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Differences in scale-dependent, climatological variation of mean areal precipitation based on satellite and radar-gauge observations

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SUMMARY

This study compares the scale-dependent variation in hourly Mean Areal Precipitation (MAP) derived from a satellite (S) and a radar-gauge (R) Quantitative Precipitation Estimate (QPE), and seeks to explain the S–R differences on the basis of errors in the satellite QPE. This study employs an analytical framework to estimate the coefficient of variation (CV) of MAP for window sizes ranging from 4 km to 512 km, using the rainfall fields of the CPC MORPHing (CMORPH) satellite QPE and a radar-gauge Multisensor QPE (MQPE) over five domains centered in Texas, Oklahoma and New Mexico. CV values based on the analytical framework are first corroborated using empirical estimates. Then, S–R differences in CV are analyzed to determine the contributions of the S–R differences from empirical fractional coverage (FC) and spatial correlograms. Subsequently, sensitivity analyses are performed to isolate the impacts of false detections and long-term, magnitude-dependent bias in CMORPH on the inaccuracies in FC and correlograms. The results are stratified by domain and season (winter and summer) to highlight the impacts of differential accuracy of CMORPH under diverse rainfall regimes. Our analyses reveal that CMORPH-based CV tends to plateau at larger window sizes (referred to as critical window size, or CWS), and is broadly higher in magnitude. The mechanisms underlying the CV differences, however, differ between winter and summer. Over the winter, CMORPH suffers from severe underdetection, which yields suppressed FC across window sizes. This underestimation of FC, together with the lack of resolution of internal rainfall structure by CMORPH, leads to an magnification of both CWS and the magnitude of CV. By contrast, over the summer, widespread false detections in CMORPH lead to inflated FC, which tends to suppress CWS but this effect is outweighed by the opposing impacts of inflated outer and inner scales (i.e., distance parameters of indicator and conditional correlograms). Moreover, it is found that introducing false detection to MQPE via a simple expansion scheme is effective in increasing the FC and inner scale in tandem, and that histogram differences are a rather minor contributor to the S–R difference in inner scale. The implications of the findings for disaggregating climate model projection and data fusion are discussed.

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1. Introduction

Satellite-based Quantitative Precipitation Estimates (QPEs), for their wide coverage and spatial continuity, have seen applications in water budget analysis, flood forecasting, soil moisture predictions and hydrologic model calibration for regions where ground sensors are lacking or deemed inadequate (Scofield and Kuligowski, 2003; Su et al., 2008; Tobin and Bennett, 2010; Habib et al., 2012b; Zhang et al., 2013; Wu et al., 2014). Evolving space-borne sensor technology and precipitation estimation techniques promise further refinement in the spatio-temporal resolutions of Satellite-based QPEs (henceforth referred to as SQPEs) and enhancements in their accuracy. For example, the recent launch of the Global Precipitation Measurement (GPM, Kidd and Huffman, 2011) satellite will refine the grid mesh of the multi-satellite products from 1/4 degree to 10 km, and improve their quality through cross-calibration of satellite sensors. Equally notable is that several satellite QPEs (e.g., the Tropical Rainfall Measurement Mission Multisatellite Precipitation Analysis, or TMPA; Huffman et al., 2007) have accumulated relatively long archives (>10 years), making them a potentially viable source of climate information, especially where a long-term, high resolution precipitation archive is absent.

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Acronyms

CMORPH	CPC MORPHing
CV	Coefficient of variation
CWS	critical window size
FAR	false alarm ratio
FC	fractional coverage
GPM	Global Precipitation Measurement
L_I	scale parameter for inner correlogram
L_o	scale parameter for outer correlogram
MAP	Mean Areal Precipitation
MPE	Multisensor Precipitation Estimator
MQPE	Multisensor Quantitative Precipitation Estimate
PMW	Passive Microwave
QPE	Quantitative Precipitation Estimate
SCaMPR	Self-calibrating Multivariate Precipitation Retrieval
SQPE	Satellite Quantitative Precipitation Estimate

Of the many opportunities presented by the improving quality and the expanding archive of SQPE data sets, yet to receive much attention is the use of SQPE for quantifying the long-term, scale-dependent temporal variability of Mean Areal Precipitation (MAP). Such information has two immediate downstream utilities, namely conditioning downscaled climate model outputs and fusing precipitation products of differing resolutions. Statistical downscaling of climate model projection, as pointed out in Fowler et al. (2007), requires long-term precipitation climatology for which variation on a subgrid scale is an important component (see Wood et al., 2004; Maraun et al., 2010 for related comments). To elaborate, inconsistency between the temporal variability represented by downscaled climate model outputs and that based on observations could hamper the former's application to the analysis and prediction of floods and droughts. This can be addressed by adjusting the model-derived MAP so to match the variability based on observations. As for data fusion, there is a potential of blending a high resolution SQPE with coarser resolution gauge-only analysis (e.g., the 2 by 2.5 degree National Weather Service Climate Precipitation Center hourly Atlas No. 7; Higgins et al., 2000) to yield a product that combines the strengths of each product. For these applications, SQPE could be used to extrapolate the variance of the coarser spatial resolution product to the finer, target resolutions.

These promising prospects notwithstanding, it needs to be noted that SQPEs remain susceptible to large biases and random errors in spite of their continuing improvements. Habib et al. (2012b), for example, illustrated the large bias in the SQPEs produced via the CPC MORPHing (CMORPH) algorithm, one of the most accurate products. Kuligowski et al. (2013) highlighted the contribution of error in microwave to that of Self-calibrating Multivariate Precipitation Retrieval (SCaMPR) SQPE. Mei et al. (2014) compared multiple SQPE products over mountainous basins and found that none of them was ideal in capturing heavy precipitation events. Despite these and related works dedicated to the evaluation of satellite QPEs (Xie et al., 2007; Sapiano and Arkin, 2009; Yilmaz et al., 2005; Bitew and Gebremichael, 2011; Tobin and Bennett, 2010; Pan et al., 2010; Zhang et al., 2013), it is yet unclear how these systematic and random errors in the SQPEs impact the scale-dependent variability of MAP as portrayed by SQPE. The present study serves precisely this purpose: it offers a dissection of the differences in the coefficient of variation (CV) of MAP derived from a SQPE and a high quality radar-gauge product, and it attempts to link these inaccuracies of the errors in the former product.

The goals of this work are threefold. The first is to compare the scale-dependent CV from CMORPH SQPE and the National Weather Service multisensor QPE that is based on radar and gauge data. Second, the work seeks to isolate the contributions of errors in scale-dependent rainfall intermittency characterized by FC, and those associated with spatial rainfall structure represented by spatial correlograms to the differences in CV based on CMORPH and MQPE (hereinafter referred to S–R difference, with S and R standing for satellite and radar, respectively). Third, the study attempts to quantify the impact of long-term bias and false rainfall detection on the fractional coverage (FC) of positive precipitation and correlograms. A unique aspect of this study lies in the use of an analytic framework developed by Seo and Smith (1996) that allows for a separation of impact of scale-dependent CV from FC and correlograms. Such a breakdown further permits an analysis of the sensitivity of CV to bias and false rainfall detection directly through perturbation experiments. This study complements the aforementioned body of literature on SQPE accuracy by offering new insights into the scale-dependent impact of SQPE inaccuracies on CV of MAP and by addressing potential impact of the inaccuracies on downscaled climate model outputs.

The remainder of the paper is organized as follows. Section 2 reviews the analytical framework of Seo and Smith (1996), and describes the data and methods. Section 3 summarizes the results. Section 4 discusses the results, and Section 5 presents the conclusions and future works.

2. Data and methodology

2.1. Analytical framework

In this section, we review the analytical framework devised by Seo and Smith (1996). Detailed derivations are omitted here and interested readers are referred to the original paper.

Let $R(\mathbf{x}, t)$ denote the hourly rainfall amount at location $\mathbf{x}$ and hour t, where $\mathbf{x}$ is the location vector with $\mathbf{x} = (x_1, x_2)$. Let M and Z be the Mean Areal Precipitation (MAP) estimates and the FC of positive precipitation for domain A, respectively; then

$$\begin{aligned} M(A,t) &= \frac{1}{||A||}\int_A R(\mathbf{x},t)d\mathbf{x} \\ Z(A,t) &= \frac{1}{||A||}\int_A I_R(\mathbf{x},t)d\mathbf{x} \end{aligned} \tag{1}$$

where $||A||$ is the size of the domain A; I_R is the indicator function that assumes unity when R is greater than a prescribed threshold and zero otherwise.

Of interest is the conditional expectation of positive hourly MAP over domain A, $E[M(A,t)|M(A,t) > 0]$. This is a long-term, climatological quantity that is only a function of A and is *independent of time*. Let us denote this quantity by $m_M(A)$. With the assumption of second-order stationarity of $R(u,t)$ within domain $A, m_M(A)$ can be decomposed into the product of expectation of positive point precipitation and that of fractional coverage:

$$E[M(A,t)|M(A,t) > 0] = E[R(t)|R(t) > 0]E[Z(A,t)|Z(A,t) > 0] \tag{2}$$

Let $m_R = E[R(t)|R(t) > 0]$, and $m_Z(A) = E[Z(A,t)|Z(A,t) > 0]$. Let the $\sigma_M^2(A)$ denote the variance of positive MAP for A, i.e., $\sigma_M^2(A) = Var[M(A,t)|M(A,t) > 0]$. $\sigma_M^2(A)$ characterizes the *temporal*