Evaluation of TRMM Multi-satellite Precipitation Analysis during the passage of Tropical Cyclones over Fiji

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Fiji is prone to the devastating effects of heavy rainfall during the passage of tropical cyclones (TCs) and as such accurate measurement of rainfall during such events is urgent for effective disaster mitigation and risk analysis. Fiji, however, has a sparse distribution of rain gauges, thus there is a deficiency in the accurate measurement of rainfall. This gap could be filled by satellite-based rainfall estimates but before they are used, they need to be validated against a reference dataset for their accuracy and limitations. This study thus validates the TRMM based Multi-satellite Precipitation Analysis (TMPA) estimates over the island of Fiji. The study shows that TMPA has moderate skill in estimating rainfall during the passage of TCs over the island of Fiji. This skill is also highly variable as it decreases with an increase in rainfall intensity, increase in distance from the cyclone centre and increasing terrain elevation. The ability of TMPA also varies case by case but we report a general underestimation of rainfall by TMPA during the passage of TCs with a larger rainfall rate (defined in our case as those TCs with average daily rainfall greater than 25 mm day^{-1}).

Keywords

Validate, TMPA, rainfall estimates, disaster response

1. Introduction

Extreme rainfall during the passage of tropical cyclones (TCs) causes devastating impacts such as flooding, landslide and death (Dare, 2013). The widespread flooding during the passage of TC Evan (2012, a category 4 TC) over Fiji inflicted colossal damage and threatened lives over parts of the country (Government of Fiji, 2013). Extreme rainfall during the passage of the TC exceeded 200 mm day^{-1}.

Accurate information on the magnitude and distribution of rainfall during such events is crucial for effective disaster mitigation and risk analysis particularly by better precipitation forecasting through improved model initialization and numerical weather model evaluation (Ebert et al., 2007; Yu et al., 2009). Fiji (geographical location shown in Figure 1) has a sparse distribution of rain gauges (see

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Figure 2) and accurate spatial and temporal representation of rainfall over this region is limited. This gap could be addressed by utilising satellite-based rainfall estimates.

These estimates, however, need to be evaluated against reference rainfall data, such as rain gauge or calibrated radar data, for their accuracy and limitations before they can be confidently used (Ebert et al., 2007). Under a program of the International Precipitation Working Group (IPWG) and the more comprehensive study called the Pilot Evaluation of High Resolution Precipitation Products (PEHRPP) (Arkin et al., 2006), work has been conducted to validate nearly all operational satellite precipitation products (Ebert et al., 2007).

In addition, some studies have evaluated the Tropical Rainfall Measuring Mission (TRMM) Multi-satellite Precipitation Analysis (TMPA) 3B42 estimates (hereafter referred to as TMPA) of extreme rainfall during the passage of TCs (Habib et al., 2009; Yu et al., 2009; Chen et al., 2013a; Chen et al., 2013c, b; Deo et al., 2016). These studies are over mainland China (Yu et al., 2009), Taiwan (Chang et al., 2013; Chen et al., 2013a), USA (Habib et al., 2009), India (Prakash et al., 2012), the Australian region (Chen et al., 2013b), Pacific atoll and "coastal and inland" sites (Chen et al., 2013c) and over New Caledonia (Deo et al., 2016). These studies in general show that TMPA has moderate skill in representing the observed rainfall but the skill is variable with respect to the magnitude of rainfall, geographical terrain, latitude, structure of the TC and TC intensity.

The above evaluations have broadened our understanding of the skill of TMPA during heavy rainfall events caused by the passage of TCs over the respective regions, but no such information is available for the Fiji region. In this study we evaluate the TMPA estimates over Fiji and show that TMPA has moderate skill in representing rainfall during the passage of TCs over Fiji. We also show that the skill statistics over Fiji differ from those other regions. Thus, this evaluation gives users some insight into the accuracy and limitations of the TMPA product over Fiji.

2. Data and methodology

2.1 TMPA Data

TMPA is a 3 hourly, 0.25º × 0.25º latitude-longitude resolution gridded product which makes use of the following datasets: the TRMM combined instrument (TCI) data comprising the TRMM Microwave Imager (TMI) and the TRMM precipitation radar used as the source of calibration; microwave (MW) data from several Low Earth Orbit (LEO) satellites; the Climate Prediction Centre (CPC-NOAA) infrared (IR) data and the Global Precipitation Climatology Project (GPCP) gridded monthly rain gauge data (Huffman et al., 2007).

TMPA is produced in four stages. First, the MW estimates from individual sensors are calibrated using the TCI and then combined. Second, the IR estimates are created with MW calibration. Third, the MW and IR data are combined such that the MW estimates are taken "as is" with the IR estimates used to fill the gaps. Finally, the monthly rain gauge analysis, which includes the Global Precipitation Climatology Centre (GPCC) analysis, is applied to minimise the bias (Huffman et al., 2007). There certainly is some overlap between the Fiji gauge data and the monthly gauge analysis used for TMPA, however, only a few Fiji rain gauges (about four – five stations out of sixteen; number obtained from GPCC website http://www.esrl.noaa.gov/psd/data/gridded/data.gpcc.html) are used in the monthly analysis. Hence, the Fiji gauge data could be considered as the more accurate rainfall data for this region.

This study utilises the research version (version 7 or V7) of TMPA. The reader is referred to Huffman et al. (2007) for a detailed description of the TMPA.

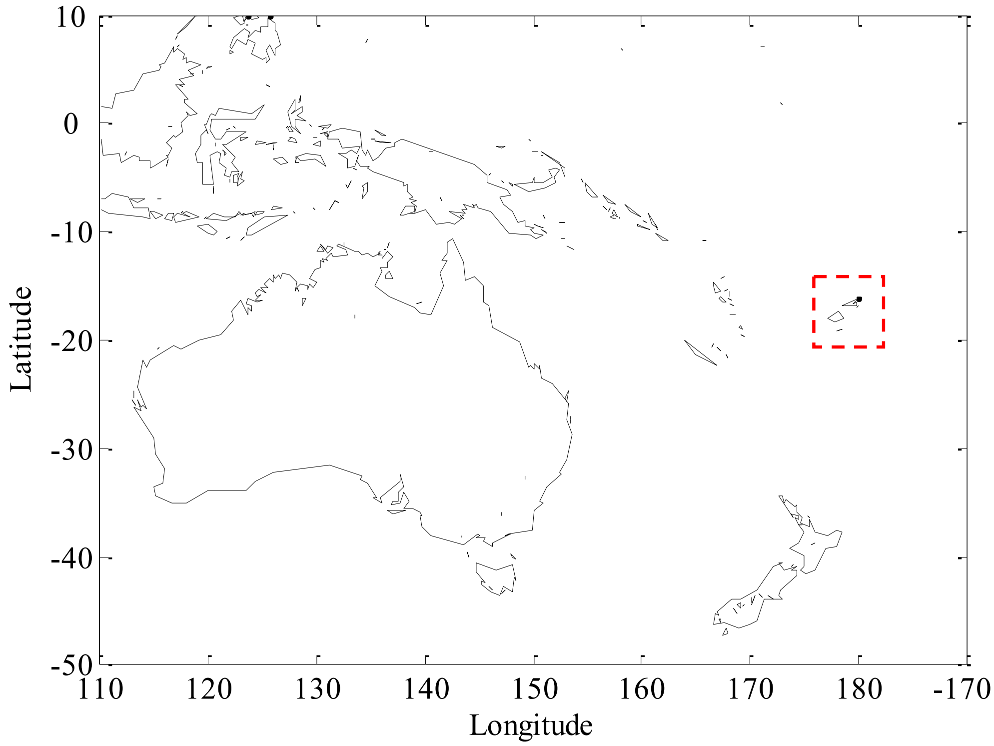

Figure 1 Location of Fiji (enclosed in the dashed red rectangular box) in the south west Pacific basin

2.2 Fiji rain gauge data

We use the Fiji rain gauge daily data to verify the TMPA estimates. The rain gauges, though, are sparsely distributed (Figure 2). The data is quality controlled by the Fiji Meteorological Service (Fiji Met) and only data that have been verified by Fiji Met are used for this study.

Rain gauge data are known to have errors (both systematic and random) with possible effects from obstruction, wind, wetting, splashing, evaporation and calibration (Habib et al., 2008). The wind-induced error is the primary source of a systematic error that increases with an increase in wind speed (Nešpor and Sevruk, 1999; Habib et al., 2008; Wang et al., 2008). As such, the wind-related error will be large during the passage of TCs and this has to be taken into consideration when comparing with TMPA. Accurate observations during extreme weather conditions are further difficult as there is a chance of some degree of uncertainty and propagation of gross, systematic and random errors due to instrumental malfunction during such weather conditions. Nonetheless, gauge data are still considered to be the most accurate and direct measurement of rainfall and the optimal choice for evaluation of satellite precipitation estimates (Ebert et al., 2007; Chen et al., 2013b, c).

2.3 Methodology

Satellites estimates could be evaluated using a grid to grid approach or a grid to point approach where the satellite estimates in the latter approach are interpolated to the gauge stations for a direct comparison. In this study we use the grid to point method (congruent with studies such as Chen et al. (2013c) and Yu et al. (2009)) to evaluate TMPA because a grid based rain gauge dataset is not available for Fiji. TMPA estimates are interpolated to the gauge stations using the inverse distance weighting (*IDW*) technique (Shepard, 1968) that uses the weighted average of data in the neighbourhood of a grid cell. A power function value of two is typically used in the *IDW*. As discussed by Chen et al. (2013c) and Yu et al. (2009), we acknowledge that the interpolation will inevitably introduce some errors since TMPA is an areal-averaged product.

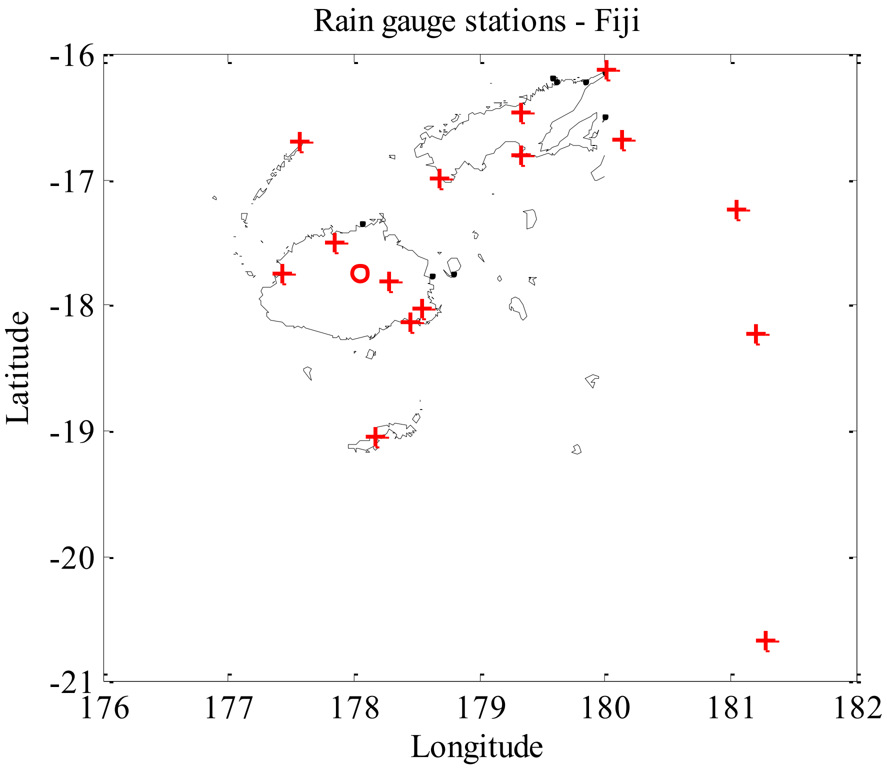

Figure 2 Rain gauge locations over Fiji. The crosses are stations with elevation less than 300 m and the circle is the station with elevation greater than 300 m

The comparison is performed on a daily (24-hour accumulated) basis. The 24-hour rainfall at a gauge station is considered to be TC related and the day is considered to be a "TC day" if the centre of a TC is within 500 km from the gauge station anytime during the accumulation period. The use of the 500 km criteria follows from studies such as Lonfat et al. (2004), Lau et al. (2008), Jiang and Zipser (2010), Nogueira and Keim (2010) and Chen et al. (2013b, c) who define TC rainfall to be mostly within this region. The position and the dates of a TC are obtained from the International Best Track Archive for Climate Stewardship data (IBTrACS) (Knapp et al., 2010) repository that has a six hour temporal resolution. A total of 15 TCs for the period 1998 – 2012 satisfied the above criteria. For the declared TC days, the 3-hour TMPA estimates are summed up to match the gauge accumulation period.

A suite of validation statistics, comprising continuous variable statistics and categorical statistics, is used for the evaluation. The continuous variable statistics used here are the correlation coefficient (r), the relative bias and the root mean square error (*RMSE*). The categorical statistics used here are the probability of detection (*POD*), the false alarm ratio (*FAR*), the frequency bias (*FBI*) and the equitable threat score (*ETS*). The categorical statistics are computed using a contingency table (Table 1) that depends on a rainfall threshold to determine a rain and no rain event. The rainfall thresholds used in this study are shown in Table 2 and the formulae of the statistics (Wilks, 2011) are given in the Appendix.

	Gauge Rain ≥ Threshold	Gauge Rain < Threshold
TMPA ≥ Threshold	Hit	false alarm
TMPA < Threshold	Miss	correct negatives

Table 1 Contingency Table

Rainfall categories (mm day^{-1})	Rainfall Threshold (mm day^{-1})
5 – 15	5
15 – 30	15
30 – 45	30
45 – 75	45
75 – 100	75
> 100	100

Table 2 Rainfall categories and thresholds. Column 1 is for the relative bias and column 2 for the categorical statistics

The uncertainty associated with some of the validation statistics are computed using the bootstrapping technique (Efron and Tibshirani, 1993) which involves re-sampling of the data. We construct 10,000 re-samples with replacement onto which bootstrapping is applied at a 95 per cent confidence level. The 50th percentile is presented as the validation statistic and the 2.5 and 97.5 percentile as the 95 per cent confidence interval.

3. Results

After combining all the TC data, a two dimensional histogram of the data is constructed first and shown in Figure 3. Some notable observations are as follows. There is a general positive linear trend between the TMPA and gauge measurements but still numerous data points have large deviations from the line of perfect agreement (1:1 line). Cases of extreme disagreement, such as a gauge measurement of 0 mm day^{-1} compared with a TMPA of 100 mm day^{-1}, are evident. Even so, the bins with a larger frequency of rainfall events (green, yellow or red bins) fall on the line of perfect agreement. Interestingly, for observed rainfall events greater than 100 mm day^{-1}, a majority of the TMPA estimates are below this value which shows that TMPA generally underestimates heavy rainfall.

Table 3 presents the results of the continuous variable statistics. The correlation coefficient between TMPA and gauge is 0.6 which is a weak linear association between the two. The overall relative bias is -0.015 (1.5 per cent), an underestimation but small in magnitude. The *RMSE* between the TMPA estimates and the gauge is 38.71 mm day^{-1}. This, when compared to the gauge average of 27.07 mm day^{-1} (a relative *RMSE* of 1.43), shows that there are large deviations in the TMPA estimates from the actual ground observations.

Figure 4 shows the relative bias for six categories of rainfall (the rainfall categories are listed in column 1 of Table 2). It is evident that TMPA overestimates light to moderate rainfall events (less than 75 mm day^{-1}) and underestimates large rainfall events. This is consistent with the findings of most of the earlier studies (Yu et al., 2009; Chen et al., 2013c, b).

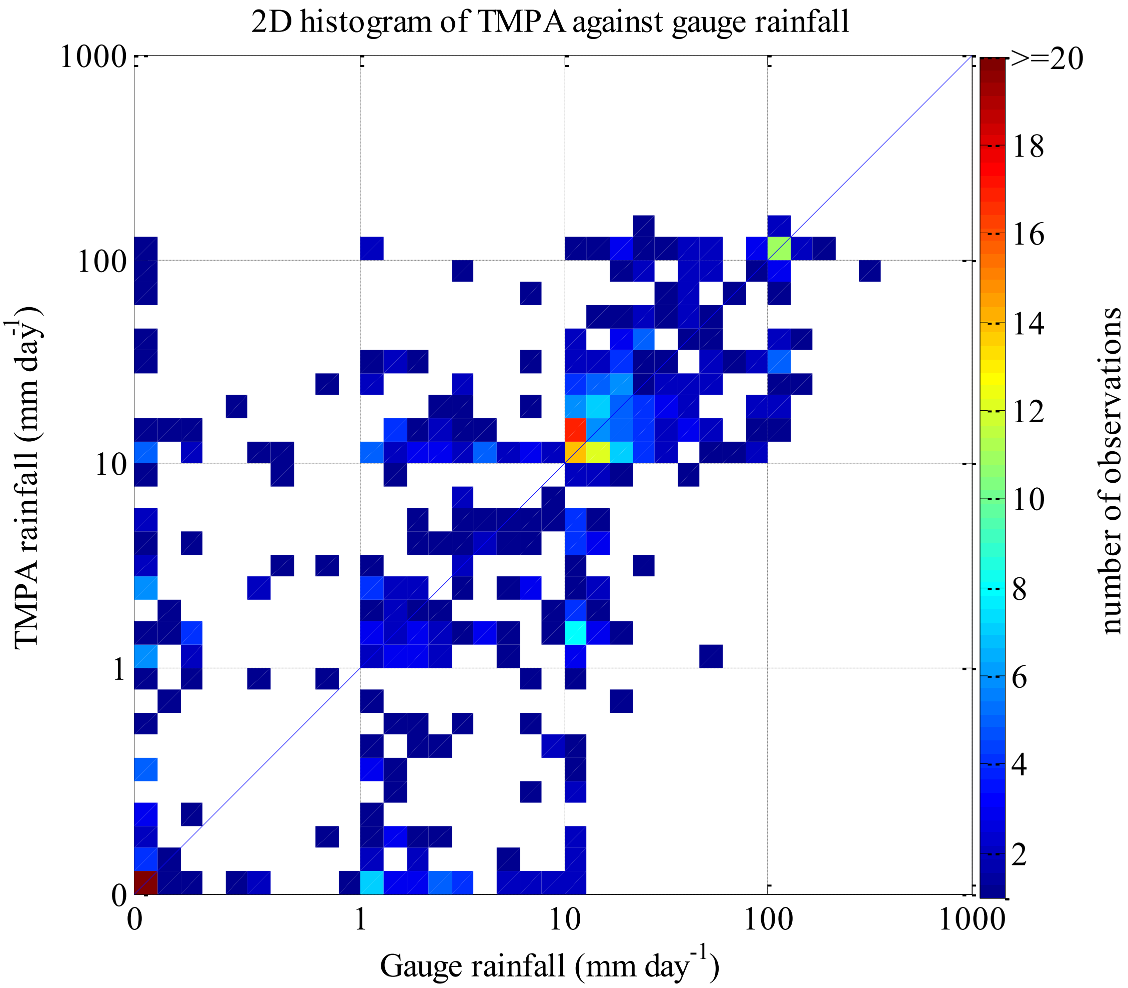

Figure 3 2D histogram of TMPA against rain gauge data together with the line of perfect agreement for the period 1998 – 2012. The colour bar shows the number of observations in each bin

Mean Gauge Rainfall (mm day^{-1})	27.07 (23.53, 31.36)
Mean TMPA Rainfall (mm day^{-1})	26.65 (23.81, 29.91)
Relative Bias	-0.015 (-0.133, 0.101)
RMSE (mm day^{-1})	38.71 (32.50, 53.18)
Relative *RMSE*	1.43 (1.20, 1.96)
Correlation Coefficient	0.60 (0.51, 0.66)

Table 3 Pattern matching statistics for comparison of TMPA estimates with rain gauge observations. The entries in the bracket are the 95 per cent confidence interval.

The categorical statistics (*POD, FAR, FBI* and *ETS*) as a function of six rainfall thresholds (the rainfall thresholds are listed in column 2 of Table 2) are presented in Figure 5. The *POD* and the *ETS* decrease with increasing rainfall rate which shows that TMPA has more difficulty in detecting larger rainfall rates. The *FBI* is around unity at all rain rates which shows that the number of events estimated to occur is almost the same as the number of events that have actually occurred with respect to the given rainfall thresholds. The *FAR* on the other hand increases with an increase in rain rate threshold which shows that of the events estimated to occur more are false alarms at larger rain rates. These results in general show that the skill of TMPA decreases with increasing rainfall rate.

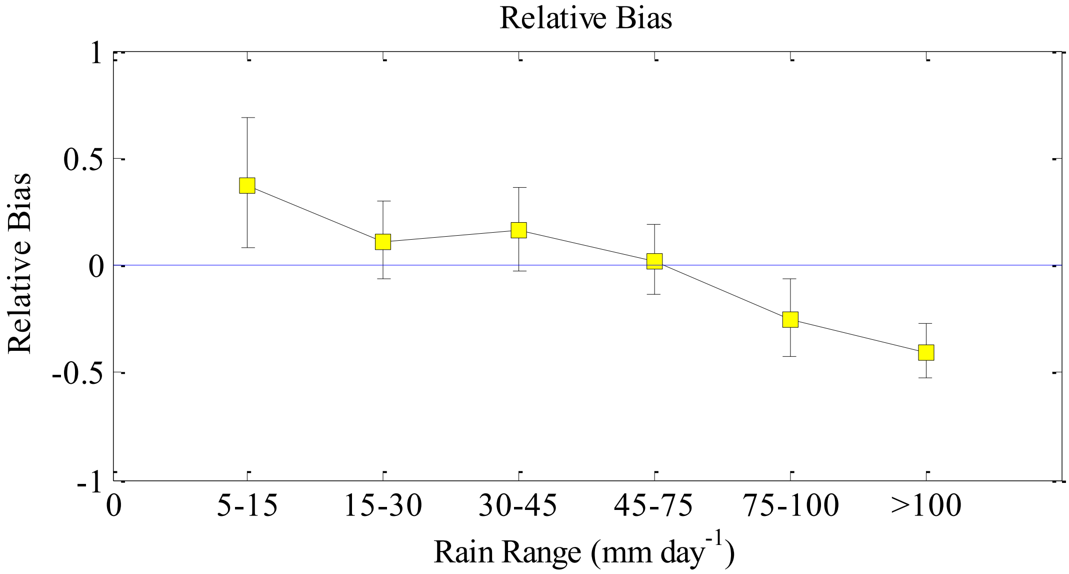

Figure 4 Relative bias as a function of gauge rainfall. The error bars indicate the 95 per cent confidence interval

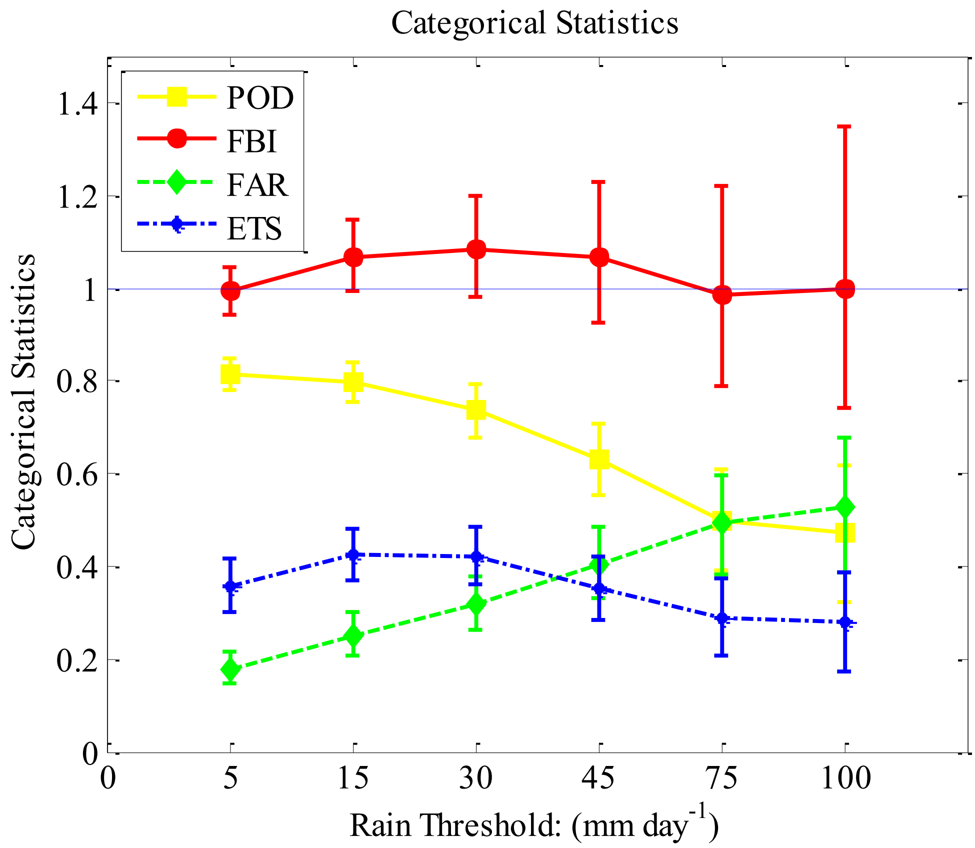

Figure 5 Categorical statistics: POD; FAR; FBI and ETS at rainfall thresholds 5, 15, 30, 45, 75 and 100 mm day^{-1}.The error bars indicate the 95 per cent confidence interval

It is known that TMPA has varying skill with terrain, where the skill decreases with increasing elevation (Chen et al., 2013b). Hence, we examine the data for the same behaviour over Fiji. To facilitate this, we compute the average TMPA and gauge rainfall and the relative bias at each station and these are shown in Figure 6. While there is only one gauge station at higher elevation (800 m at Monasavu) it nonetheless shows that TMPA has less skill at higher elevation. The TMPA average (20 mm day^{-1}) at the higher elevation is significantly lower than the observation (55 mm day^{-1}) with a relative bias of -0.55 (55 per cent), the largest underestimation in comparison to other, lower elevation stations. The observed rainfall at Monasavu is also the largest which could be associated with orographic enhancements.

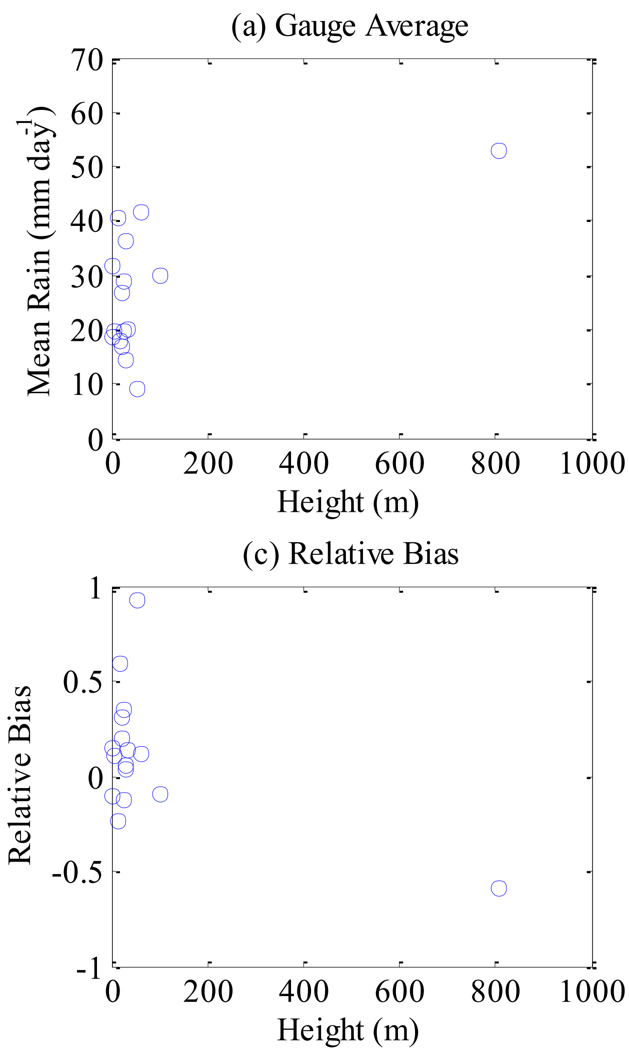

Figure 6 Average TC rainfall of gauge observations (a), TMPA estimates (b) and the relative bias (c) at station sites which have at least 10 samples

Given that most of the heavy rainfalls occur closer to the TC centre, we therefore examine the skill of TMPA with respect to the distance from the TC centre. Samples are grouped into distances < 200 km and > 200 km. This criteria follows studies such as Lonfat et al. (2004) who note that TC regions < 200 km on average could be considered as eye-wall and inner rainfall regions and regions > 200 km as outer rainfall regions. The size and structure of an individual TC would vary however (Kimball and Mulekar, 2004). For the fifteen TCs considered here, heavy rainfall does occur closer to the TC centre as we note that the average rainfall for the < 200 km group is 53.2 mm day^{-1} whereas for the > 200 km group it is 14.7 mm day^{-1}. Figure 7 shows the *POD*, *FAR* and the *ETS* statistics. It is evident that TMPA has more skill near the TC centre (< 200 km). The *POD (FAR)* of the < 200 km group is larger (smaller) than that of the > 200 km at all rainfall rates and the *ETS* of the < 200 km group is larger than that of the > 200 km group especially at larger rainfall rates.

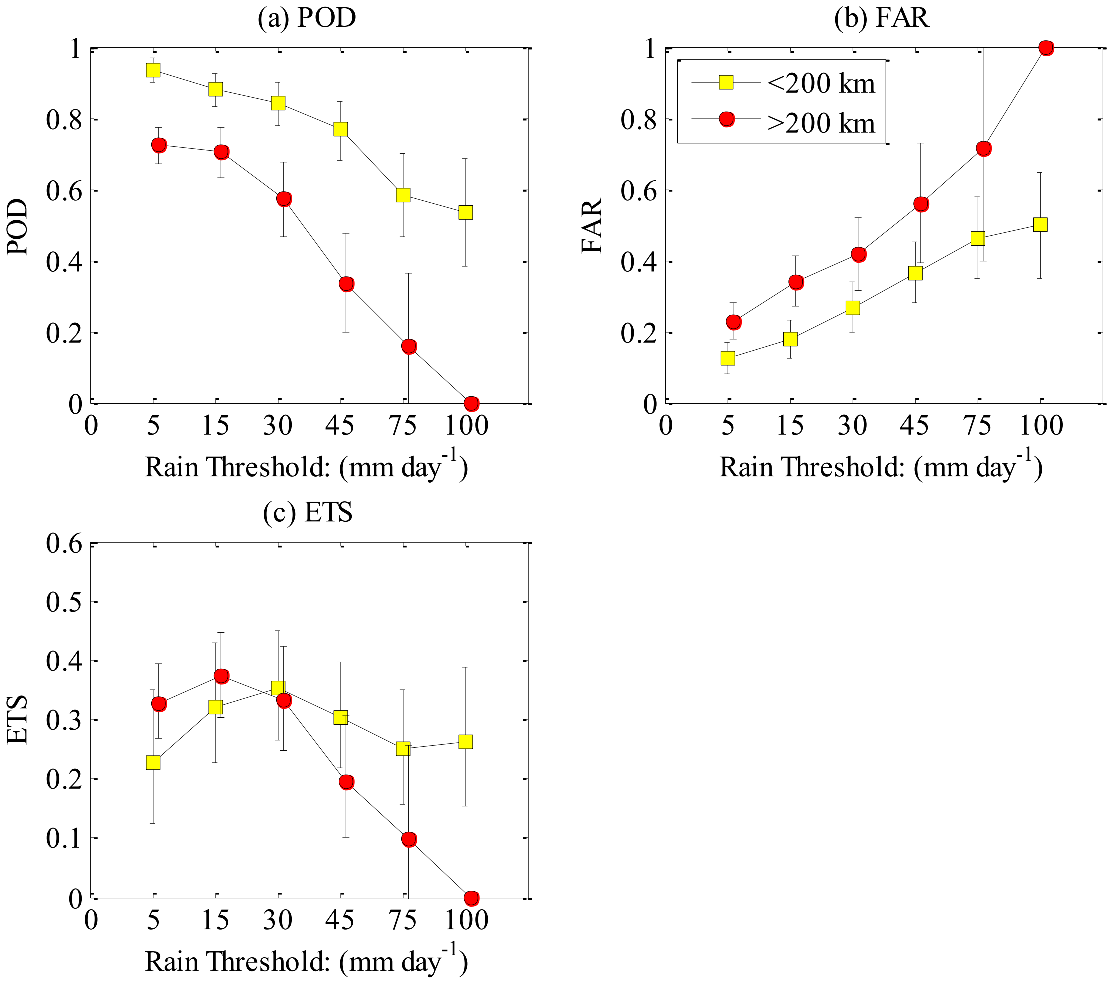

Figure 7 Categorical statistics (a) POD; (b) FAR and (c) ETS for rain within 200 km of the TC centre and greater than 200 km from the TC centre. The error bars indicate the 95 per cent confidence interval

4. Case studies

Figure 8a shows the average TMPA and gauge rainfall and the relative bias of individual TCs. The average gauge rainfall of the individual TCs does not differ much as most of them (thirteen out of fifteen) have values between 20 and 30 mm day^{-1}. Comparing the gauge with TMPA, it is shown that the TMPA average is mostly larger (smaller) than the gauge average for TCs with relatively smaller (larger) gauge average. Correspondingly, for TCs with a smaller average rainfall (TC 1 – 8) we get a relative bias that is mostly larger than zero (an overestimation by TMPA) and a relative bias of mostly less than zero (an underestimation by TMPA) for TCs with a larger average rainfall (TC 9 and above). Yet the confidence intervals for the satellite and gauge values overlap in each case, which suggests that the TMPA values are reasonable estimates of the observed rainfall. The correlation (Figure 8b) is highly variable except that it is lowest for TC 1 which has the lowest average rainfall. Note that the samples of individual TCs (the size of which is shown in Figure 8b) will not be completely independent with each other that is, for each TC day, the errors in the satellite estimates will not be independent of each other.

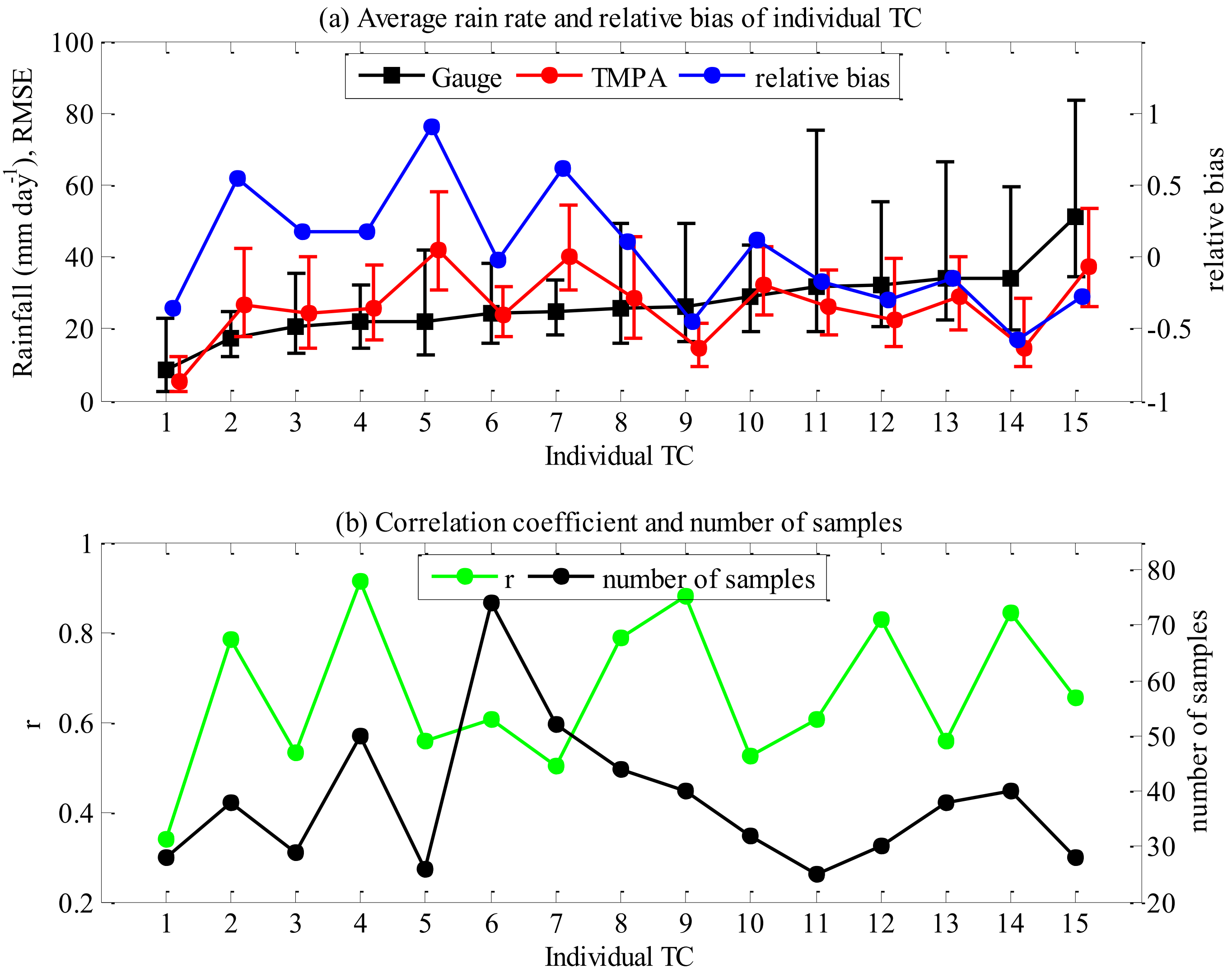

Figure 8 Mean gauge rainfall, the corresponding mean TMPA estimates and the relative bias of the fifteen TCs that have at least ten observations and whose spatial correlation coefficient (r) between the TMPA estimates and gauge observations are statistically significant at 95 per cent confidence level. The TCs are arranged in the order of ascending average gauge rainfall. The TCs used as case studies (Figure 9) to demonstrate the ability of TMPA are shown in the brackets (name and year). The error bars indicate the 95 per cent confidence interval. b) The spatial correlation coefficient (*r*) and number of samples (spatial data points) of the individual TCs

Figure 9 shows the spatial distribution of the 24-hour TMPA and gauge rainfall for TC Cliff (2007), Gene (2008) and Tomas (2010). These are land-falling TCs or TCs that have tracks close to mainland Fiji. It is evident that TMPA is able to show the overall distribution of the observed rainfall, yet it tends to underestimate the magnitude of the heavy rainfall events.

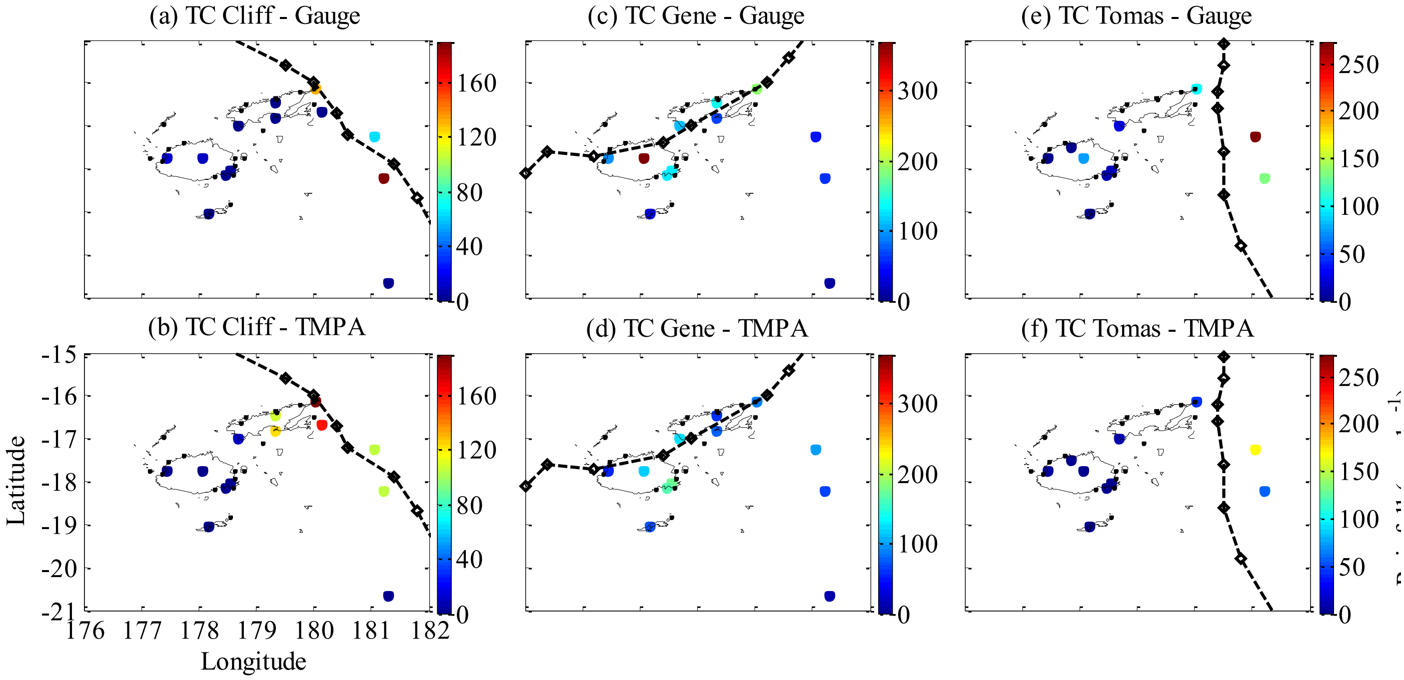

Figure 9 24 hour accumulated gauge and TMPA estimate rainfall of TC Cliff (a and b respectively), Gene (c and d respectively) and Tomas (e and f respectively). The black dashed lines show the track of the TCs

5. Discussion and summary

The above set of results show that TMPA has skill in representing the 24 hour observed rainfall during the passage of TCs over Fiji. Yet a correlation (*r*) of only 0.6 shows that the linear association between the TMPA estimates and the observations is weak. Also the average deviation between the TMPA estimates and the observations is large (*RMSE* = 38.7 mm day^{-1}). Moreover, during moderate to extreme rainfall events, which are of greatest concern during the passage of TCs, there is a significant underestimation by TMPA. The reasons for the fairly weak association of TMPA with the observations could include the retrieval error of the satellite algorithm, the sampling error related to generating daily values from satellite "snapshots", low sample size (due to a small number of gauges) and gauge under-catch.

Comparing the ability of TMPA over different regions, the *r* obtained here is smaller than that over Australia (*r* greater than 0.72; Chen et al. (2013b)) but it is comparable with that over China (*r* = 0.62 to 0.66; Yu et al. (2009)), the Pacific coastal and inland sites (*r* = 0.55; Chen et al. (2013c)) and New Caledonia (*r* = 0.66; Deo et al. (2016). Considering the heavier rainfall events (usually greater than 75 mm day^{-1} and which are of greatest concern during TCs), the *ETS* we report here approaches zero which is comparable with that over the Pacific coastal and inland sites (Chen et al., 2013c) and that reported over mainland China (Yu et al., 2009). The *ETS* for the same rainfall events over Australia (Chen et al., 2013b) and New Caledonia (Deo et al., 2016) however is greater than zero.

Considering the effects of terrain and the structure of the TC, TMPA is less skilful at higher elevations and at distances further from the TC centre. The decrease in the skill of TMPA with elevation is also reported by other studies (Chen et al., 2013a; Chen et al., 2013c, b) and this has been attributed to the inability of TMPA to capture short-lived orographically enhanced rainfall. In particular, the resolution of TMPA (three hourly and 0.25° × 0.25°) might not be enough to resolve the rapidly evolving small scale orographic enhancements over the small scale mountainous terrain in Fiji. Similarly, previous studies (Chen et al., 2013b) also show better skill of TMPA closer to the centre of TCs. This could be attributed to the more organised convection and greater concentration of liquid and frozen hydrometeors in the vicinity of the eye-wall (usually the region of the extreme rainfall) than in the outer rainbands, leading to a relatively stronger scattering of MW signal which is then better correlated with surface rainfall.

The implication of this study is that it provides users of TMPA with information over Fiji on the accuracy and limitation of this product, for use in NWP model evaluation, for example. Moreover, TMPA could be used to create a blended gauge-satellite gridded rainfall product for Fiji that will exploit the strengths and mitigate the limitations of each product. Methods for such blending have been discussed by some studies such as Mitra et al. (2009), Vila et al. (2009), Li and Shao (2010) and Renzullo et al. (2011).

TRMM was retired from operations and the Global Precipitation Measurement (GPM) mission Integrated Multi-satellite Retrievals for GPM (IMERG) provides the next-generation global rainfall estimates (Hou et al., 2014). The satellite constellation and blending algorithm in the GPM are not very different from what was used in TMPA (Hou et al., 2014), hence the estimates from TMPA and IMERG over Fiji may be comparable, as shown by some studies over other regions: for example, (Tang et al. (2016)) over southeast China (this study is not related to TCs though). A more confident answer, however, would require an evaluation of IMERG during the passage of tropical cyclones over Fiji in the near future.

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Appendix

$$\text{Correlation coefficient } r = \frac{\sum\left(E-\overline{E}\right)\left(O-\overline{O}\right)}{\sqrt{\sum\left(E-\overline{E}\right)^2}\sqrt{\sum\left(O-\overline{O}\right)^2}} \tag{1}$$

$$\text{Relative Bias} = \frac{\overline{E}-\overline{O}}{\overline{O}} \tag{2}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(E_i-O_i\right)^2} \tag{3}$$

$$\text{Relative } RMSE = \frac{RMSE}{\overline{O}} \tag{4}$$

where E = TMPA estimate; O = gauge observation and n = number of samples

$$POD = \frac{hits}{hits + misses} \tag{5}$$

$$FAR = \frac{false\,alarms}{hits + false\,alarms} \qquad (6$$

$$FBI = \frac{hits + false\,alarms}{hits + misses} \tag{7}$$

$$ETS = \frac{hits - hits_{random}}{hits + misses + false\,alarms - hits_{random}} \tag{8}$$

where $$hits_{random} = \frac{\left(hits + misses\right)\left(hits + false\,alarms\right)}{hits + misses + false\,alarms + correct\ negatives} \tag{9}$$