Hydrol. Earth Syst. Sci. Discuss., 12, C1982–C1989, 2015
www.hydrol-earth-syst-sci-discuss.net/12/C1982/2015/

Hydrology and Earth System Sciences
Discussions

Interactive comment on "Characterization of precipitation product errors across the US using multiplicative Triple Collocation" *by* S. H. Alemohammad et al.

S. H. Alemohammad et al.

hamed_al@mit.edu

Received and published: 6 June 2015

We thank Dr. Crow for his constructive and insightful comments. Here, we respond to the general and specific comments included in the review:

General Comments:

- The paper describes the application of a modified triple collocation approach to the problem of evaluating large-scale precipitation data sets. The proposed modification allows for the more appropriate treatment of precipitation errors as multiplicative in nature. Issues surrounding the potential impact of error cross-

correlation are examined via the decomposition of triple collocation error results over heavily-gauged reference sites. Overall, this is a high-quality paper on a topic of significant interest. The application of a log-transform to deal with multiplicative precipitation errors is a very nice methodological extension and clearly superior to the existing approach (of naively assuming that all errors are additive in nature in order to shoehorn them into a TC framework).

I also appreciated the effort to explicitly examine the role of error cross-correlation on TC-derived error estimates (in Section 5). However, the one important thing I felt was missing was a re-examination of results in Section 4 based on the (non-trivial) impacts of cross-correlated errors (isolated in Section 5). For example, a key result in Section 4 is the relative lack of accuracy for the GPI precipitation product. However, in Section 5 (and the supplementary materials) we also see that GPI is relatively more independent (i.e. contains less error cross-correlation) than the other precipitation data sets. Given that TC will penalize GPI for this lack of dependence . . . does this mean that the analysis in Section 4 is truly even-handed? Is GPI being unfairly penalized due to being truly independent from the other products – as opposed to it being FAIRLY penalized for its weak relationship with "true" precipitation? So basically, I'd like a little bit of guidance about how the conclusions presented in Section 4 should be re-examined given the cross-correlation issues presented in Section 5. Should the reader really trust that relative rankings presented in Section 4?

I understand that this is a generic problem with any TC analysis; however, I think there are a couple of things that the authors could do to better address this point. First, they could examine whether or not the relative rankings that they derive using TC (at the 6 reference pixel sites examined in Section 5) accurately reflect the rankings they achieve when comparing all the products against the high-quality rain gauge observations acquired at each sites. If TC can successfully replicate the gauge-based rank correlation analysis at these 6 sites – that would be good evidence that the spatially-distributed TC results in Section 4 are robust in a relative sense (despite the known bias issues associated with the neglect of error cross-correlation).

Response/Action: *This is a very interesting comparison and we appreciate it. In all of the 6 pixels that we conducted the gauge-based analysis, the TRMM 3B42 and NEXRAD products are ranked 1st and 2nd for the lowest error based on the RMSE from TC, respectively. Looking at the rankings in the gauge-based TC analysis (σ_{TRE} in Figures 8, S3, S4 and S5 in the original submission) in 5 out of the 6 pixels, TRMM 3B42 has the lowest error, and in 4 out of the 6 NEXRAD has the best error after TRMM 3B42. Therefore, in general, we can make the conclusion, the relative rankings for the products with the lowest error remains almost the same. However, GPCP 1DD and GPI rankings are only preserved on 3 out of the 6 pixels. This makes it hard to make the conclusion that these rankings are preserved for all the cases. Nevertheless, this is based on only 6 pixels out of the 75 pixels across the whole domain. So it is not possible to extend this conclusion to the whole study. We can conclude from this comparison that the cross-correlation error can impact the performance ranking of the precipitation products, but the relative impact needs further analysis. We included this comparison in the final submission with detailed explanations.*

- Another step that could be taken would be replace the TMPA 3B42 dataset with its "real-time" (RT) equivalent (TMPA 3B42RT) which is not gauge-corrected. This transition would make the "TRMM" precipitation product relatively more independent from the NEXRAD and GPCP datasets (which also have a gauge-correction component). Therefore, this transition towards greater error independence should lead to an increase in TC-derived error for the NEXRAD and GPCP products and a decrease in error for GPI (when considered as part of triplet that includes GPI) . The size of this increase (or decrease) could be used of an indication of how serious the cross-correlation problem is across the entire study

domain. Does it – for example – significantly close the gap between GPI and NEXRAD TC results over the eastern part of the study area?

Response/Action: *We implemented this analysis, and included the detailed results in the final paper. Here, we present two figures showing the result of applying TC to the two sets of triplets while replacing TRMM 3B42 with TRMM 3B42RT (Figures 1 and 2). These figures indicate that using the real-time product of TRMM 3B42 will increase the TC-derived errors in NEXRAD and TRMM products and decrease the errors in GPI. This is a direct result of the non-zero cross-correlation. However, the general pattern of the error and the relative values between the the three products remains the same. The TRMM 3B42RT is still doing a better job compared to NEXRAD and GPI; then, NEXRAD is ranked 2nd in performance and GPI is the last one. From this example, we can conclude that the cross-correlation problem is a not a major issue in applying TC analysis to precipitation products in this case; however, it definitely impacts the absolute value of RMSEs derived from TC.*

- Therefore, prior to publication, I would strongly recommend that the authors address this issue in some manner. At the very least, add 2-3 sentences describing the consequences of the analysis in Section 5 on earlier results in Section 4.

Minor Suggestions:

1. Page 2536, Line 9-11: Clarify what exactly is meant by “homogeneous”? You mean homogeneous in a statistical climate sense . . . correct?

   Response/Action: *Exactly, this refers to the spatial homogeneity of the precipitation in a statistical climate sense. The statement will be revised in the final paper to clarify this.*

2. Page 2535, Line 20-22: I don’t see how zeros would violate the assumption of error independence . . . however I can see how they would cause fatal problems

in a logtransform analysis. The authors might want to re-write this sentence (or improve its clarity). Also, what about extremely low rainfall values (right at the edge of numerical precision) . . . can they skew results conducted in log-transform space?

Response/Action: *The issue with zeros is both violation of the error independence and log-transformation. Precipitation can only take values greater and equal to zero; therefore, it is bounded from one side. And if the precipitation estimate at a specific time and space is equal to zero; then, the error in that estimate can be from a limited set of numbers (basically any number greater than zero). So, it is dependent on the measurement (or equivalently the truth). As a result, if we have zero value in the precipitation measurement for all the triplets, the error of each of them is dependent on the measurement; and therefore, on each other. This error dependence decreases as the measurement value moves away from zero, and it can be present for rainfall values close to numerical precision of the system. This is also a minor problem when using TC on soil moisture data that is a bounded variable but is it a major issue with daily and subdaily precipitation data which has a lot of zeros. Therefore, in our analysis we are using biweekly accumulation and excluding the few percentage of zero values to reduce the impact of this dependence. Moreover, it is not possible to represent a non-zero error together with zero precipitation as the truth in the multiplicative model of Eq. (1).*

3. Page 2541, Line 1-4: I had to read this sentence several times to follow it . . . I'd recommend re-writing to clarify its meaning (e.g. be a bit more specific . . . representativeness error in what? . . . and cross-correlation in errors between what and what?).

   Response/Action: *We believe this statement refers to page 2542, Lines 1-4. Assuming this, we revised the sentence to the following in our final submission to clarify the points: "It is understood that gauge data also have errors including*

representativeness error (they are point measurements unlike the other products that provide an average value over each pixel); however, as it is shown in Yilmaz and Crow (2014) (Appendix) the representativeness error in the gauge measurements causes a positive bias in the TC-based RMSE estimates while the cross-correlation between the errors of different products in each triplet causes a negative bias."

List of Figures

1. **Figure 1**: RMSE of the precipitation rate estimated from TC using triplets in group 1; a) NEXRAD, b) TRMM 3B42RT, c) GPI. Panel d) shows the number of data points (biweekly measurements) in each pixel that are used for error estimation in TC analysis.

2. **Figure 2**: RMSE of the precipitation rate estimated from TC using triplets in group 2; a) NEXRAD, b) TRMM 3B42RT, c) GPCP 1DD. Panel d) shows the number of data points (biweekly measurements) in each pixel that are used for error estimation in TC analysis.

Interactive comment on Hydrol. Earth Syst. Sci. Discuss., 12, 2527, 2015.

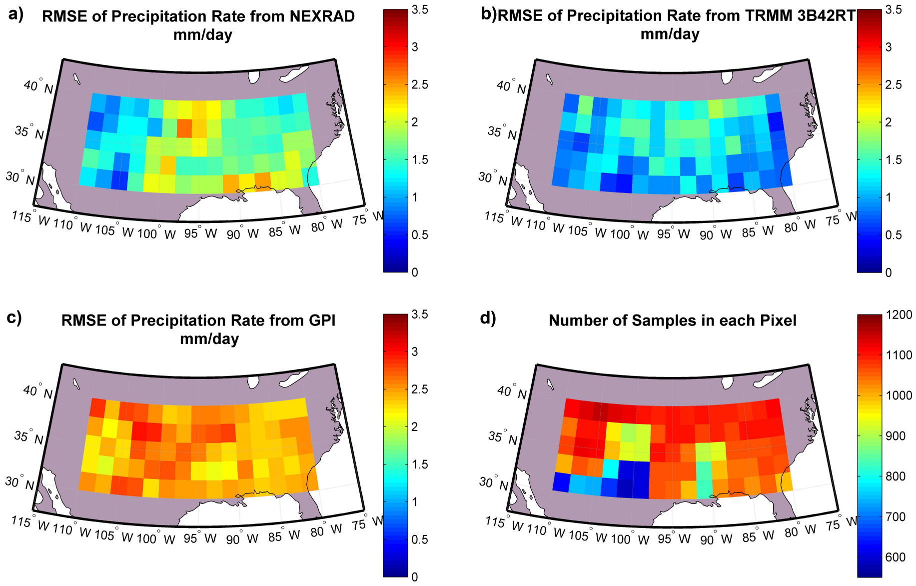
a) RMSE of Precipitation Rate from NEXRAD
mm/day
b)RMSE of Precipitation Rate from TRMM 3B42RT
mm/day
c) RMSE of Precipitation Rate from GPI
mm/day
d) Number of Samples in each Pixel
40° N
35° N
30° N
115° W 110° W 105° W 100° W 95° W 90° W 85° W 80° W 75° W
0 0.5 1 1.5 2 2.5 3 3.5
600 700 800 900 1000 1100 1200

Fig. 1.

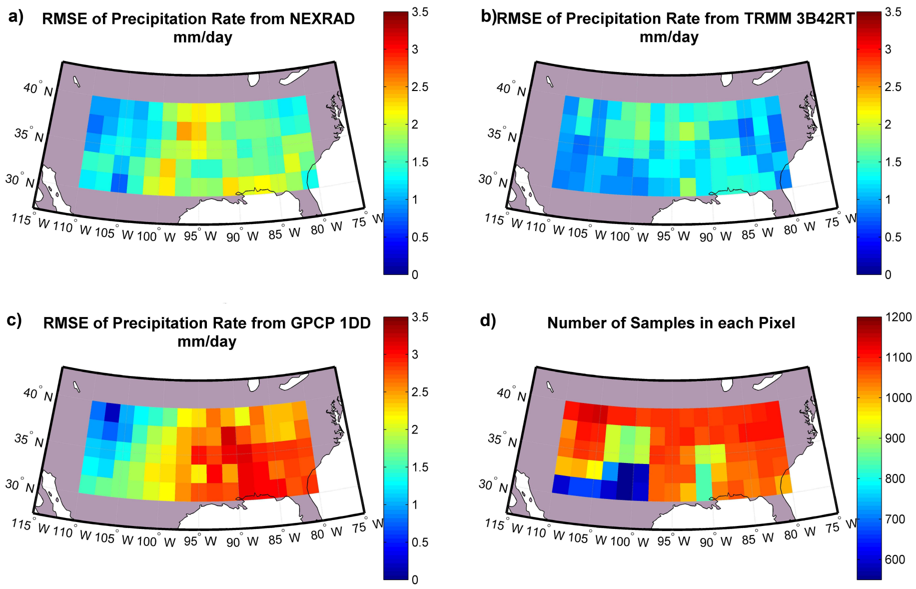
a) RMSE of Precipitation Rate from NEXRAD
mm/day
b)RMSE of Precipitation Rate from TRMM 3B42RT
mm/day
c) RMSE of Precipitation Rate from GPCP 1DD
mm/day
d) Number of Samples in each Pixel
40° N
35° N
30° N
115° W 110° W 105° W 100° W 95° W 90° W 85° W 80° W 75° W
0 0.5 1 1.5 2 2.5 3 3.5
600 700 800 900 1000 1100 1200

Fig. 2.