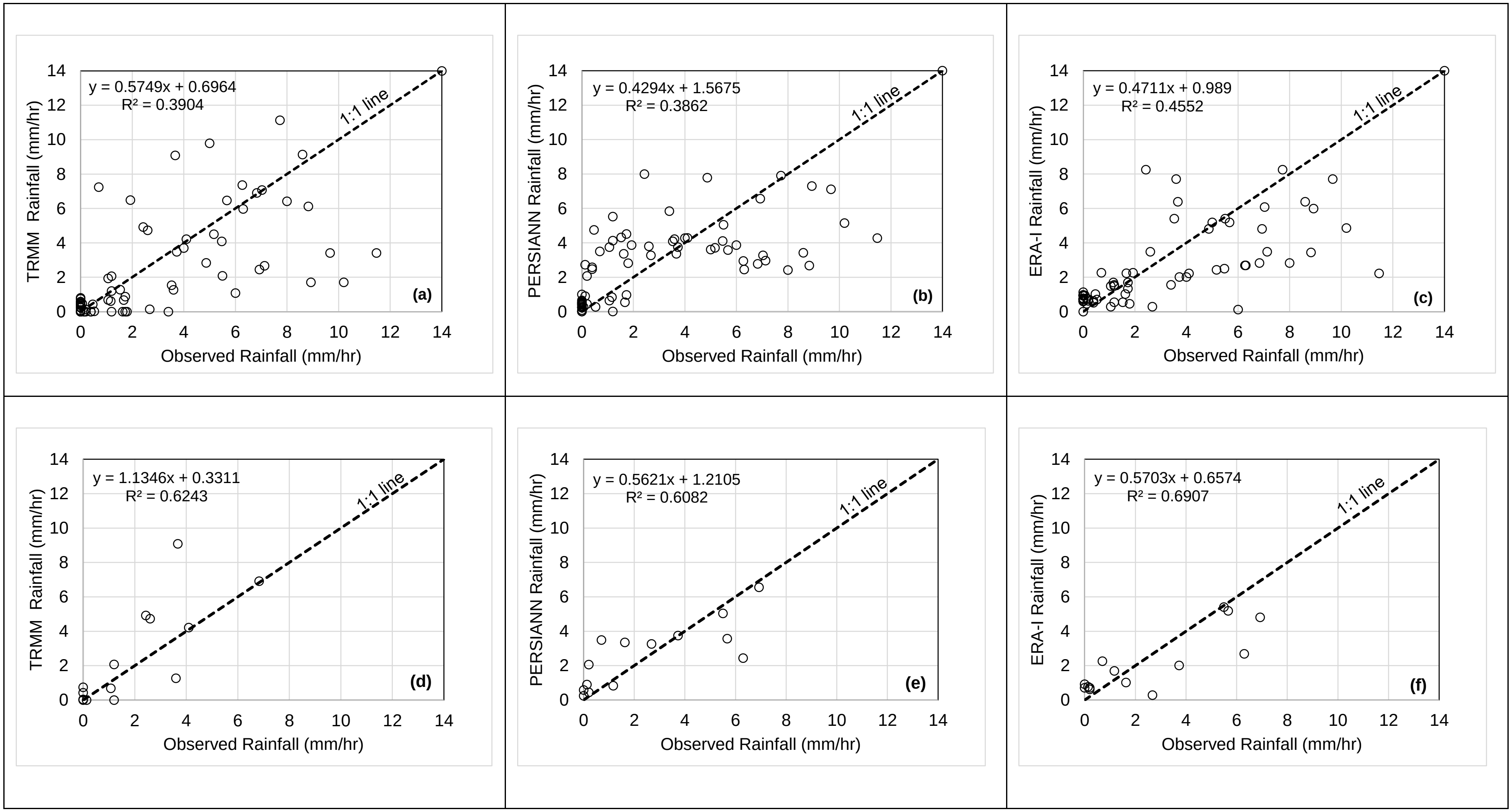

Figure 5. Scatter plots of rainfall intensity from the three products and rain-gauge (a) network average TRMM, (b) network PERSIANN, (c) network ERA-I, (d) TRMM at Vauclin, (e) PERSIANN at Morne Rouge & Saint-Pierre, and (f) ERA-I at Morne Rouge/Saint-Pierre. The diagonal line on each plot represents the 1:1 line expected for a skilled predictor.

Table 1. Contingency table applied at each gauge

Event Estimated	**Event Observed**		
	Yes	No	Marginal Total
Yes	H	F	H + F
No	M	Z	M + Z
Marginal Total	H + M	F + Z	H+ M + F + Z = N

Table 2. Average hits (with percent of total), bias, threat score (TS), and equitable treat score (ETS) for light (0 – 2.5 mm/hr), moderate (2.5 – 10 mm/hr) and heavy (10 -50 mm/hr) rainfall TRMM, PERSIAN and ERA-I data.

Rainfall (mm/hr)	TRMM					PERSIANN					ERA-I				
	Hits	Bias	RMSE	TS	ETS	Hits	Bias	RMSE	TS	ETS	Hits	Bias	RMSE	TS	ETS
0 - 2.5	37 (52.9)	1.15	0.69	0.76	0.47	27 (38.6)	0.73	0.76	0.64	0.41	39 (55.7)	1.18	0.72	0.81	0.57
2.5 - 10	19 (27.1)	0.82	2.66	0.59	0.43	26 (37.1)	1.46	2.52	0.60	0.36	21 (30.0)	0.82	2.86	0.70	0.57
10 - 50	0 (0.0)	-	-	0.00	-0.01	0 (0.0)	-	-	0.00	0.00	0 (0.0)	-	-	0.00	0.00