Statistical Evaluation of Combined Daily Gauge Observations and Rainfall Satellite Estimations over Continental South America.

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Abstract

This paper describes a comprehensive assessment of a new high-resolution, high-quality gauge-satellite based analysis of daily precipitation over continental South America during 2004. This methodology is based on a combination of additive and multiplicative bias correction schemes in order to get the lowest bias when compared with the observed values. Inter-comparisons and cross-validations tests have been carried out for the control algorithm (TMPA real-time algorithm) and different merging schemes: additive bias correction (ADD), ratio bias correction (RAT) and TMPA research version, for different months belonging to different seasons and for different network densities. All compared merging schemes produce better results than the control algorithm, but when finer temporal (daily) and spatial scale (regional networks) gauge datasets is included in the analysis, the improvement is remarkable. The Combined Scheme (CoSch) presents consistently the best performance among the five techniques. This is also true when a degraded daily gauge network is used instead of full dataset. This technique appears a

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suitable tool to produce real-time, high-resolution, high-quality gauge-satellite based analyses of daily precipitation over land in regional domains.

1. Introduction

The spatial and temporal distribution of precipitation around the globe is needed for a variety of scientific uses such as climate diagnostic studies, and societal applications such as water management for agriculture and power, drought relief, flood control and flood forecasting (Arkin and Xie, 1994). The task of quantifying the distribution is complicated by the fact that no single currently available estimate of precipitation has the necessary coverage and accuracy over the whole globe. While a suite of sensors flying on a variety of satellites have been used to estimate precipitation on a global basis, generally speaking, the performance of satellite precipitation estimates over land areas is highly dependent on the rainfall regime and the temporal and spatial scale of the retrievals (Ebert et al, 2007). On the other hand, gauge observations continue to play a critical role in observations systems over global land areas. In addition, gauge observations are the only source that is obtained through direct measurements. Both the radar and satellite estimates are indirect in nature and need to be calibrated or verified using the gauge observations (Xie and Arkin 1995; Ebert et al, 2007). While it is possible to create rainfall estimates using a combination of different satellite data (i.e. CMORPH; Joyce et al. 2004), researchers have increasingly moved to using 'the best of both worlds' in order to improve accuracy, coverage, and resolution. The first such combinations were performed at a relatively coarse scale to ensure reasonable error characteristics. For example, the Global Precipitation Climatology Project (GPCP) satellite–gauge (SG) combination is computed on a monthly 2.5° x 2.5° latitude–longitude grid (Huffman et al. 1997; Adler et al. 2003), while finer-scale products initiated by the GPCP include the

Pentad (Xie et al. 2003) and One-Degree Daily (Huffman et al. 2001) combination estimates of precipitation.

The GPCP combination method is designed to use the strengths of each input dataset to produce merged global, monthly precipitation fields that are superior to any of the individual datasets. The technique is also designed to reduce bias in each step by using the input original or intermediate product with the presumed smallest or zero bias to adjust the bias of other products. A large-scale (5 x 5 grid box) average of the multisatellite analysis is adjusted to agree with the large scale average of the gauges (over land and where available). This keeps the bias of the satellite and gauge combination close to the (presumably small) bias of the gauge analysis on a regional scale. Finally, the gauge adjusted, multisatellite estimate and the gauge analysis are combined with inverse-error–variance weighting to produce the final, merged analysis. This gauge–satellite combination approach allows the multisatellite estimate to provide important local variations in gauge-sparse areas, while still retaining the overall gauge bias (Adler et al, 2003). In this case, the monthly gauge analysis is performed by the Global Precipitation Climatology Centre (GPCC). This gauge data is analyzed using an empirical interpolation method SPHEREMAP (Willmott et al., 1985) which is routinely used at the GPCC since 1991 for the calculation of grid point results of 0.5° lat./long.

The One-Degree Daily methodology uses GPCP retrievals by scaling the short-period estimates to sum to a monthly estimate that includes monthly gauge data (Huffman et al. 2001). A similar approach is used in Huffman et al. 2007 (H07, hereafter) to scale 3-hourly estimates using the real-time TMPA (TRMM Multisatellite Precipitation Analysis), where all available 3-hourly merged estimates are summed over a calendar month to create a monthly multisatellite (MS) product. The MS and gauge are combined as in Huffman et al. (1997) to create a post real-time monthly SG combination. Then, the field of SG/MS ratios is computed on the 0.25° x 0.25° grid (with controls) and applied to scale each 3-hourly field in the month, producing the research version, and also called version-6 of 3B42 product (3B42V6 hereafter).

Among multiple applications, precipitation at fine resolution along with increasing computational capacity allows operational and research studies in hydrology across different temporal and spatial scales. However interaction between different scales to resolve land surface hydrology and atmospheric dynamics still needs progress (Tao et. al, 2003) and well balanced high resolution precipitation datasets play an essential role in such land-atmosphere interactions. One of the motivations for this paper is the potential use of high resolution atmospheric datasets for land surface hydrology studies and numerical modeling over South America by combining surface observations with remotely sensed information. Such data fusion was made possible by the onset of Land Data Assimilation Systems (LDAS) initiatives (Mitchell et al.,2004; Rodell et al., 2004). A South American LDAS (SALDAS – de Goncalves et al., 2006a,b) is particularly challenging when proposing to combine high resolution remote sensing and surface observations using LSM’s over a continent with sparse observation networks. Precipitation (along with radiation) represents one of the most important drivers for LSM’s and motivates this paper as part of the efforts of combining satellite precipitation with raingauges for SALDAS forcing composition and evaluation (de Goncalves et al., 2007).

This paper describes and evaluates a new methodology to merge rainfall satellite estimations and daily gauge data. In this case, real-time TMPA (where no rain gauges are incorporated) is used as high quality rainfall algorithm (H07), while CPTEC daily rain gauge database is used to correct the bias on daily basis over South America. Section 2 describes the dataset used in this paper while in section 3 the merging methodology is presented. The experimental design and the validation scheme are discussed in section 4. The results and the conclusions are presented in section 5.

2. Datasets

a. Real-time TRMM Multisatellite Precipitation Analysis

This algorithm is fully described in H07. The main features of this algorithm, including the real-time adjustment, will be outlined in this section. The first stage of the algorithm consists in calibrate and combine microwave precipitation estimates. Passive microwave fields of view (FOVs) from TMI, AMSR-E, and SSM/I are converted to precipitation estimates at the TRMM Science Data and Information System (TSDIS) with sensor-specific versions of the Goddard Profiling Algorithm (GPROF; Kummerow et al. 1996; Olson et al. 1999), while AMSU-B are converted to precipitation estimates at the National Environmental Satellite, Data, and Information Service (NESDIS) with the operational version of the Weng et al. (2003) algorithm. In the case of real-time version, the calibration is made using TMI estimates from TRMM because TCI (TMI-PR estimations) are not available. Also in this version, the calibration coefficients are performed using the last 6 available pentads (5-day period).

In a second step, the infrared precipitation estimates are created using the calibrated microwave precipitation. Histograms of time–space matched combined microwave (high quality precipitation rates) and IR Tb’s, each represented on the same 3-hourly 0.25° x 0.25° grid, are accumulated for a five trailing and one current (partial) pentad (for real-time version) into histograms on a 1° x 1° grid, aggregated to overlapping 3° x 3° windows, and then used to create spatially varying calibration coefficients that convert IR Tb’s to precipitation rates. In the final stage, the microwave and IR estimates are combined. The physically based combined microwave estimates are taken “as is” where available, and the remaining grid boxes are filled with microwave-calibrated IR estimates. A detailed description of this algorithm can be found in H07. The daily accumulation is obtained summing the individual 3-hour files from 15:00Z of the previous day (12:00Z – 15:00Z period) to 12:00Z (09:00Z – 12:00Z period) of the current day.

b. Rain gauge database

The data sources for the daily surface precipitation observations used, in addition to those of the World Meteorological Organization (WMO), are obtained through an INPE compilation of the following agencies: (a) Agência Nacional de Energia Eléctrica (ANEEL; National Agency for Electrical Energy), (b) Agência Nacional de Águas (ANA; National Water Agency), (c) Fundação Cearense de Meteorologia e Recursos Hídricos (FUNCEME; Meteorology and Hydrologic Resources Foundation of Ceará), (d) Superintendência do Desenvolvimento do Nordeste (SUDENE; Superintendence for Development of the Northeast), (e) Departamento de Águas e Energia Elétrica do Estado de São Paulo (DAEE; Department of Water and Electrical Energy for the State of São Paulo), in collaboration with the Centro de Previsão de Tempo e Estudos Climáticos (CPTEC; Brazilian Weather Forecast and Climate Studies Center), and (f) Technological

Institute of Paraná (SIMEPAR). In all cases, the accumulation time is from 12:00Z of the previous day to 12:00Z of the current day. It's important to point out that with the addition of observations from local South American agencies and Brazilian automated weather stations; the number of observations in the CPTEC/INPE database is somewhat 4 times larger than GPCC datasets. This addition will help to retain the overall gauge bias in finer scales.

3. Merging Methodology

The determination of the methodology for constructing a merging technique for daily rainfall estimates over land using a satellite-based algorithm and rain gauge network involves three major issues: 1) define the algorithm/s to be used in the merging process; 2) design the merging technique and; 3) define an validation strategy to asses the results.

In the first case, the Experimental Real-Time daily TRMM Multi-Satellite Precipitation Analysis (TMPA-RT) (H07) is used as the base algorithm for retrieving precipitation because TMPA is successful at approximately reproducing the surface observation–based histogram of precipitation, as well as reasonably detecting large daily events (control algorithm).

In the second issue, two options are suitable to merge rain gauges and satellite retrievals: interpolate the observed values and then merge both fields or define a bias against satellite retrievals and then apply some interpolation technique to get the merged field. Some studies argued that anomaly schemes (additive and multiplicative) are suitable to remove the bias of satellite estimations because some of the spatial variation of total precipitation is associated with finer scales processes (topography, local circulation, etc.) and is thus steady (Dai et al, 1997). In this case, additive and multiplicative correction schemes are used to remove the bias of satellite retrievals. While the first scheme, suggest that the ratio between the observed and estimated value is suitable to remove the bias of satellite retrievals on daily basis, this methodology is not useful to determine the magnitude of the precipitation when the retrieved satellite value is zero and the observed value is different from zero (i.e., warm clouds and/or clouds with no ice structure). On the other hand, additive correction scheme produces large differences when exist large discrepancies between the observed and estimated values.

The proposed scheme, hereafter called Combined Scheme (CoSch), combines these two approaches in a single method to remove the bias of satellite estimations.

The additive bias correction (ADD) is defined as follows:

$$rr^{+} = rr_{sat} + (\overline{rr_{obs} - rr_{sat}}) \qquad (1)$$

Where rr_{sat} is the satellite based estimation and rr_{obs} is the accumulated 24-hours rainfall. The bias between the observed rainfall and satellite retrievals is represented by the second term $(\overline{rr_{obs} - rr_{sat}})$. This bias is interpolated using the inverse distance weight algorithm.

The ratio bias correction (RAT) is performed according to the following equation:

$$rr^{*} = rr_{sat} * (\frac{\overline{rr_{obs}}}{rr_{sat}}) \qquad (2)$$

Where the same conventions than in additive bias correction (Equation 1) were used.

After this procedure, rain gauge observations are interpolated using the nearest neighbor method (no explicit interpolation, original values are retained) masking out all regions with a distance greater than 5 grid points from the closer station. In this case, the grid size is 0.25 degrees to match with satellite estimation.

In the last stage, the bias-corrected rainfall is defined as follows: satellite estimation remains with no correction in those areas masked out in the previous procedure, while the bias-corrected rainfall is defined as the value of such correction scheme (ratio or additive) whose difference with the closest observed value (defined in the previous step) is minimum on pixel by pixel basis.

In order to evaluate the decision rule described in the previous paragraph, January 2004 (southern hemisphere summer) was selected in order to know if any correction scheme shows some preference over the other, or if any geographical region tends to use more one scheme than other. Figure 1 shows the percentage of pixels, for a given day, that certain correction scheme was selected. The result shows a pretty steady situation along the month where around 54% of the pixels are corrected according to ADD scheme while only 46% of the time RAT technique is chosen. Considering these mean values for both schemes, the difference between the number of days (in %) that a given scheme was chosen and the mean value for January 2004 was calculated for both bias-removal techniques (ADD and RAT). The spatial distribution of RAT relative bias is presented in Figure 2a. Due to construction constrains, the sum of RAT and ADD (not shown) is equal 0. It can be observed that over southern South America (approximately southward 20S), RAT scheme is selected 20% above the average (46%, in this case), while this behavior is opposite over most of part of the Brazilian territory and Bolivia. The largest deviations from the average are observed along the coast of Chile, Peru, Colombia, Venezuela and the Guyanas. Those regions exhibit the scarcest gauge networks in the region. One hypothesis about this behavior is that the selection of a given scheme is related with the precipitation regime. Figure 2b shows a close agreement between the RAT bias and the accumulated monthly rainfall: larger values of rainfall are associated with negative/(positive) values of RAT/(ADD), while RAT/(ADD) is more/(less) frequently chosen in those regions with less rainfall. Other factors such as circulation and gauge density also should influence these results.

The third issue, about the validation strategy, will be described in the next section.

4. Validation Strategy and Experimental Design

For testing this bias-removal technique, a daily rain gauge dataset for South America during 2004 (see section 2b for more details) were used in two ways in a cross-correlation process. Gauge reports at 10%, randomly selected of the stations were withdrawn and those at the remaining 90% of the stations were used in the bias-removal process. This cross correlation process was conducted 10 times so that each gauge was withdrawn once. The corrected rainfall estimation was then compared with the corresponding observation to examine the performance of the proposed technique (Chen et al. 2002). For comparison purposes four other estimations were included in this study: additive bias-removal and ratio bias-removal (as defined in the previous section) and the research and real-time version of TMPA (3B42V6 and 3B42RT). For the first two correction schemes (ADD and RAT), the same cross correlation process is performed, while in the last case, values of 3B42V6 and 3B42RT (control run) were selected and compared for the same validation dataset (10% of rain gauges randomly selected, conducted 10 times) to make all the statistical results comparable among them. Table 1 shows the monthly mean (calculated on daily basis) of bias (in mm), root mean square error (in mm) and correlation coefficient for the five proposed models for January, April, July and October 2004. Bold values are the better result obtained for a particular month and for each statistical parameter. In this case, it can be shown that CoSch has a better performance than ADD and RAT separately, but also has a better performance than 3B42V6. This situation is highly remarkable when RMSE and CORR are compared among different estimations. Among these five different estimations, the worse performance is for 3B42RT (control algorithm), where no rain gauge information is added. This result shows that the combined scheme (CoSch) adds some extra value to the ADD and RAT when used separately, retaining some local spatial variability on daily rainfall.

In 2003 the International Precipitation Working Group (IPWG) began a project to validate and intercompare satellite rainfall estimates (Ebert et al, 2007). Some categorical statistics such as bias score (BIAS), probability of detection (POD), false alarm ratio (FAR) and Equitable Threat Score (ETS) can be computed for different rain rate thresholds as follows: 1, 2, 5, 10, 20 and 50 mm. All these parameters can be computed from a rain / no-rain contingency table and measure the performance of a given algorithm (see Wilks, 1995 for more details).. Figure 1 shows the annual mean of the aforementioned categorical statistics (based on daily estimates) for 3B42RT, 32B42V6 and CoSch for all rainfall thresholds, except 50 mm because the lack of events above that threshold can affect the robustness of the statistics. It can be shown that the performance of CoSch is better for all rainfall thresholds. POD (Figure 1a) is higher for all thresholds suggesting that CoSch can get more correct estimates in each category, while FAR (Figure 1b) is smaller for all categories, suggesting that the amount of false alarms estimated by CoSch is smaller than other estimates. Bias Score (BIAS – Figure 1c) shows similar values for all estimations (close to one, the ideal value). Nevertheless, CoSch tends to overestimate lower values and underestimate the largest ones. ETS (Figure 1d) measures the fraction of observed and/or estimated events that were correctly estimated, adjusted for hits associated with random chance (for example, it is easier to correctly forecast rain occurrence in a wet climate than in a dry climate). This parameter is sensitive to hits, because it penalizes both misses and false alarms in the same way. In this case, the improvement is clear for all rainfall thresholds when compared with 3B42RT and 3BR2V6.

To further quantify the impact of the gauge network density to the accuracy of all different estimations, cross-validation tests were conducted using just only 10% (ramdomly selected) of available data to perform the additive, ratio and the combined scheme. Other 10 % (excluding those chosen to perform the correction) was used to validate the results of the aforementioned schemes and also 3B42RT and 3B42V6. This experiment was carried out 10 times so that each gauge was withdrawn once and both results (using 90% of the gauges in one case and using just only 10% to perform the correction in a second experiment) are statistically comparables. This analysis gives us the opportunity to examine the impacts of varying gauge density to the quantitative accuracy of the methodology. Table 2 shows the same statistics parameters than Table 1 but, in this case, with just only 10% of the gauges have been used to perform the bias-removal process. As expected, performance of these methodologies (CoSch, ADD and RAT) improves with increasing density of gauge network, while the other estimates (3B42RT and 3B42V6) show approximately the same values, because the number of gauges used to validate remains the same (10% randomly selected for each one of 10 experiments). Nevertheless, it’s important to point out that despite the fact of using 10% of available gauges to compute the bias-removal process, the technique show better results than 3B42V6 (that uses GPCC data to perform a bias removal process as explained in section 2) and 3B42RT. On the other hand, CoSch perform better than ADD and RAT separately. Nevertheless, it’s also important to point out that; in this case, the difference between CoSch and RAT and between CoSch and ADD is closer than in the previous analysis, suggesting that, for very sparse rain gauge networks, the added value of the combination is less effective than in the previous case. A similar situation can be observed with the rest of the categorical statistics (Figure 2). The performance of CoSch is better for all rainfall thresholds, but the difference, as expected, is smaller than the previous analysis. POD (Figure 2a) is higher for all thresholds suggesting that, despite of the fact that the network density is very scarce, CoSch can get more correct estimates in each category, while FAR (Figure 2b) is smaller, suggesting that less false alarms are estimated by CoSch in all categories than other estimates. Bias Score (BIAS – Figure 2c) shows similar values for all estimations (close to one, the ideal value), while ETS (Figure 2d) show an improvement for all rainfall thresholds when compared with 3B42RT and 3BR2V6.

5. Summary and conclusions

A comprehensive assessment has been performed to examine the performance of a new methodology (CoSch) to merge satellite estimations and daily gauge data over South America during 2004. For comparison purposes, 3B42RT (control algorithm) and 3B42V6 (which also include monthly gauge data form GPCC), where also included in this analysis. Two intermediate results (ADD and RAT) used in the combined scheme, were also examined in order to determine how the proposed methodology works.

Inter-comparisons and cross-validations tests have been carried out for the control algorithm and the different merging schemes over South American region during 2004, for different months belonging to different seasons and for different network densities. The results can be summarized as follows:

- The election of the bias-removal technique seems to be related with the rainfall regime: where the additive bias correction scheme is selected above the mean value when the rainfall rate is lower and the inverse case occurs with the ratio-based scheme.

- It can be shown, looking at the RMSE and Correlation coefficient that the combined scheme (CoSch) performs better than ADD and RAT separately, suggesting that an extra value is added when the proposed scheme is used. CoSch also show the best results of all analyzed merged schemes.

- The control algorithm (3B42RT) presents the poorest performance. This result is expected because this algorithm doesn’t use any gauge data, while 3B42V6, which includes just only the GPCC monthly data, tends to improve all statistic parameters when compared with 3B42RT using an independent gauge dataset to validate,

- In term of the performance for different rainfall thresholds, CoSch again shows the best performance when compared with other merging techniques and the control run.

- Quality of the rainfall estimation degrades as the gauge network used became sparser. Nevertheless, the result is still better than those based on monthly gauge data, in particular due to CoSh being applied directly to the daily timescales rather than dissagregated from monthly mean precipitation.

Based on these results, future work will be focused in the evaluation of this technique under different rainfall regimes and different region of the world. This experience could be replicated using different control algorithms (i.e. CMORPH) in order to get provide to the scientific community a suite of high-resolution, high-quality gauge-satellite based analyses of daily precipitation over land in global and regional domains. Nonetheless, due to the high resolution precipitation datasets constrained by daily observations, what is suitable for land surface and weather application, this technique has been identified as one of the best candidates for precipitation data forcing production for the South American LDAS over the entire continent.

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