Validation of Tropical Rainfall Potential (TRaP) Forecasts for Australian Tropical Cyclones

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31 March 2005

Final version
Australian Meteorological Magazine

Abstract

Tropical Rainfall Potential (TRaP) forecasts provide estimates of 24 h rainfall accumulation in landfalling tropical cyclones based on the advection of a field of satellite-estimated precipitation. Validation of TRaP forecasts for five Australian tropical cyclones during the 2003-04 season showed significant skill in predicting heavy rainfall. The predictions of maximum rain at landfall compared well with gauge observations in most cases. In terms of spatial rain coverage and amount, the TRaPs based on data from the Advanced Microwave Sounding Unit (AMSU) performed noticeably better than those based on the Special Sensor Microwave Imager (SSM/I), giving higher correlations with the observations, more accurate estimates of rain area and conditional rain rate, and lower root mean squared errors. The TRaPs performed neither better nor worse than mesoscale numerical weather prediction models. A decomposition of the TRaP error for regions of heavy rain suggests that only a small portion was related to errors in the track forecasts. Pattern errors, which relate to the shape, size, and fine scale structure of the forecast, accounted for about half of the total error, while rain volume error was about one third of the total error. These relate to errors in the satellite rain rate retrieval as well as the assumption of a steady state rain pattern. An ensemble of TRaP forecasts could account for some of these uncertainties, leading to more useful objective guidance.

1. Introduction

Tropical cyclones cause a great amount of damage to coastal settlements, and are associated with roughly one quarter of the average annual economic cost of natural disasters in Australia (Bureau of Transport Economics, 2001). To help mitigate against the devastating impact of cyclone-related flooding, it is important to be able to estimate and predict the amount of rainfall occurring in landfalling tropical cyclones (Elsberry, 2002).

To address this need the Satellite Services Division (SSD) of NOAA's National Environmental Satellite, Data, and Information Service (NESDIS) issues short-term space-based rain forecasts called Tropical Rainfall Potential (TRaP). TRaP forecasts provide estimates of 24 h rainfall accumulation in landfalling tropical cyclones (TCs) based on the horizontal translation of a field of satellite-estimated precipitation. Areal TRaPs were first issued experimentally for Atlantic hurricanes during the 2000 season. They are now available for most tropical storms around the globe (Kidder et al., 2005; see also the TRaP home page, http://www.ssd.noaa.gov/PS/TROP/trap-img.html), potentially providing a very useful forecast aid for numerous countries.

Post-event validation of TRaP forecasts against surface observations of precipitation is vital for assessing the quality and accuracy of those products. Forecasters need to know the error characteristics of the TRaP products so that they can interpret them appropriately. For example, they need to be aware of any systematic errors associated with TRaPs based on rainfall estimates from a particular satellite sensor, or during various evolutionary phases of a cyclone. They also need to know whether the satellite-based TRaP forecasts are likely to perform better than the alternative source of guidance, namely, numerical weather prediction (NWP) models. Developers of the TRaP system need detailed information on the performance of the algorithm so that improvements can be made.

TRaPs have been validated for hurricanes in the western hemisphere during the 2001 and 2002 seasons (Ferraro et al., 2002, 2005). Since the primary objective of the TRaP is to provide an early warning of potential maximum rainfall for locations near the coast, the emphasis of Ferraro et al.'s (2002) validation was on the location and magnitude of the predicted rain maximum. Examining results for seven storms they found that the errors in TRaP maximum rainfall ranged from -79% to +77% when compared to maxima observed at rain gauges. This is due partly to inaccuracies in hurricane track forecasts. However, there was no systematic relationship between errors in storm motion and under- or over-estimates of rain, suggesting that errors in the satellite rain rate retrievals, combined with the simplifying assumption of a steady state spatial rain distribution in the travelling storm, also contributed strongly to the total error.

A study of TRaPs for the 2002 hurricane season focused on the validation of spatial rain forecasts (Ferraro et al., 2005). Using 24 h accumulations calculated from the National Centers for Environmental Prediction (NCEP) Stage IV hourly gauge-radar rainfall analysis as validation data, they found that the most accurate TRaP forecasts were those based on the Tropical Rain Measuring Mission (TRMM) rainfall estimates, but all TRaPs tended to underestimate the maximum rainfall. The TRaP forecasts outperformed Eta NWP model forecasts according to most statistical measures.

The aim of this study is to validate TRaP forecasts for tropical cyclones in the Australian region during the 2003-04 season. In particular, we separate the errors resulting from inaccurate track forecasts from those associated with the satellite rain retrievals and the assumption of steady state rain. The next section briefly describes how TRaPs are constructed. The validation methodology and results for five Australian TCs follow, including comparison of TRaPs to numerical forecasts from the Australian Bureau of Meteorology's mesoscale model. The paper concludes with a discussion of the results and some suggestions for potential improvements to the TRaP forecast system.

2. TRaP forecasts

The history and details of the current Tropical Rainfall Potential technique are described by Kidder et al. (2004). The original TRaP forecasts were based on manual analysis of infrared (IR) imagery from geostationary satellites (Spayd and Scofield, 1984). Four cloud types were identified in the imagery, each with a prescribed rain rate R_i, based on the cloud top temperature trend. Given estimates of the storm's velocity, V, a straight line was drawn through the heaviest rain in the direction of storm motion. To make the 24 h forecast two simplifying assumptions were made: (1) the velocity of the storm remains constant during the 24 h period of interest, and (2) the rain distribution within the storm circulation remains constant in a Lagrangian sense during the 24 h period. If D_i is the length of the transect through the storm through cloud type i, the rainfall accumulation was then calculated as

$$TRaP = \frac{\sum_{i=1}^{4} R_i D_i}{V} \qquad (1)$$

Objective microwave rainfall estimates were first evaluated for TRaP in 1992 and replaced the subjective IR estimates by the end of the decade, as they were shown to give more accurate estimates of instantaneous rainfall (e.g., Ebert et al., 1996). This also made the generation of TRaP much easier and faster. Good results were achieved with rain estimates from the Special Sensor Microwave Imager (SSM/I) and, later in the 1990s, with the Advanced Microwave Sounding Unit (AMSU). Rain estimates from the TRMM Microwave Imager (TMI) were added in 2001. The laborious manual computations gave way to computer-generated TRaPs, and in 2000 areal TRaPs became the standard product. The areal TRaP is computed as

$$TRaP(x,y) = \int_t R(x,y,t)dt \qquad (2)$$

where x and y denote the spatial location and t is the time. The rain rate is still assumed constant in a Lagrangian sense, but the storm motion is now obtained from official track forecasts from operational centres including the Australian Tropical Cyclone Warning Centres (TCWCs) in Brisbane, Darwin, and Perth.

Recent improvements to the TRaP generation process include the ability to automatically retrieve the microwave rain rates from polar satellite overpasses, and decode TC bulletins from numerous operational centres around the globe. These improvements allow TRaP forecasts to be made without any human intervention. TRaPs are routinely generated for cyclones that are 24-36 hours or less from landfall, using all satellite overpasses with AMSU, SSM/I, or TRMM views of the storm and track forecasts from one or more operational centres. Analysts at SSD subjectively choose the "best" TRaP forecasts according to spatial completeness and reasonableness criteria (typically about 10% of the total number) to release in near real time on the web as GIF images at 4 km horizontal resolution. Users can request to be put on an e-mailing list so that they will be automatically informed whenever a new TRaP is issued in their region of interest. The digital forecasts can also be downloaded from SSD as McIDAS[1] areas or text files.

For this study the complete set of automated areal TRaPs were available for validation. In practice, most users have access to only the vetted (checked and approved) TRaPs, which would be expected to be of the highest quality because they are evaluated and checked by an operational satellite meteorologist. Validation results are presented here both for the vetted set and the complete set of TRaP forecasts.

3. Validation methodology

Australia has a national network of over 5000 rain gauges that measure 24 h rain accumulation at 9 am local time each day[2]. These rain gauge observations were used to validate the maximum rainfall predicted by the TRaPs by comparing the observed maximum rainfall at the first 9 am observation time after landfall to all TRaP forecasts valid within ±12 h of that time. To investigate the impact of timing differences, a second comparison was made using only TRaPs valid within ±3 h of the rainfall observations.

This maximum rainfall validation methodology is less than ideal, for a few reasons. Gaps in the rain gauge network and gauge "undercatch" at high wind speeds mean that the true maximum rain accumulation is unlikely to be observed. As noted, timing differences between the TRaP and the observations will lead to apparent errors in the predicted rainfall, even for a perfect TRaP. Since TRaP forecasts are derived from coarser resolution satellite rainfall estimates, they do not represent the spatial scale of the point observations from gauges and thus the comparison suffers from errors of representativeness. Nevertheless, to the extent that users are tempted to take TRaP estimates of maximum rainfall at face value, the comparison is appropriate.

The areal distribution of rainfall in the TRaP forecasts was validated against the Australian operational daily rainfall analysis. The gauge data are analyzed onto a 0.25° latitude/ longitude grid using a 3-pass variable length scale Barnes objective analysis scheme (Weymouth et al., 1999). In the absence of gauge-calibrated radar estimates the gauge analysis provides the best estimate of spatial rainfall distribution. It is limited in its accuracy by gaps in the network in the tropics (spacing of roughly 1 gauge per 60 km except in the vicinity of Darwin, where the density is much greater) and therefore cannot represent the strongest spatial gradients in the cyclone rainfall.

The TRaP rainfall fields were remapped onto the same grid as the gauge analysis for the spatial validation. To focus only on the rainfall of interest, the validation domain was limited to a (moving) 10° latitude/longitude box centered on the observed cyclone position. The post-analysed best track cyclone positions were provided by the responsible TCWC based on a careful analysis of satellite imagery and synoptic observations.

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[1] McIDAS stands for Man computer Interactive Data Access System

[2] 9 am local time corresponds to 2300 UTC in Queensland, 2330 UTC in the Northern Territory, and 0100 UTC in Western Australia.

The spatial validation was performed for the 85 TRaP forecasts with valid times falling within ±3 h of the observations; of these, nine TRaPs were vetted. TRaPs constructed from satellite passes with incomplete coverage were not included in the validation. All spatial validation results refer to the portion of the TRaP that was over land.

As pointed out by Kidder et al. (2005) there are three main sources of uncertainty in TRaP rainfall forecasts:

- the satellite-estimated rain rates,
- the forecast storm track,
- the invariant spatial structure.

Different validation strategies are more appropriate for assessing each source of error, as discussed below.

Considering first the errors in instantaneous rainfall rates diagnosed by the AMSU, SSM/I, and TMI instruments, previous validation studies have found typical error magnitudes of 100% or more in the tropics (Ebert et al., 1996; Smith et al., 1998). Different sensors have different measurement error characteristics. For example, the SSM/I and TRMM TMI algorithms used at NOAA are known to systematically underestimate low rain rates and overestimate heavy rain rates over land and ocean, while the AMSU algorithm tends to overestimate the area of light rain over land (R. Ferraro and S. Kusselson, unpublished results). Errors in the satellite rainfall "snapshot", compounded by the assumption of steady state rainfall, will be reflected as errors in the predicted 24 h accumulation. These will be seen mainly as errors in rain amount and extent, which can be quantified using statistics such as the mean absolute error (MAE) and root mean square error (RMSE), and the ratio of forecast to observed rain amount (multiplicative bias) or area (frequency bias).

Another source of uncertainty is the predicted cyclone motion, which originates from human forecasters in the various tropical cyclone prediction centers. If the storm is forecast to move too quickly or too slowly, the rain extent and accumulation will be incorrect. If the predicted direction of motion is incorrect the TRaP will put the forecast rain in the wrong location. The correlation coefficient is a good indicator of whether the rain pattern is correct. The threat score (TS) measures the ratio of the number of hits (rain both predicted and observed) to the number of points with rain either predicted or observed (Wilks, 1995). In other words, TS is the fraction of correct predictions when the non-raining points are excluded. To help interpret the threat score it is useful to compute the probability of detection (POD), which measures how often the observed rain was correctly predicted, and the false alarm ratio (FAR), which is the fraction of rain predictions that were false alarms. It is common to set a rain threshold for computing the frequency bias, POD, FAR, and TS; we use values of 1 mm d^{-1} to measure success for rain / no rain prediction, and 20 mm d^{-1} to measure success for the heavier, more important, rain.

Errors due to incorrect storm motion versus those due to incorrect rainfall amount and spatial structure were separated using the object-oriented "contiguous rain area" (CRA) method of Ebert and McBride (2000). Forecast and observed rain entities were defined by a rain threshold of 20 mm d^{-1} to isolate the heavier rain. The location error of a forecast entity relative to the observed entity can be estimated using objective pattern matching, or it can be specified externally. For this study we used the best track cyclone position determined by the Australian TCWC responsible for monitoring the TC to specify the position error of the forecast. The properties of the forecast entity, namely, the rain area, volume, conditional rain rate (mean intensity given that it was raining), and maximum rain rate, as well as the spatial pattern of rainfall, were verified after horizontally translating the forecast rain to the corrected location. This should be a reasonable approximation of the TRaP that would be obtained with a perfect track forecast. The CRA methodology allows the total error to be decomposed into contributions from volume error, location error, and pattern error (see Appendix).

To help assess the value of the TRaP forecasts for forecasting rain from Australian tropical cyclones, a parallel validation was done for 24 h quantitative precipitation forecasts from two versions of the Bureau of Meteorology's mesoscale model, the Limited Area Prediction System (LAPS) (Puri et al., 2001). The operational 0.125° resolution mesoscale model (mesoLAPS) provides numerical guidance out to 36 h over the whole of Australia. The second version of the model is a variable domain, 0.15° resolution, tropical cyclone-centered mesoscale model called TC-LAPS (Davidson and Weber, 2000). TC-LAPS is run whenever a named tropical cyclone is present in the Australian region. These forecasts were validated on the same grid as the TRaP forecasts to ensure a fair comparison.

4. Validation results for Australian tropical cyclones

TRaP forecasts were available for five tropical cyclones in the Australian region during the 2003-04 season. The observed cyclone tracks are shown in Fig. 1. Three of the TCs (Debbie, Fritz, and Evan) affected the northernmost tropical latitudes of Australia, while two (Monty and Fay) produced heavy rainfall in the subtropical northwestern part of the continent. TRaP forecasts were generated using rainfall estimates from three different sensors, AMSU, SSM/I and TRMM, and track forecasts from Australian TCWCs and the United States Joint Typhoon Warning Center (JTWC).

We first give some validation results for each of the cyclones, then discuss the validation results for all cyclones together. To facilitate the discussion, a comparison of TRaP and observed maximum rainfall for each cyclone except Evan is shown in Fig. 2. The spatial validation results for all TRaPs valid within ±3 h of observation time are summarized in Table 1, while Tables 2 and 3 give the spatial and CRA validation results, respectively, for all of the vetted TRaPs. Note that the dates for which TRaPs were available and validated do not correspond precisely to those dates in which the storms were classified as tropical cyclones, but rather focus on the period when the storms were close to or over land.

a. TC Debbie, 19-20 December 2003

Tropical cyclone Debbie formed in the monsoon trough over the eastern Arafura Sea. After deepening and moving west it turned toward the southwest, approaching the coast at about 10 km h^{-1}. Landfall occurred about 250 km east northeast of Darwin at about 1130 UTC on 20 December, bringing heavy rain to the Top End and causing flooding in many catchments.

The 19 TRaPs validated for TC Debbie were found to be less skilful in general than those for the other storms. The maximum rain estimates from AMSU-based TRaPs were generally smaller than those from SSM/I- and TRMM-based TRaPs (also found for TRaPs in the Western Hemisphere), but all were consistently too high for this storm (Fig. 2). The rain area was too low (frequency bias less than 1 in Table 1). The most successful of the vetted TRaPs was the AMSU–based forecast valid at 2250 UTC on 19 December, shown alongside the verifying gauge analysis in Fig. 3. The heaviest rain was predicted at the northernmost tip of the Top End, in agreement with observations. Although the mean and maximum rain intensity were well predicted, the spatial extent of the rain was far less than observed, leading to a 79% underestimate in rain volume and a poor value of the threat score, 0.27. The CRA error decomposition suggests that most of the error in this TRaP was due to incorrect prediction of rain volume (Table 3).

b. TC Fritz, 13 February 2004

Tropical cyclone Fritz developed off the northeast Queensland coast and was named on 10 February. Moving westward across Cape York it weakened, then reformed in the Gulf of Carpenteria. Fritz made landfall on 12 February, producing heavy rain and flooding in the Gulf country and surrounding regions.

Only three TRaP forecasts could be validated for this storm, one from each satellite sensor. The mean and maximum rain intensities were well predicted by TRaPs based on all three instruments, but the rain extent and volume were again underestimated, particularly by the TRMM-based TRaP (Table 1). The SSM/I-based TRaP valid at 2340 UTC on 12 February is shown in Fig. 4. The pattern of heavy rain near the center of the cyclone was well reproduced, as reflected by the high value of the correlation coefficient, 0.67. However, the absence of predicted rain to the south meant that the TRaP rain volume was too small by a factor of two.

c. TC Monty, 28 February-3 March 2004

Tropical cyclone Monty developed from a low pressure center off the northwest coast on 27 February. It travelled westward, increasing in intensity, before turning to the southeast and crossing the coast at about 1300 UTC on March 1. Widespread rainfall led to significant flooding, destroying homes and bridges.

Twenty-five TRaPs from a five-day period were validated, including four vetted TRaPs. Fig. 5 shows the CRA validation for the SSM/I-based TRaP valid at 2341 UTC on March 1. One advantage of the CRA approach is that the unrelated rain observed in the southern part of the domain is excluded from the validation. There was a slight mislocation of the cyclone to the southwest; when this was corrected the RMSE and correlation both improved markedly. The rain volume and area exceeding 20 mm d^{-1} were both slightly overestimated by this TRaP. Just over 10% of the total error was attributable to volume error, while about a third of the error was related to the incorrect location and the remainder related to pattern error.

In general, the TRaP forecasts of maximum rainfall in TC Monty were quite close to the observed value of 196 mm (Fig. 2). The area of heavy rain was also well estimated with average frequency bias values of 1.14 for the AMSU-based TRaPs and 0.80 for the SSM/I-based TRaPs (Table 1). The rain volume estimates were fairly accurate as a result of two compensating errors, the overestimation of the conditional rain rate and the underestimation of the extent of light rain.

d. TC Evan, 3-5 March 2004

Although tropical cyclone Evan was not a very strong storm in terms of wind, its associated heavy rain led to widespread flooding over the Top End and closure of the Sturt Highway. Approaching from the east, Evan crossed the coast of Arnhem Land around 2100 UTC on 1 March.

Unfortunately all of the TRaPs generated for TC Evan were valid well after landfall so it was not possible to check the predicted maximum rainfall at landfall. The spatial validation results were similar to those for TC Fritz, in that the TRaPs made good estimates of conditional rain rates but underestimated the rain extent and therefore the total rain volume (Table 1). The spatial pattern of the AMSU-based TRaPs had an average correlation of 0.69 with the gauge analysis, while the SSM/I-based TRaPs had a lower mean correlation, 0.32.

A sample AMSU-based TRaP from 2054 UTC on 2 March is shown in Fig. 6. The predicted maximum rainfall was in the right location but slightly greater than observed. The moderate rain observed in the northern and western parts of the domain were not captured by this TRaP.

e. TC Fay, 24-28 March 2004

A westward moving tropical low intensified into tropical cyclone Fay in the Timor Sea west of Darwin on 16 March. Fay remained near the coast for several days, intensifying to category 5 on the Australian TC severity scale and bringing heavy rain to the Kimberley region. After changing direction a few times Fay made landfall at about 0000 UTC on 27 March near 20°S, 130°E. Little damage was reported in the sparsely populated region.

Due to Fay's prolonged proximity to the coast, there were 29 TRaPs that could be validated, including 7 based on TRMM observations. The CRA validation of a vetted TRMM-based TRaP valid at 0303 UTC on 25 March is shown in Fig. 7. The magnitude and location of the maximum rainfall were in error, but since the track forecast was fairly accurate (36 km error), the source of the error likely relates to the assumption of steady state rainfall. The areal extent of heavy rain was very well estimated, but the total rain volume was too great. The error decomposition attributed 60% of the total error to pattern error, 30% to volume error, and only 10% to displacement error.

As with TC Debbie, the SSM/I-based and TRMM-based TRaPs had a tendency to over-estimate the maximum rain at landfall (Fig. 2). The highest mean threat score for rain / no rain detection, 0.51, was achieved by the AMSU-based TRaPs for TC Fay, primarily as a result of their high PODs (Table 1). Similar to the earlier TRaPs, the conditional rain rate was well reproduced but the predicted rain volume was typically about half of the observed value because of the frequent underestimation of rain extent.

f. Aggregated results

The results in Fig. 2 suggest that the TRaPs usually predicted reasonably good values of maximum rainfall when compared to gauge observations. Looking first at the results for TRaP forecasts valid within ±12 h of the observation time, the AMSU-based TRaP estimates appeared to be the most reliable and conservative, with a mean relative error for maximum rainfall of 34% of the observed value. The SSM/I-based TRaPs were too high by a factor of three for TCs Debbie and Fay, but gave quite accurate estimates (mean relative error of 11% of the observed maximum) for TCs Fritz and Monty. TRaPs computed from TRMM data had a mean relative error for maximum rainfall of 56%, and seemed to suffer some of the same overestimation problems found with the SSM/I-based TRaPs. Comparisons of validation results for TRaP forecasts valid within ±3 h versus ±12 h of the observation time show no consistent improvement, but with such a small sample size it is impossible to draw any strong conclusions.

Mean values of the validation statistics for AMSU- and SSM/I-based TRaPs are given at the bottom of Table 1. Aggregated values for TRMM-based TRaPs are not included here because only one storm was well sampled by this sensor. 95% confidence intervals on these values were determined using a bootstrapping method (Wilks, 1995). For the Australian 2003-04 tropical cyclone season, the AMSU-based TRaPs performed noticeably better than the SSM/I-based TRaPs, giving higher correlations with the observations, more accurate estimates of rain area and conditional rain rate, and lower values of MAE and RMSE.

The SSM/I-based TRaPs produced unrealistically high rain maxima in two of the storms. If this was related mainly to the spatial resolution of the satellite observations then the SSM/I-based TRaPs would be expected to have lower rain maxima than the TRMM-based TRaPs, which was not the case (Fig. 2). The errors in track forecasts for SSM/I-based TRaPs were similar to those for the other TRaPs. We therefore believe that this overestimation problem is related to errors in the satellite rain rate retrievals. In contrast, Ferraro et al. (2005) found that for U.S. hurricanes the TRaPs from all three sensors underestimated the maximum rain at landfall when compared to the Stage IV gauge-radar analysis (TRaP maxima of 65-220 mm d^{-1} compared to radar maxima of 225-475 mm d^{-1}). This difference may be related to the higher spatial density of surface observations in the US validation and the inherent differences between gauge and radar analyses. The frequency biases for rain ≥1 mm d^{-1} reported by Ferraro et al. (2005) were in the range 0.6-1.0, higher than the values found here, 0.2-0.7. According to all other measures, the performance of TRaP forecasts over Australia was similar to that found over the US.

Comparison of the results in Tables 1 and 2 suggests that the vetted TRaPs were not very much more accurate than the set of all (vetted and unvetted) TRaPs. This implies that, subject to an additional range-checking step to screen out TRaPs with unrealistically high rainfall[3], it may be possible to release all automated TRaPs without any large loss of skill or confidence.

The CRA validation focused on the regions of rain exceeding 20 mm d^{-1} in the forecast and observations (Table 3). Compared to the results for the full 10° spatial domain, where a threshold of 1 mm d^{-1} was used to compute validation statistics (Table 2), the conditional rain and volume ratios were closer to 1 and the normalized RMSE was lower, implying relatively better performance of the TRaPs for the heavier rain. The location (track) errors ranged from 0 to 113 km, with a mean value of 55 km. The error decomposition suggests that on average less than 20% of the forecast error was related to track errors. Pattern errors, which relate to the shape, size, and fine scale structure of the forecast entity, accounted for about half of the total error. The rain volume error component was quite variable but averaged about one third of the total error. It appears that the errors associated with the rain rate retrieval and the assumption of steady state rain distribution in the 24h period outweigh the errors associated with incorrect track forecasts.

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[3] In practice, it may be difficult to specify appropriate criteria for "unrealistically high rainfall". Australian forecasters expect, as a general rule of thumb, rainfall maxima not to exceed 200 mm d^{-1} for storms moving at "average" speeds and 400 mm d^{-1} for slow movers (N. Davidson, personal communication). Perhaps consistency among TRaPs from different sensors would be a more suitable test.

Correcting the location of the TRaPs had the effect of more than doubling the average correlation coefficient for rain exceeding 20 mm d^{-1}, but was equally likely to decrease or increase the RMSE. This is in contrast with Ferraro et al.'s (2005) findings that recomputing the TRaP using the best track often improved, but never degraded, the RMSE.

To test whether the TRaPs gave better rainfall forecasts than the mesoscale NWP guidance, the validation results were compared for the eight days (spread over four cyclones) during which AMSU- and SSM/I-based TRaPs and mesoLAPS and TC-LAPS model 24 h rain forecasts were all available. Fig. 8 shows examples of model forecasts for TC Monty for the same date as the TRaP shown in Fig. 5. The model forecasts have quite a different, arguably more realistic, appearance to the TRaPs, with a suggestion of rotation rather than streakiness. However, the excessively heavy rain in the TC-LAPS forecast, and to a lesser degree in the mesoLAPS forecast, appeared to be a common occurrence.

Fig. 9 shows the distributions of selected verification statistics for the four forecast products. Looking first at rain volume, the mesoLAPS model gave the best estimates while TC-LAPS overestimated it quite severely, leading to large errors. The correlations were highest for the AMSU-based TRaPs and the TC-LAPS model. The AMSU-based TRaPs and mesoLAPS model gave the best estimates of heavy rain area. The TC-LAPS model had the highest probabilities of detection, which contributed to it achieving the highest median threat score of the four products. Based on this comparison, there is no clear-cut "winner" – the choice of forecast product would vary, depending on which quantities were deemed most vital to predict correctly.

5. Discussion and suggestions for improvement

Validation of TRaPs for five Australian tropical cyclones during the 2003-04 season shows that these satellite-based rainfall extrapolation products clearly have skill in predicting heavy rainfall. The AMSU-based TRaPs gave more reliable estimates of heavy rain magnitude at landfall than the SSM/I-based TRaPs or the mesoscale NWP models. The TRaPs and models had comparable skill in predicting the location of the heavy rain, as measured by the threat score and correlation coefficient, but the mesoLAPS model gave better estimates of rain volume.

These results were based on a small number of cases. Validation efforts should continue so that more robust conclusions can be drawn. Australia does not currently have an hourly gauge-radar analysis similar to the Stage IV product in the US, so it must continue to rely on 24 h rain gauge observations for the bulk of the observational data. Some of the difference in the results between this study and the Ferraro et al. (2005) study are undoubtedly related to the differences in the reference data between Australia and the United States. Differences in environmental influences on TC rainfall may also be an important factor.

The areal TRaP is still being further developed and improved (Kidder et al., 2005). The CRA error decomposition suggests that most of the error is due to errors in rain volume and pattern, as opposed to incorrect track forecasts. As long as the tracks are reasonably accurate, and given that the TRaP methodology does not "grow" or "decay" rain, systematic errors in rain volume will be primarily associated with errors in the satellite rain retrieval. Further validation of satellite rain rates against estimates from coastal radar, the TRMM precipitation radar, or gauge observations from atolls and island stations might help clarify some of the rain retrieval errors. The pattern errors are related to the assumption of steady state (in a Lagrangian sense) rain including the lack of rotation in the advected rain field. The excessively streaky appearance of the TRaPs that results from advection of local rain maxima and minima is clearly unrealistic and may deter some forecasters from having confidence in the product.

Several physically based improvements are possible. Rotation of the rain pattern could be incorporated into the storm motion. Atmospheric moisture retrievals from passive microwave measurements could be used to increase or decrease the TRaP rainfall based on moist or dry advection. Similarly, a shear factor, perhaps derived from NWP, could be used to increase or decrease TRaP rainfall. Including a statistical adjustment for orographic enhancement of rainfall might produce more realistic land-based rain estimates, especially along the Queensland coast.

Statistical simulation of rain evolution using stochastic models (e.g., Pierce et al., 2004) is probably beyond the scope of this project, but some simple statistical methods could be applied to reduce the streakiness of the TRaPs to give a more realistic looking, and more accurate, TRaP forecast. The simplest approach is to apply a spatial smoother to the TRaP output, but this has the undesirable effect of reducing the maximum rain. To overcome this problem probability matching can be used to transform the smoothed rain rates back to the original rain frequency distribution. An example of such a massaging operation is shown in Fig. 10 for the SSM/I-based TRaP from TC Fritz, where the value at each grid box was replaced by the average value over a centred 200 km window, followed by rain rate transformation using probability matching. Compared to the original TRaP in Fig. 4, the massaged TRaP is much smoother looking, with lower errors and a higher correlation coefficient.

Rain probabilities can also be estimated by sampling the rain distribution in the local (spatial) neighbourhood of each pixel. For example, due to uncertainties in track forecasts (c.f. Table 3) all rain estimates from pixels within 50 km radius of the pixel of interest could be considered equally likely, so that the probability of precipitation exceeding a given threshold would be simply the fraction of pixels with rain exceeding that threshold. Such an approach was successfully demonstrated by Theis et al. (2004) and Ebert and Jakob (2003) using mesoscale NWP model output; the principle would be equally applicable to high resolution TRaP forecasts.

A better strategy would be to generate an ensemble of TRaPs by adding realistic perturbations to the forecast speed and direction of the cyclone, as suggested by Kidder et al. (2005). The parameters of the microwave rain rate retrieval could also be varied to provide several initial fields. The ensemble strategy acknowledges that there are many uncertainties in the forecast, and explicitly takes them into account. The ensemble mean TRaP, corrected using probability matching as above, would almost certainly be a more skilful forecast than a single realization (i.e., the current TRaP product), partly because the less predictable small scale features are filtered out via the averaging process. The great advantage of the ensemble approach is the ability to easily produce probability forecasts for critical rain thresholds. This would add enormous value to the TRaP product in decision-critical situations like tropical cyclones approaching landfall.

Numerous studies have demonstrated that combining independent forecasts into a consensus forecast generally produces a superior product, so long as the components have no large biases. Ferraro et al. (2004) showed that the climatological schemes that estimate maximum rainfall as a simple function of storm speed often gave better estimates than the TRaPs. The

Rainfall Climatology and Persistence (R-CLIPER) algorithm developed at the NOAA Hurricane Research Division gives the radial distribution of rain intensity in a tropical cyclone (Marks et al., 2002). NWP models can make good predictions of rain in cyclones, although it may be necessary to first remove systematic biases. Returning to its original inspiration, TRaPs can be automatically derived from geostationary satellite observations on a 30-minute basis using the Hydroestimator algorithm (Scofield and Kuligowski, 2003). TRaPs based on one or more sensors could be statistically combined with other sources of cyclone rainfall forecasts to produce a "super-ensemble" (e.g., Shin and Krishnamurti, 2003a, 2003b). TRaP rainfall might be used in the TC initialization process in NWP models, or advected according to the model's deep layer mean (950-500 hPa) wind, combining the best features of both prediction systems. These strategies should be tested.

Acknowledgements

Expert technical assistance was provided by Jianbin Yang and Rowen May. Noel Davidson provided the TC-LAPS forecasts and the TC track data, as well as useful feedback on the manuscript. Bob Kuligowski, John McBride, and Geoff Garden also provided very useful comments.

Appendix. CRA error decomposition

Ebert and McBride (2000) showed how the total error in a spatial rain forecast could be decomposed into terms related to location error, volume error, and pattern error. Recently Grams et al. (2005) proposed an alternative error decomposition to be used when the criterion for pattern matching is maximizing the pattern correlation rather than minimizing the squared error as was done by Ebert and McBride (2000). For TRaP validation using the contiguous rain area (CRA) methodology we use the difference between the forecast and observed cyclone positions to specify the track error. Since this resulted in an improved correlation between the forecast and the observations in almost all cases (but not necessarily an improved RMSE), the Grams et al. (2005) error decomposition was chosen. Its derivation is given below.

Murphy (1995) presented a decomposition of the mean squared error, *MSE*, of a forecast field, *F*, relative to the observed field, *O*:

$$MSE = (\overline{F} - \overline{O})^2 + (s_o - r\, s_F)^2 + (1 - r^2) s_F^2 \qquad \text{(A1)}$$

In this expression $\overline{F}$ and $\overline{O}$ are the mean values of the forecast and observed fields, s_F and s_O are their sample standard deviations, and r is the correlation of F and O. For CRA validation these terms are computed over the domain comprising the union of the forecast and observed rain entities (before correcting the forecast locations). This contains both the observed and forecast rain areas but excludes the regions of no real interest to the validation. Rearranging the second and third terms gives

$$\begin{aligned} MSE &= (\overline{F} - \overline{O})^2 + [s_O^2 - 2r\, s_O s_F + s_F^2] \\ &= (\overline{F} - \overline{O})^2 + (s_O - s_F)^2 + 2 s_O s_F (1 - r) \end{aligned} \qquad \text{(A2)}$$

The pattern error should be reflected by the optimal correlation for location-corrected forecast, *c*. By adding and subtracting r_{corr} in the third term and rearranging, we arrive at the final expression for the CRA error decomposition:

$$MSE = (\bar{F} - \bar{O})^2 + 2s_F s_O(r_{corr} - r) + 2s_F s_O(1 - r_{corr}) + (s_F - s_O)^2 \qquad \text{(A3)}$$

The first term in (A3) is the squared difference in mean rainfall, and thus reflects an intensity or volume error (MSE_{volume}). The second term includes the difference between the spatial correlations before and after correcting the forecast location. The smaller the displacement, the smaller this term is likely to be; this term represents the contribution due to location error ($MSE_{location}$). If there was no shape error in the forecast (perfect correlation between forecast and observations, r_{corr}=1) then the third term would be zero. The fourth term compares the sample standard deviations of the forecast and observations, which would also need to be identical for a conditionally unbiased forecast. The third and fourth terms together comprise the contribution due to pattern error ($MSE_{pattern}$).

The error decomposition (A3) assumes that correcting the location error of the forecast will improve its correlation with the observations. This is not guaranteed when the location error is specified externally rather than by correlation-based pattern matching. If the correlation decreases then $MSE_{location}$ has a negative value.

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Table 1. Spatial validation results for the complete set of automated TRaPs, grouped by storm and by satellite instrument. These statistics were constructed by first computing daily mean values, then averaging the daily values. The frequency bias, POD, FAR, and TS were computed from daily mean values of hits, misses, and false alarms. Except for TC Fay when SSM/I-based TRaPs were not available for the last day of the period, the all validation results for each storm were based on the same set of days for all instruments.

							1 mm d^{-1}				20 mm d^{-1}			
Sensor	# of TRaPs	Cond. $\overline{R}$ (fcst/obs)	Volume (fcst/obs)	$\frac{MAE}{\overline{R}}$	$\frac{RMSE}{\overline{R}}$	Corr. coeff.	Freq. bias	POD	FAR	TS	Freq. bias	POD	FAR	TS
TC Debbie, $\overline{R}$ =14.5 mm d^{-1}														
AMSU	8	1.33	0.26	0.93	1.16	0.28	0.22	0.22	0.02	0.22	0.24	0.17	0.29	0.16
SSM/I	11	3.62	1.07	1.54	2.98	0.10	0.30	0.30	0.01	0.29	0.60	0.23	0.62	0.17
TC Fritz, $\overline{R}$ =31.6 mm d^{-1}														
AMSU	1	0.82	0.48	0.60	0.91	0.64	0.59	0.51	0.13	0.47	0.56	0.46	0.18	0.41
SSM/I	1	0.88	0.43	0.59	0.91	0.67	0.49	0.46	0.07	0.44	0.53	0.45	0.15	0.42
TRMM	1	0.63	0.13	0.73	1.16	0.53	0.20	0.20	0.03	0.20	0.16	0.16	0.00	0.16
TC Monty, $\overline{R}$ =21.0 mm d^{-1}														
AMSU	12	1.34	1.04	0.54	1.09	0.56	0.71	0.57	0.20	0.50	1.14	0.60	0.47	0.39
SSM/I	13	1.59	0.76	0.56	1.20	0.38	0.42	0.34	0.18	0.32	0.80	0.45	0.43	0.34
TC Evan, $\overline{R}$ =19.3 mm d^{-1}														
AMSU	4	0.97	0.57	0.57	0.99	0.69	0.47	0.46	0.02	0.46	0.59	0.46	0.22	0.41
SSM/I	5	0.99	0.42	0.69	1.19	0.32	0.37	0.36	0.04	0.35	0.43	0.27	0.38	0.23
TC Fay, $\overline{R}$ =23.7 mm d^{-1}														
AMSU	11	0.73	0.45	0.48	1.00	0.43	0.66	0.56	0.15	0.51	0.62	0.43	0.32	0.36
SSM/I	11	1.03	0.48	0.51	1.09	0.44	0.38	0.36	0.04	0.29	0.39	0.23	0.41	0.20
TRMM	7	1.05	0.50	0.54	1.19	0.39	0.46	0.39	0.15	0.37	0.48	0.35	0.28	0.31
Aggregated results for all TRaPs, $\overline{R}$ =20.5 mm d^{-1}														
AMSU	**36**	**1.09**	**0.69**	**0.57**	**1.02**	**0.50**	**0.59**	**0.50**	**0.16**	**0.45**	**0.74**	**0.47**	**0.37**	**0.37**
95% confidence interval		0.93, 1.27	0.53, 0.88	0.52, 0.64	0.95, 1.08	0.41, 0.58	0.50, 0.68	0.44, 0.55	0.10, 0.22	0.40, 0.49	0.61, 0.90	0.40, 0.54	0.29, 0.43	0.32, 0.41
SSM/I	**41**	**1.75**	**0.67**	**0.76**	**1.52**	**0.33**	**0.37**	**0.33**	**0.10**	**0.32**	**0.59**	**0.34**	**0.42**	**0.27**
95% confidence interval		1.45, 2.09	0.53, 0.81	0.64, 1.31	1.31, 1.77	0.26, 0.41	0.31, 0.42	0.28, 0.37	0.06, 0.14	0.27, 0.36	0.47, 0.70	0.27, 0.41	0.36, 0.49	0.22, 0.32

Table 2. Spatial validation results for the vetted TRaPs.

								1 mm d^{-1}				20 mm d^{-1}			
Date and time	Track forecast	Sensor	Cond. $\overline{R}$ (fcst/obs)	Volume (fcst/obs)	$\frac{MAE}{\overline{R}}$	$\frac{RMSE}{\overline{R}}$	Corr. coeff.	Freq. bias	POD	FAR	TS	Freq. bias	POD	FAR	TS
TC Debbie															
20031219 2250	Darwin	AMSU	0.77	0.21	0.83	1.02	0.52	0.27	0.27	0.00	0.27	0.17	0.17	0.04	0.17
20031219 2344	Darwin	SSMI	2.98	1.12	1.53	2.60	0.05	0.38	0.38	0.00	0.38	0.55	0.24	0.56	0.18
TC Monty															
20040228 2206	Perth	AMSU	2.11	0.91	0.49	1.14	0.58	0.43	0.38	0.11	0.36	0.87	0.60	0.31	0.47
20040301 2216	JTWC	SSMI	2.03	1.40	0.66	1.23	0.61	0.69	0.49	0.29	0.41	1.29	0.69	0.46	0.43
20040301 2300	Perth	AMSU	1.25	1.15	0.58	1.03	0.57	0.91	0.63	0.30	0.50	1.38	0.72	0.48	0.44
20040301 2341	Perth	SSMI	2.12	1.25	0.63	1.26	0.58	0.59	0.45	0.24	0.40	1.11	0.65	0.42	0.44
TC Fay															
20040325 0303	Perth	TRMM	1.90	1.54	0.64	1.42	0.72	0.81	0.75	0.08	0.71	0.90	0.64	0.29	0.50
20040325 0303	JTWC	TRMM	2.06	1.68	0.70	1.53	0.66	0.82	0.76	0.07	0.72	1.02	0.69	0.32	0.52
20040327 2245	JTWC	AMSU	0.49	0.22	0.57	1.22	0.28	0.45	0.43	0.04	0.42	0.41	0.29	0.28	0.26
Aggregated results for all vetted TRaPs															
all			**1.63**	**0.97**	**0.70**	**1.33**	**0.51**	**0.58**	**0.50**	**0.15**	**0.46**	**0.83**	**0.50**	**0.40**	**0.38**
95% confidence interval			1.13, 2.14	0.57, 1.35	0.60, 0.87	1.16, 1.62	0.37, 0.62	0.46, 0.72	0.41, 0.60	0.06, 0.23	0.38, 0.55	0.56, 1.12	0.36, 0.65	0.33, 0.45	0.30, 0.46

Table 3. CRA validation results for the vetted TRaPs. The statistics refer to the location-corrected TRaPs.

									Error decomposition (%)		
Date and time	Track forecast	Sensor	Max. rain (fcst/obs)	Cond. $\overline{R}$ (fcst/obs)	Volume (fcst/obs)	$\frac{RMSE}{\overline{R}}$	Correlation coefficient	Track error (km)	Location	Volume	Pattern
TC Debbie											
20031219 2250	Darwin	AMSU	1.27	1.08	0.33	0.78	0.57	0	0	72	28
20031219 2344	Darwin	SSMI	7.19	3.05	2.49	2.52	-0.18	28	9	15	76
TC Monty											
20040228 2206	Perth	AMSU	0.33	0.48	0.12	0.87	0.38	83	30	0	70
20040301 2216	JTWC	SSMI	1.08	1.03	1.03	0.86	0.68	113	44	18	38
20040301 2300	Perth	AMSU	0.77	0.87	1.24	0.68	0.57	52	37	4	59
20040301 2341	Perth	SSMI	1.17	1.16	1.20	0.89	0.48	60	31	12	57
TC Fay											
20040325 0303	Perth	TRMM	1.93	2.11	2.5	1.50	0.42	93	X*	X*	X*
20040325 0303	JTWC	TRMM	1.60	2.10	2.0	1.32	0.39	36	10	30	60
20040327 2245	JTWC	AMSU	0.76	0.44	0.19	0.98	-0.25	28	1	51	48
Aggregated results for all vetted TRaPs											
all			**1.40**	**1.17**	**1.01**	**1.01**	**0.34**	**55**	**20**	**25**	**54**
95% confidence interval			0.88, 2.31	0.80, 1.70	0.54, 1.64	0.86, 1.25	0.11, 0.52	32, 76	10, 31	11, 42	44, 65

* The correction of the track error for this TRaP resulted in a lower correlation so that the error decomposition was not possible (see Appendix).

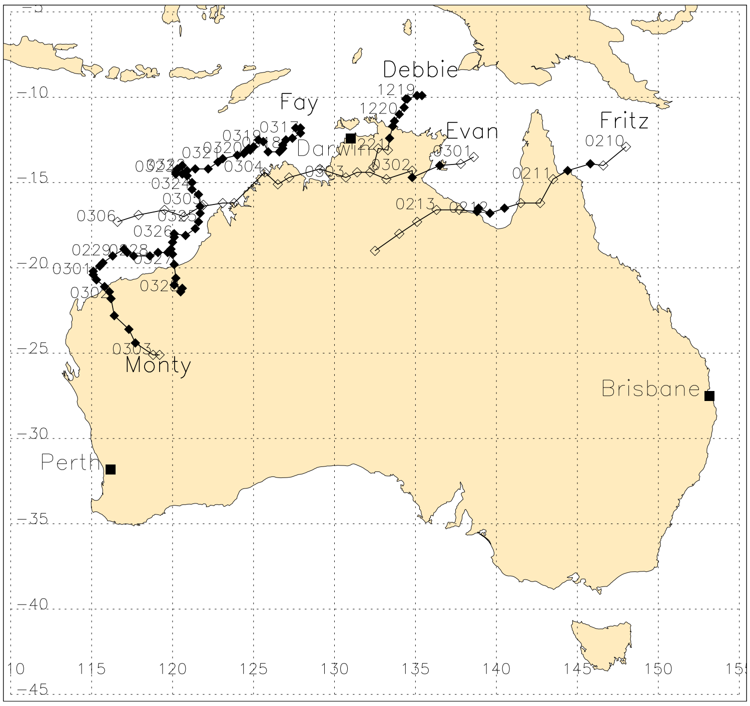


Fig. 1. Observed tracks of five tropical cyclones during the 2003-04 season. The labelled dates, given as mmdd where mm is the month and dd is the day, indicate the 0000 UTC position of the storm. The open symbols denote times when the storm did not have tropical cyclone status.

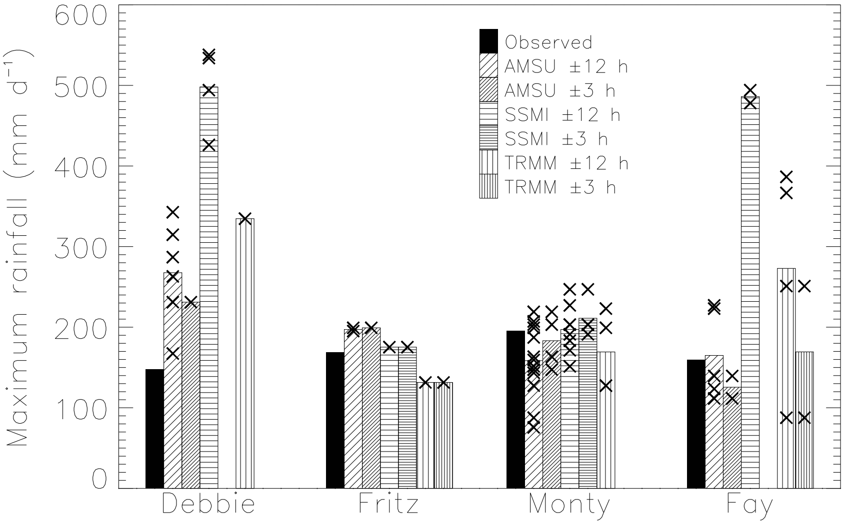
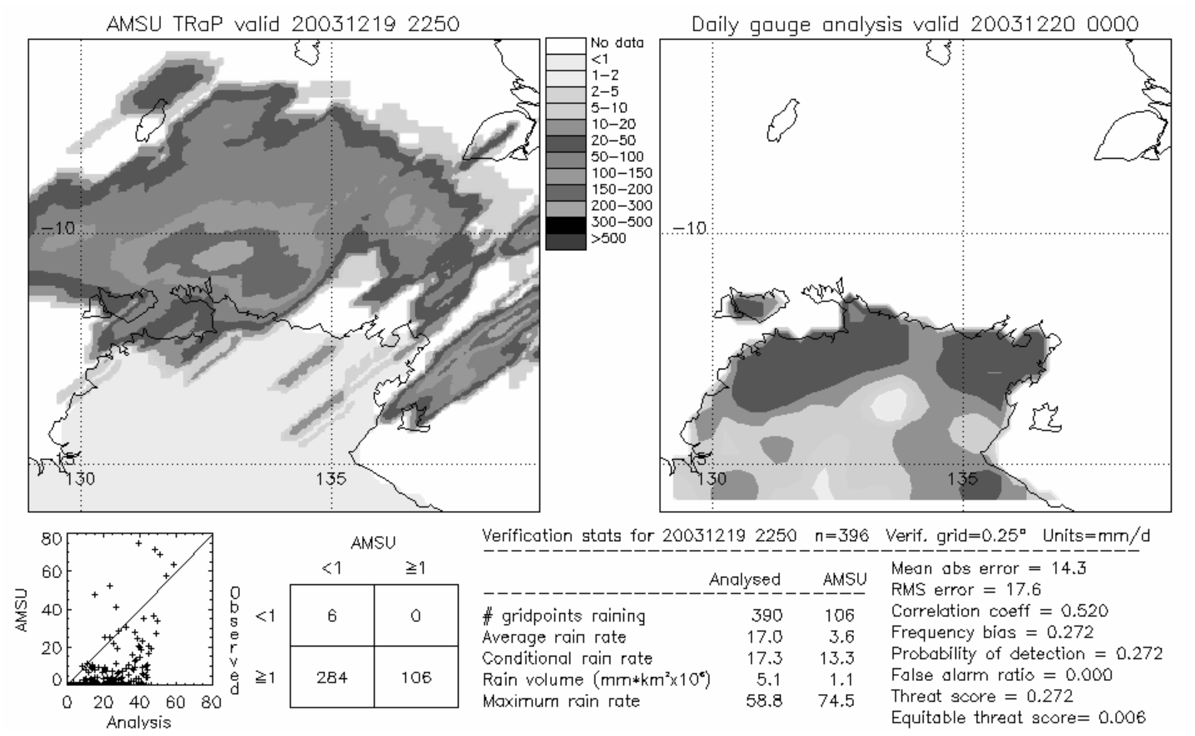


Fig. 2. Maximum rainfall corresponding to 9 am local time on the first day following landfall. The black bars represent the gauge observations, while the shaded and textured bars give the mean TRaP values. The left bar (lighter shade) in each pair corresponds to TRaPs valid within ±12 h of the observation, while the right bar (darker shade) corresponds to TRaPs valid within ±3 h of the observation. The individual estimates are shown by the X's. For TC Evan no TRaPs were valid within 12 h of landfall.



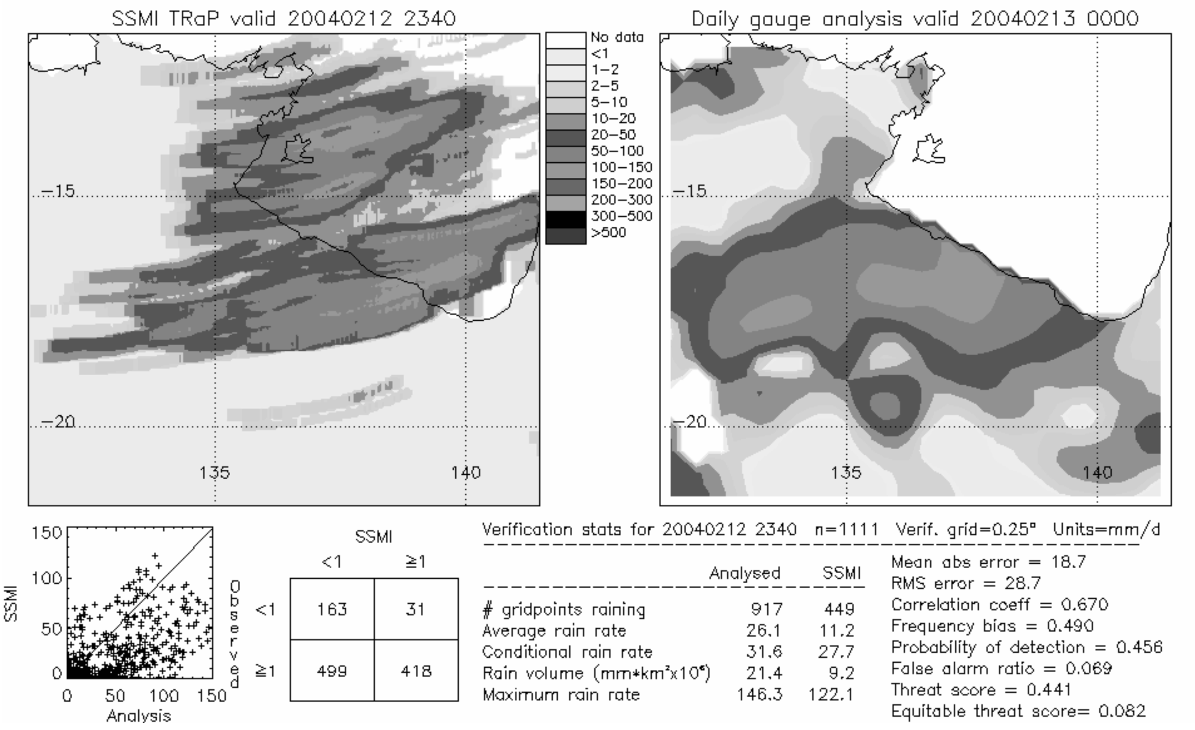
AMSU	<1	≥1
Observed <1	6	0
Observed ≥1	284	106

Verification stats for 20031219 2250 n=396 Verif. grid=0.25° Units=mm/d

	Analysed	AMSU
# gridpoints raining	390	106
Average rain rate	17.0	3.6
Conditional rain rate	17.3	13.3
Rain volume (mm*km^{2}x10^6)	5.1	1.1
Maximum rain rate	58.8	74.5

Mean abs error = 14.3
RMS error = 17.6
Correlation coeff = 0.520
Frequency bias = 0.272
Probability of detection = 0.272
False alarm ratio = 0.000
Threat score = 0.272
Equitable threat score= 0.006

Fig. 3. Validation of AMSU-based TRaP rainfall (left panel) against the gauge analysis (right panel) for Tropical Cyclone Debbie, valid at 2250 UTC on 19 December 2003.



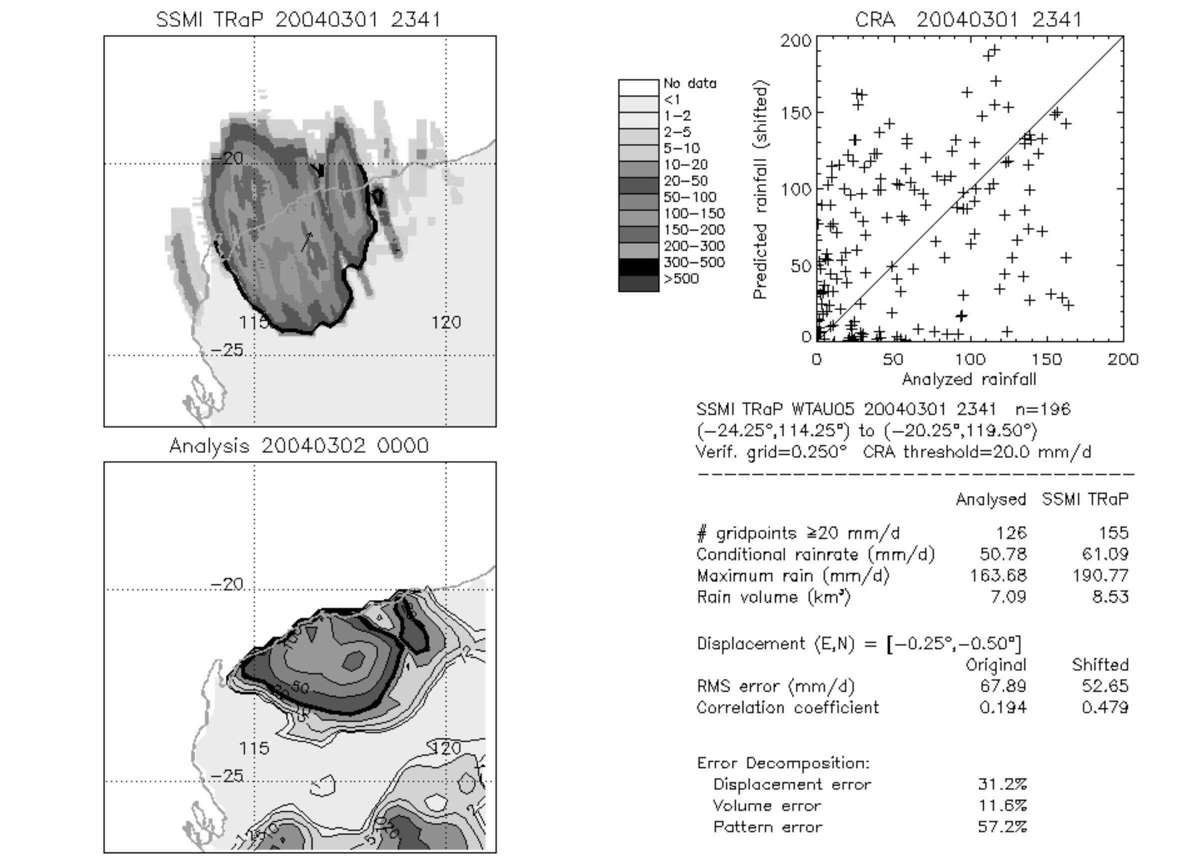
SSMI	<1	≥1
Observed <1	163	31
Observed ≥1	499	418

Verification stats for 20040212 2340 n=1111 Verif. grid=0.25° Units=mm/d

	Analysed	SSMI
# gridpoints raining	917	449
Average rain rate	26.1	11.2
Conditional rain rate	31.6	27.7
Rain volume (mm*km^{2}x10^6)	21.4	9.2
Maximum rain rate	146.3	122.1

Mean abs error = 18.7
RMS error = 28.7
Correlation coeff = 0.670
Frequency bias = 0.490
Probability of detection = 0.456
False alarm ratio = 0.069
Threat score = 0.441
Equitable threat score= 0.082

Fig. 4. Validation of SSM/I-based TRaP rainfall (left panel) against the gauge analysis (right panel) for Tropical Cyclone Fritz, valid at 2340 UTC on 12 February 2004.



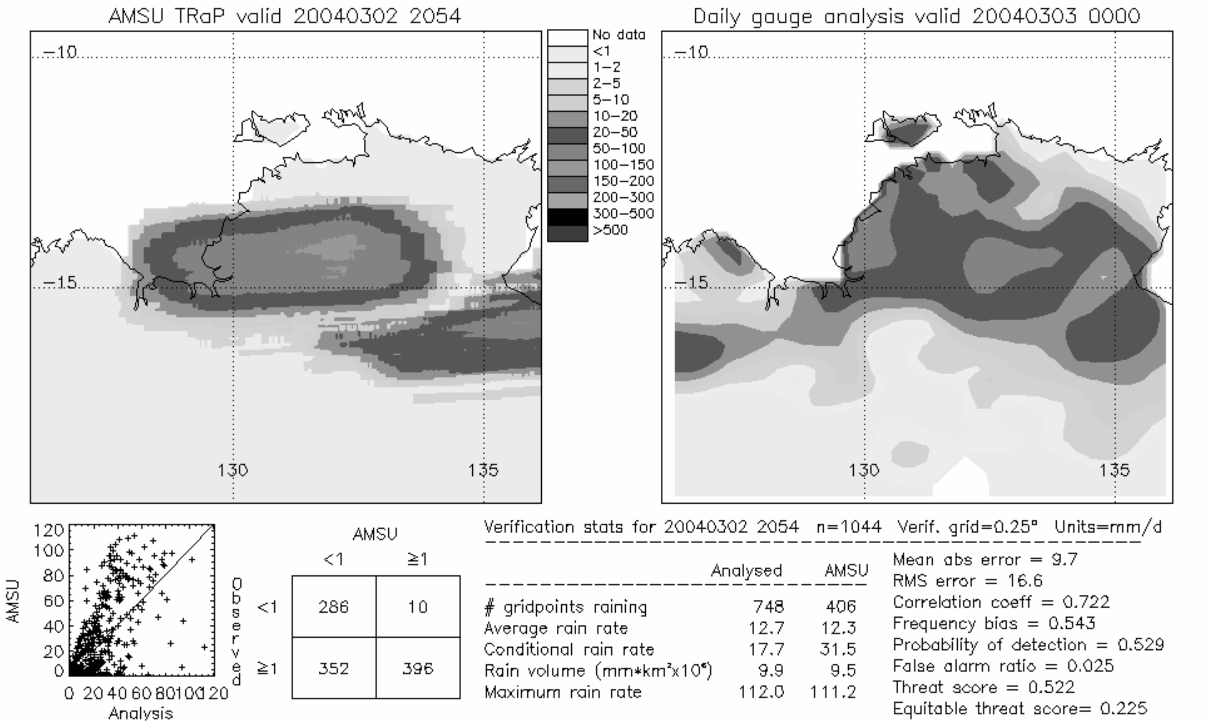
```
SSMI TRaP WTAU05 20040301 2341  n=196
(-24.25°,114.25°) to (-20.25°,119.50°)
Verif. grid=0.250°  CRA threshold=20.0 mm/d
-----------------------------------------
                              Analysed  SSMI TRaP

# gridpoints ≥20 mm/d             126        155
Conditional rainrate (mm/d)     50.78      61.09
Maximum rain (mm/d)            163.68     190.77
Rain volume (km³)                7.09       8.53

Displacement (E,N) = [-0.25°,-0.50°]
                             Original    Shifted
RMS error (mm/d)                67.89      52.65
Correlation coefficient         0.194      0.479


Error Decomposition:
  Displacement error            31.2%
  Volume error                  11.6%
  Pattern error                 57.2%
```

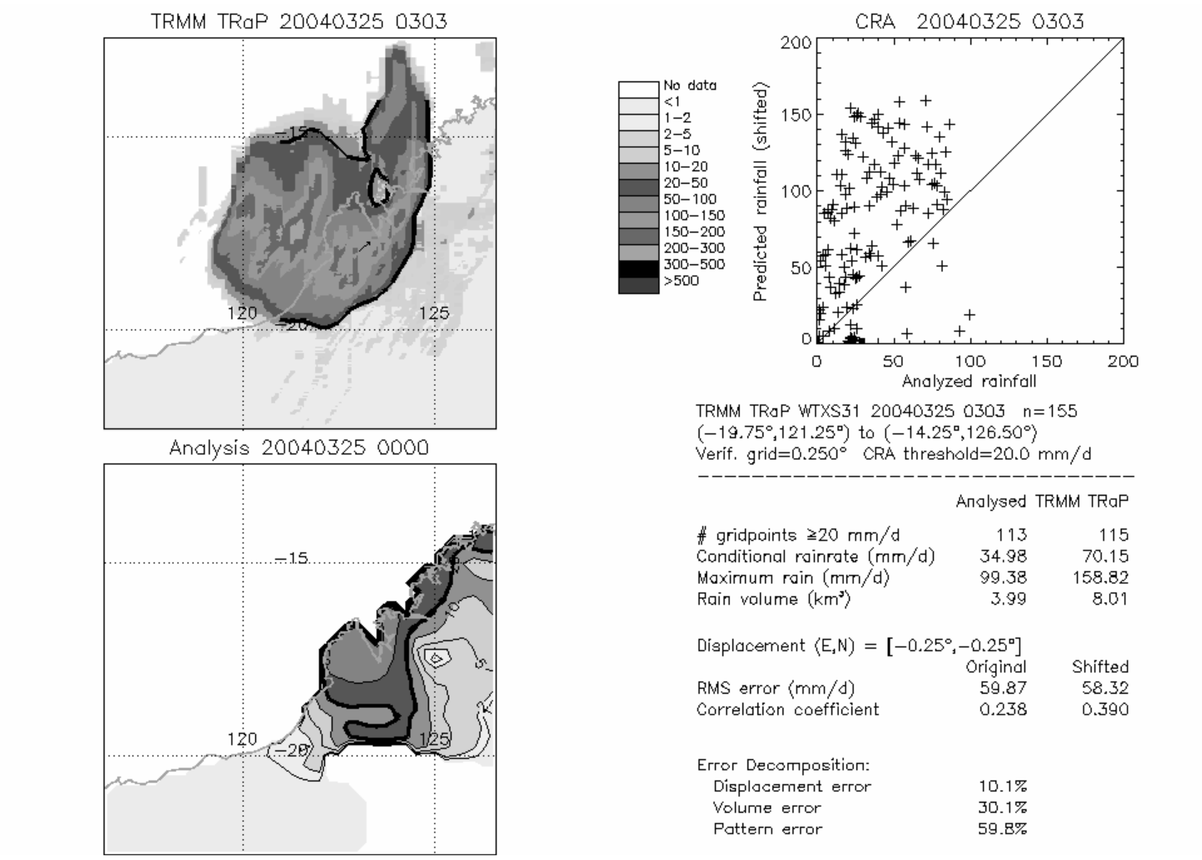
Fig. 5. CRA validation for the SSM/I-based TRaP rainfall valid at 2341 UTC on 1 March 2004 (Tropical Cyclone Monty).



		AMSU <1	AMSU ≥1
Observed	<1	286	10
Observed	≥1	352	396

```
Verification stats for 20040302 2054  n=1044  Verif. grid=0.25°  Units=mm/d
-----------------------------------------------------------------
                                                 Mean abs error = 9.7
                              Analysed   AMSU    RMS error = 16.6
-------------------------------------------      Correlation coeff = 0.722
# gridpoints raining              748     406    Frequency bias = 0.543
Average rain rate                12.7    12.3    Probability of detection = 0.529
Conditional rain rate            17.7    31.5    False alarm ratio = 0.025
Rain volume (mm*km²x10⁶)          9.9     9.5    Threat score = 0.522
Maximum rain rate               112.0   111.2    Equitable threat score= 0.225
```

Fig. 6. Validation of AMSU-based TRaP rainfall (left panel) against the gauge analysis (right panel) for Tropical Cyclone Evan, valid at 2054 UTC on 2 March 2004.



```
TRMM TRaP WTXS31 20040325 0303  n=155
(−19.75°,121.25°) to (−14.25°,126.50°)
Verif. grid=0.250°  CRA threshold=20.0 mm/d
----------------------------------------------
                             Analysed TRMM TRaP

# gridpoints ≥20 mm/d            113       115
Conditional rainrate (mm/d)     34.98     70.15
Maximum rain (mm/d)             99.38    158.82
Rain volume (km³)                3.99      8.01

Displacement (E,N) = [−0.25°,−0.25°]
                             Original   Shifted
RMS error (mm/d)                59.87     58.32
Correlation coefficient         0.238     0.390

Error Decomposition:
  Displacement error            10.1%
  Volume error                  30.1%
  Pattern error                 59.8%
```

Fig. 7. CRA validation for the TRMM-based TRaP valid at 0303 UTC on 25 March 2004 (Tropical Cyclone Fay).

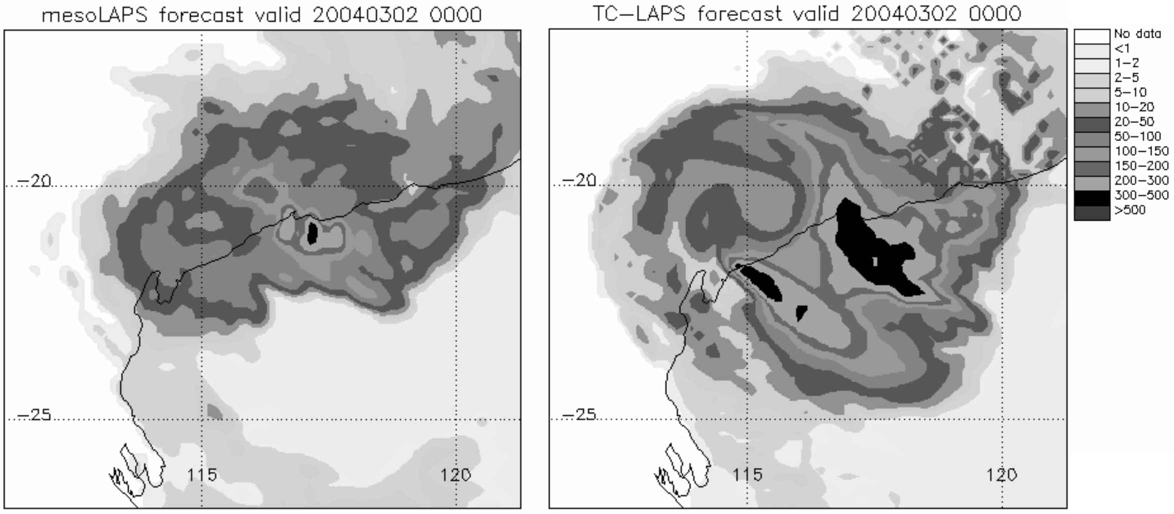


Fig. 8. 24 h rain forecasts from the mesoLAPS and TC-LAPS models valid at 0000 UTC on 2 March 2004 (Tropical Cyclone Monty).

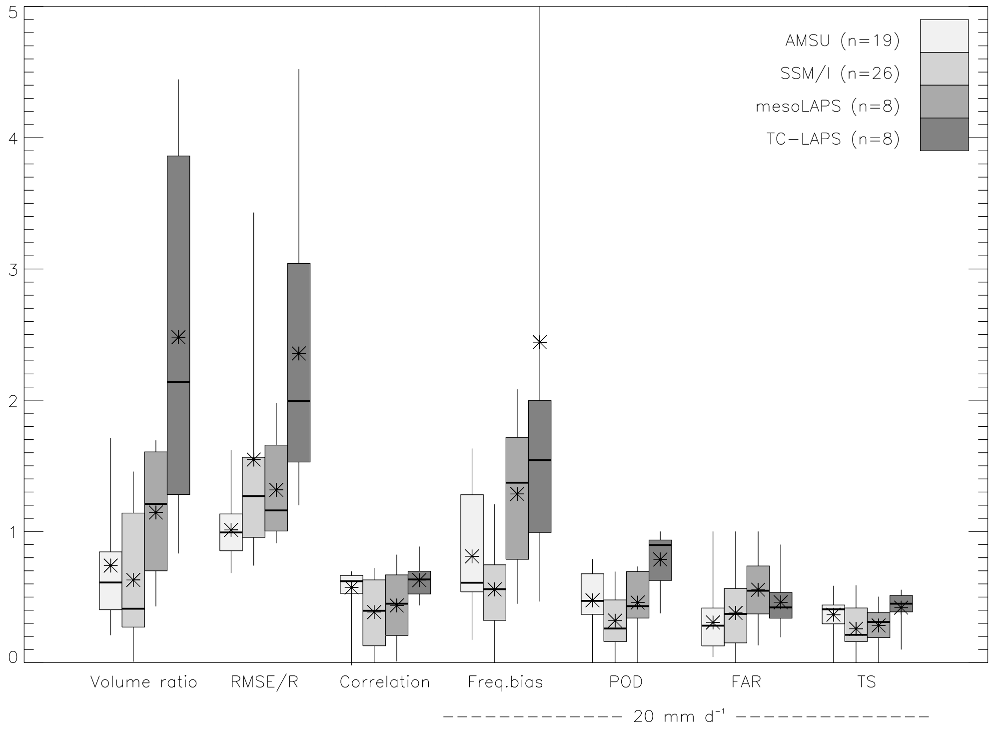
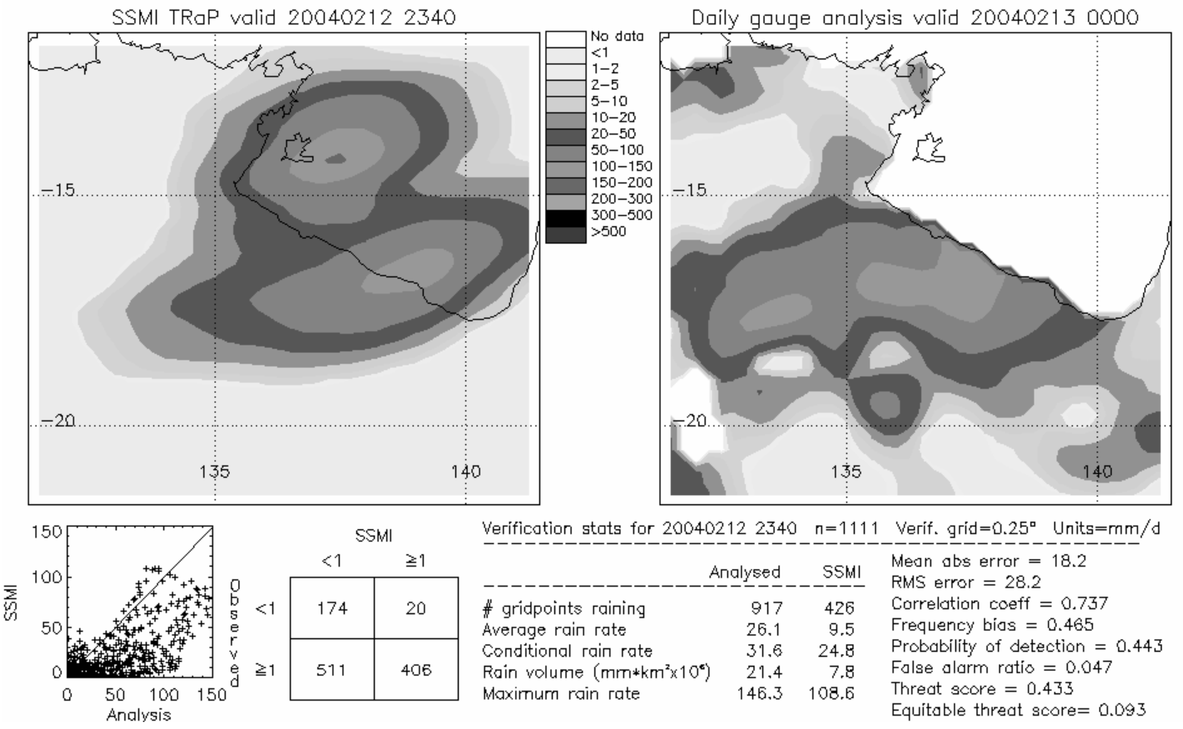


Fig. 9. Box plots of selected validation statistics as a function of satellite sensor or NWP model. The boxes indicate the 25th, 50th, and 75th percentiles of the distribution, and the vertical lines indicate the full range. The asterisks denote the mean values.



		SSMI <1	SSMI ≥1
Observed	<1	174	20
Observed	≥1	511	406

Verification stats for 20040212 2340 n=1111 Verif. grid=0.25° Units=mm/d

	Analysed	SSMI
# gridpoints raining	917	426
Average rain rate	26.1	9.5
Conditional rain rate	31.6	24.8
Rain volume (mm*km²x10⁶)	21.4	7.8
Maximum rain rate	146.3	108.6

Mean abs error = 18.2
RMS error = 28.2
Correlation coeff = 0.737
Frequency bias = 0.465
Probability of detection = 0.443
False alarm ratio = 0.047
Threat score = 0.433
Equitable threat score= 0.093

Fig. 10. Validation of SSM/I-based TRaP rainfall, massaged using smoothing and probability matching (left panel), against the gauge analysis (right panel) for Tropical Cyclone Fritz, valid at 2340 UTC on 12 February 2004.