

An Assessment of Statistically Blended Satellite-Gauge Precipitation Data for Daily Rainfall Analysis in Australia

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Abstract – The effect of rain gauge number and density on the performance of blended satellite-derived and gauge rainfall analyses for Australia is examined. The TRMM multi-satellite precipitation analysis (TMPA) product, 3B42, and daily rainfall observations from the network of surface rain gauges were used. A kernel-based statistical blending algorithm was used to produce gauge-only and blended satellite-gauge gridded rainfall estimates at approximately 5-km resolution across the continent. Daily rainfall surfaces were generated from simulated distributions of between 100-4,000 real-time rain gauges and assessed – using Australia-wide average error statistics – against an independent set of daily gauge measurements. Results indicate that with more than 1,000 gauges there is marginal benefit of including the satellite rainfall retrievals in the interpolation of gauge observations. The use of TMPA data improves upon gauge-only analyses in regions of the continent with densities < 4 gauges per 10,000 km².

Keywords: Satellite rainfall, rain gauge, statistical blend

1. INTRODUCTION

Satellite-derived precipitation estimates have the potential to greatly improve spatially-distributed hydrological modelling capability (Pan et al., 2010). Unlike the isolated point measurements provided by rain gauges, satellite-based precipitation estimates offer greater spatial coverage with higher temporal frequency than many of the current gauging networks. However, the coarse spatial resolution of many of the satellite precipitation products currently available is considered one of the impediments to their wide-spread adoption in hydrological modelling. Moreover, the fact that the precipitation products are retrievals derived from thermal and/or (more recently) microwave radiance observations, makes them less desirable than the direct measurements made by rain gauges.

In Australia, continental interpolated surfaces of rain gauge data are available at 0.05° resolution (Jeffrey et al, 2001; Jones, et al., 2009). The density of rain gauge data is largest in the populous areas of Australia and smallest in the dry interior (Figure 1), confounding straightforward interpolation across the continent. Satellite-based estimates provide synoptic images of the spatial distribution of precipitation events at 0.5–3 hourly intervals, at between 0.07° – 0.25° resolution (Joyce et al., 2004; Kubota et al., 2007; Huffman et al, 2007).

While the absolute accuracy of satellite rainfall products is questionable, and remains subject of on-going worldwide assessment (Ebert et al, 2007; Ebert, 2011), they nevertheless provide unique information on the spatial extent of the rainfall, particularly for those regions of the continent where the network of rain gauges is sparse. By exploiting the accuracy of station-level rain gauge measurements and the spatial coverage of the

gridded rainfall products, it has been asserted that the blending of these two sources of information mitigates the shortcomings of the respective data sets to produce blended precipitation estimates at continental scales (Xiong et al., 2008; Vila et al., 2009; Rozante et al., 2010).

An investigation was conducted into the performance of a number of statistical blending techniques to produce daily rainfall analyses from satellite precipitation products and rain gauge observation for the Australian continent (Renzullo et al, in prep.). An examination of the Australia-wide average performance statistics reveals that in terms of accuracy (e.g. root mean squared error (RMSE), mean absolute error (MAE) and bias), there appears little difference between blended satellite-gauge estimates and gauge-only analyses; a finding consistent with other studies (e.g. Oke et al, 2009). Table 1 summarises the findings for some of the blending methods: i.e. ordinary point kriging (pk) of gauge data only; co-kriging of gauge and satellite data with pixel values collapsed to the gauge point locations (clpspk); co-kriging of gauge and satellite data with gauge values up-scaled to the resolution of the satellite estimates (coinpk); and the kernel-based algorithm of Li and Shao (2010) used to generate gauge-only (LSg) and blended satellite-gauge analyses (LSb). The table shows that the gauge-only methods (pk and LSg) in most measures out perform the blending methods, suggesting that in terms of overall performance there is no advantage to including the satellite precipitation product in the generation of daily rainfall analyses (more details in Renzullo et al., in prep).

This paper attempts to explain why the satellite precipitation product used in Renzullo et al. (in prep) does not appear to improve interpolator performance over the use of gauge data alone. We performed Monte Carlo simulations to observe the effect of gauge number on national average error statistics of daily rainfall estimates in Australia. Next we assessed the changes in relative performance of an interpolator with or without the use of satellite data for different levels of gauge density across Australia.

Table 1. Daily Australian average performance statistics over 31 May 2009 – 31 May 2010 for some interpolations methods (see text for explanation).

	pk	clpspk	coinpk	LSg	LSb
RMSE (mm)	3.66	3.84	3.90	3.54	3.59
MAE (mm)	0.87	0.93	0.92	1.04	1.08
Bias (mm)	0.29	0.23	0.37	-0.33	-0.36

2. DATA AND METHOD

Daily gauge data used in this investigation covering the period 31 May 2009 – 31 May 2010 were obtained from the data holdings of the Australian Bureau of Meteorology (BoM). The observations are interpreted as the 24-hour accumulated rainfall to 9am (local time) on the day of interest. The data include the measurements from the network of gauges reporting in near real-time (NRT), i.e. within 24 hours of 9am on the day of

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interest, and the measurements from a larger post real-time (PRT) monitoring network reporting daily rainfall for the day of interest some days to months later (Figure 1). Note that the number of gauges identified in the NRT network is larger than what is available in practise (~1,500 gauges) because not all the identified NRT gauges report daily rainfall every day. It is typical, however, for there to be twice as many PRT gauges as NRT gauges.

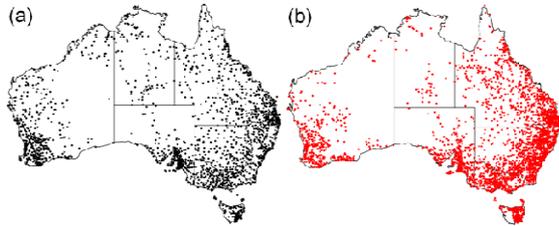


Figure 1. Spatial distribution of rain gauges reporting daily rainfall for 7 September 2009 in (a) near real-time (1951 gauges) and (b) post real-time (3105 gauges).

The satellite precipitation data used in the study were obtained from the Tropical Rainfall Measuring Mission (TRMM) multi-satellite precipitation analysis (TMPA) system (Huffman et al., 2007). The system provides a range of satellite products with quasi-global coverage and generates one of the longest continuous archives of high quality products, known as 3B42 (starting 1 Jan 1998). The 3B42 (and its NRT equivalent, 3B42RT) are based on retrievals from combined microwave and thermal remote sensing observations to estimate precipitation rate (in mm per hour) daily at 3-hourly intervals (Huffman et al., 2007). The 3B42 has the added enhancement, not available in NRT, of bias adjustment against a global gauge network that includes a subset of Australian gauges, much fewer than those displayed in Figure 1 (~7,000 worldwide; GPCC, 2011).

A daily satellite rainfall product was produced by linearly interpolating each pixel value of the 3B42 rain rates through time and then accumulating the series such that the daily totals have a consistent interpretation with the daily gauge observation (Renzullo, 2008). Figure 2a shows the daily satellite-based rainfall estimates from 3B42 for 1 March 2010.

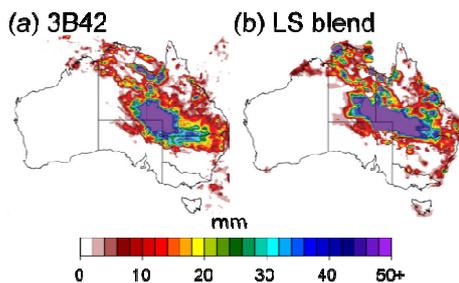


Figure 2. Daily rainfall estimates for 1 March 2010: (a) derived from the TMPA 3B42 rain rates; and (b) 3B42-gauge blend from the Li and Shao (2010) method (LS).

To limit the scope of the investigations to the effect of satellite product on gauge data interpolation, we consider here only one interpolation method. The performance of alternative interpolation methods is described elsewhere (Renzullo et al., in prep). The method used here is the kernel-based double-smoothing algorithm of Li and Shao (2010). The method has been shown to be comparable in performance to co-kriging, for example, however unlike co-kriging (which requires a co-varying field) the method is not as affected by an all-zero

covariate in the generation of gridded rainfall estimates. An alternative would be to use kriging for gauge-only estimates and co-kriging for the blended satellite-gauge estimates. Focusing on Li and Shao (LS) means that the one method is used to generate gauge-only (hereafter LS gauge-only, LSg) or blended satellite-gauge (hereafter LS blended, LSb) rainfall analyses.

An example of the blended satellite-gauge gridded rainfall estimates generated using the LS method, using the full complement of gauge data (i.e. NRT + PRT) is displayed in Figure 2b. We can see that it possesses many of the features of the input satellite rainfall product (notably the spatial patterns), but the effect of gauge data on the rainfall estimates is also visible (e.g. northern NSW).

To further limit the scope of the investigations we consider the gauge and satellite data for the month of March 2010. In March 2010 wide-spread flooding occurred in western, central and southern Queensland with some areas receiving their average annual rainfall in a single day (BoM, 2011). In Western Australia, severe thunderstorms on 21-22 March resulted in significantly higher rainfall in the south-west land division with many new daily rainfall records set in and around the Perth metropolitan area (BoM, 2011). Six days in March 2010 with extensive rainfall patterns (e.g. 1 March, Figure 2) were chosen for the simulations described below.

For six days in March 2010, a de-clustered random sample was selected from the complete set of gauge observations to serve as the independent validation data for each day. De-clustering was performed to minimise the impact of the dense grouping of gauges in populated areas (Figure 1) on the error statistics. The number of validation data for each day ranged from 1301 – 1717. Random samples of 100, 250, 500, 750, 1000, 1500, 2500 and 4000 gauges from the remaining set provided the fitting gauge data for our investigations. The random sampling was repeated 100 times for each sample size. Figure 3 provides an example of the sampled gauge data from 1 March 2010.

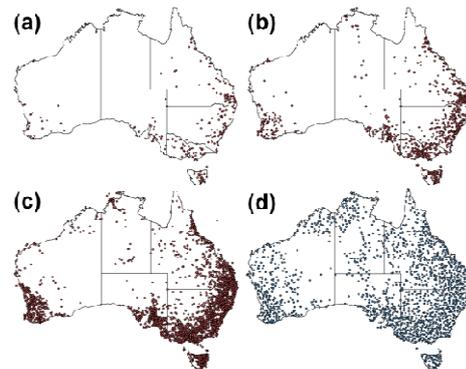


Figure 3. Random samples of daily gauge data (NRT + PRT) for 1 March 2010: fitting data sets based on (a) 250, (b) 1000 and (c) 4000 gauges; (d) de-clustered distribution of 1717 gauges used to validate the interpolated surfaces

3. RESULTS AND DISCUSSION

For each day the LS method was applied to each of the 100 replicates of fitting gauge data. LSg estimates were derived using the gauge data and a spatially uniform background field of zeros. The LSb estimates used the same gauge data but also the satellite-derived daily rainfall products. Examples of the resulting daily rainfall maps are provided in Figure 4.

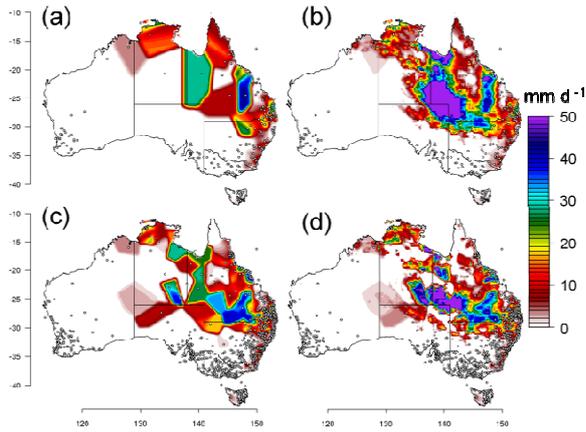


Figure 4. Daily gridded rainfall estimates for 1 March 2010 based on simulated fitting data: LS gauge-only estimate using (a) 250 and (c) 1,000 samples; and LS blended estimates using (b) 250 and (d) 1,000 samples.

Figure 4 shows that with a very small number of fitting data across the country, the LSb estimates are more realistic in terms of spatial pattern than the LSg estimates. In this case the satellite data are the dominant source of estimation skill ('skill' defined below). As the number of fitting gauge data increases, the effect of satellite-derived daily rainfall on the resulting estimates is that the interpolation artefacts become less pronounced, as the gauge values dominate the estimation.

Continental average RMSE, MAE and bias were calculated for all LSg and LSb estimates using the validation gauges (e.g. Figure 3d). Generally, as the number of fitting gauge data increased from 100-4,000 the RMSE and MAE decreased by on average 30-40%. Differences in error statistic between LSg and LSb estimates were largest for low number of gauges (with gauge-only errors being greater) but rapidly decreased as gauge numbers increased. Figure 5a shows the average MAE for the 6 days for both LSg and LSb estimates. It can be seen that above 1,000 gauges differences in MAE is less than 1%.

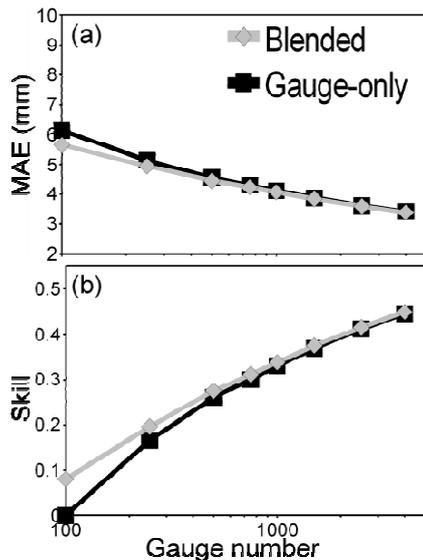


Figure 5. Summary of continental MAE and skill for the LS gauge-only and LS blended estimates averaged over the 6 days and 100 simulations in March 2010.

Estimation 'skill' was computed as the relative difference of the errors compared to reference error values. In our case the reference values were the RMSE or MAE, respectively of the gauge-only RMSE and MAE using 100 gauges. The skill calculated with MAE is displayed in Figure 5b. The skill for LSg estimates using 100 gauges samples is (by definition) zero. LSb estimates for 100 gauges are observed to have some skill (albeit a small amount), suggesting that at such low gauge numbers the satellite data improve the performance of the LS method over the use of gauge data alone. As the fitting gauge number increases so too does the skill for both approaches, and the difference in skill between methods is on average < 3% between 1,000-1,500 gauges.

To understand the effect of gauge density on the performance of the LS method, we partitioned Australia into large $N^\circ \times N^\circ$ cells. The number of fitting gauges falling within each cell was used to define the gauge density. We used all 100 simulations for each fitting data set to account for different gauge configuration within each cell. The LSg and LSb estimates coinciding with the validation gauges were used to compute the RMSE and MAE for each gauge density. The relative difference in blended to gauge-only RMSE's is displayed in Figure 6 for a $5^\circ \times 5^\circ$ cell size. We see that for densities less than 80 gauges per $5^\circ \times 5^\circ$ cell, the blended estimates had smaller RMSE than the gauge-only estimates by as much as 20% on average. Similar results were obtained for different cell sizes, namely 125, 160, 205 and 220 gauges per 6° , 7° , 8° and 9° cells, respectively. Standardising these results yields densities of between 3-4 gauges per $1^\circ \times 1^\circ$ cell. This suggests that for regions with low gauge density the satellite data improved estimates over the use of gauge data alone. Above 4 gauges per $1^\circ \times 1^\circ$ cell the LSg estimates appear to provide better fits on average than the LSb estimates.

Figure 6 also displays the relative difference in RMSE between the 3B42-derived daily rainfall estimates and LSg estimates. The results suggest that for regions of Australia with densities less than 15 gauges per $5^\circ \times 5^\circ$ cell (equivalent to < 1 gauge per $1^\circ \times 1^\circ$ cell) the satellite-derived product performs better than the gauge-only rainfall analysis. Above that density LSg provides the better estimates. We can also infer from Figure 6 that the blended estimates are always an improvement on the satellite data alone.

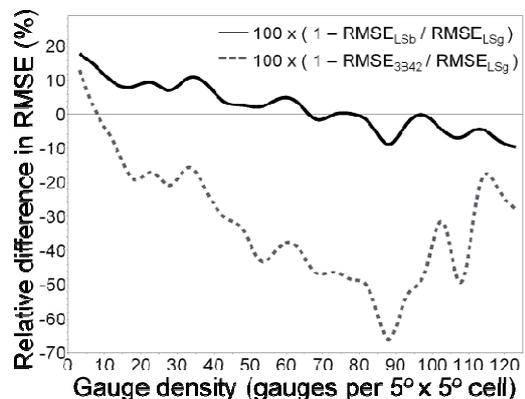


Figure 6. Relative differences in RMSE between LSb and LSg (black solid line) and 3B42 daily rainfall and LSg estimates (dashed grey line) for different density of gauges in $5^\circ \times 5^\circ$ cells across Australia.

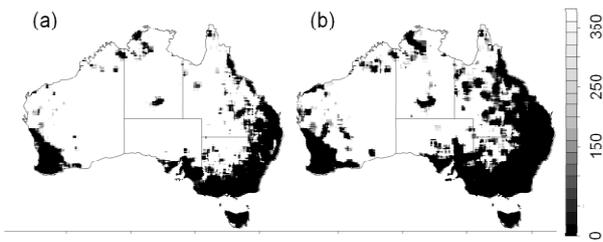


Figure 7. Number of days out of 366 between 31 May 2009 - 31 May 2010 where density is less than 4 gauges per $1^{\circ} \times 1^{\circ}$ cell for (a) NRT and (b) combined NRT+PRT rain gauge networks.

The density of gauges over the 31 May 2009 – 31 May 2010 period is summarised in Figure 7 for both NRT gauges and all (NRT+PRT) gauge networks. White regions correspond to the areas of the country where for 366 days the density of daily rain gauges was less than 4 per $1^{\circ} \times 1^{\circ}$ cell. Conversely, regions of the country where the density was never less than 4 gauges per $1^{\circ} \times 1^{\circ}$ cell are highlighted in black (0 days). Based on Figure 6, it is expected that satellite data will only improve LS blended rainfall estimates in the white region of Figure 7.

4. CONCLUSIONS

An examination of continental average error statistics on blended satellite-gauge precipitation data reveals that when the number of gauges is low, inclusion of the 3B42 satellite rainfall estimates is an improvement over the use of gauge data alone. The difference in performance of the LSg and LSb estimates is negligible above 1,000 fitting gauges. In Australia, the number of gauges reporting daily rainfall in near real-time is $\sim 1,500$, well above the 1,000 gauge threshold for satellite data to make a difference to the estimates. In reality, as in our simulations, as gauge numbers increase we find that they appear in the already well populated regions of the continent. Our examination of the effect of gauge density shows that the inclusion of satellite-based 3B42 daily rainfall estimates are only expected to make a difference in the interior of Australia. Indeed, in very low density areas satellite data alone appeared to be more skilful than LSg estimates. In parts of the country with densities greater than 4 gauges in approximately $10,000 \text{ km}^2$, we do not expect to see the satellite data improving rainfall estimates over gauge-only interpolation. Further investigation is required to explore the interaction of gauge density and configuration on the results.

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