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Improving high-resolution quantitative precipitation estimation via fusion of multiple radar-based precipitation products

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SUMMARY

For monitoring and prediction of water-related hazards in urban areas such as flash flooding, high-resolution hydrologic and hydraulic modeling is necessary. Because of large sensitivity and scale dependence of rainfall–runoff models to errors in quantitative precipitation estimates (QPE), it is very important that the accuracy of QPE be improved in high-resolution hydrologic modeling to the greatest extent possible. With the availability of multiple radar-based precipitation products in many areas, one may now consider fusing them to produce more accurate high-resolution QPE for a wide spectrum of applications. In this work, we formulate and comparatively evaluate four relatively simple procedures for such fusion based on Fisher estimation and its conditional bias-penalized variant: Direct Estimation (DE), Bias Correction (BC), Reduced-Dimension Bias Correction (RBC) and Simple Estimation (SE). They are applied to fuse the Multisensor Precipitation Estimator (MPE) and radar-only Next Generation QPE (Q2) products at the 15-min 1-km resolution (Experiment 1), and the MPE and Collaborative Adaptive Sensing of the Atmosphere (CASA) QPE products at the 15-min 500-m resolution (Experiment 2). The resulting fused estimates are evaluated using the 15-min rain gauge observations from the City of Grand Prairie in the Dallas–Fort Worth Metroplex (DFW) in north Texas. The main criterion used for evaluation is that the fused QPE improves over the ingredient QPEs at their native spatial resolutions, and that, at the higher resolution, the fused QPE improves not only over the ingredient higher-resolution QPE but also over the ingredient lower-resolution QPE trivially disaggregated using the ingredient high-resolution QPE. All four procedures assume that the ingredient QPEs are unbiased, which is not likely to hold true in reality even if real-time bias correction is in operation. To test robustness under more realistic conditions, the fusion procedures were evaluated with and without post hoc bias correction of the ingredient QPEs.

The results show that only SE passes the evaluation criterion consistently. The performance of DE and BC are generally comparable; while DE is more attractive for computational economy, BC is more attractive for reducing occurrences of negative estimates. The performance of RBC is poor as it does not account for magnitude-dependent biases in the QPE products. SE assumes that the higher-resolution QPE product is skillful in capturing spatiotemporal variability of precipitation at its native resolution, and that the lower-resolution QPE product provides skill at its native resolution. While the above assumptions may not always be met, the simplicity and robustness observed in this work make SE an extremely attractive choice as a simple post-processor to the QPE process. Also, unlike the other procedures considered in this work, it is extremely easy to update the statistical parameters of SE in real time, similarly to the real-time bias correction currently used in MPE, for improved performance via self-learning.

1. Introduction

In the U.S., more than three-quarters of the population live in urban areas, which collectively comprise only about 3% of the land area. According to the U.S. Census Bureau, the urban population increased by 12.1% from 2000 to 2010 compared to the overall increase of 9.7% for the same period. For the 486 large urbanized areas, the rate was even higher at 14.3%. Given the high population density, high-resolution observing and modeling capabilities are necessary in urban areas for monitoring and prediction of water-related hazards such as flash floods. Increasing occurrences of extreme precipitation expected from climate change put such

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areas in a particularly vulnerable position where even a small-scale but intense rainfall event can cause deadly flash floods and extensive damages.

For high-resolution observing and modeling of water-related hazards in large urban areas, the use of weather radar and distributed hydrologic modeling is a natural progression. Quantitative precipitation estimates (QPE) from radars, however, are subject to various sources of error (Moreau et al., 2009; Seo et al., 2010; Villarini and Krajewski, 2010). High-resolution distributed modeling is subject to nonlinear growth of errors due to the errors in QPE and in model parameters and structures (Koren et al., 2004). For hydrologic, hydraulic and water quality modeling and prediction in urban areas, it is hence necessary that the QPE is made as accurate as possible at the highest resolution possible. The purpose of this work is to explore fusing multiple radar-based precipitation products to obtain a higher-quality QPE that improves over the ingredient QPEs at their native resolutions for a wide spectrum of hydrologic, hydrometeorological and hydroclimatological applications. Necessarily, fusion can take place only after all ingredient QPE products are made available. As such, the fused QPE may not be available as quickly as the ingredient high-resolution QPEs, an inherent limitation of fusion for those applications for which timeliness is of the essence.

In the Dallas–Fort Worth Metroplex area (DFW), there are currently three real-time radar-based QPE products available: the Multisensor Precipitation Estimator (MPE, Seo, 1998), Q2 (Next Generation QPE, Zhang et al., 2011) and CASA (Collaborative Adaptive Sensing of Atmosphere, Chandrasekar and Cifelli, 2012). Because the radar systems, the sources of additional information, and/or processing algorithms differ, the above QPE products have different error characteristics and nominal spatiotemporal resolutions. Whereas multisensor merging of satellite, radar and/or rain gauge data has been widely investigated (Seo et al., 2010; Li and Shao, 2010; Woldemeskel et al., 2013; Berndt et al., 2014; Chang et al., 2014; Delrieu et al., 2014), fusion of multiple gridded QPEs of different spatiotemporal resolutions is relatively new (Ebtehaj and Foufoula-Georgiou, 2013, Chandrasekar and Cifelli, 2012). High-resolution fusion is particularly challenging because of high dimensionality and likely under-determinedness of the estimation problem. In this work, we formulate and comparatively evaluate four relatively simple procedures for fusing gridded QPEs of different resolutions. The targeted outcome is a fusion algorithm that may be implemented as a post-processor to the QPE operation in which multiple gridded QPE products are processed.

The general methodology used in this work for fusion is Fisher estimation (Schweppe, 1973; Bras and Rodriguez-Iturbe, 1985) and its conditional bias-penalized variant (Seo, 2013; Seo et al., 2014). If the penalty for Type-II conditional bias (Jolliffe and Stephenson, 2003) is not assessed, conditional bias-penalized estimation reduces to Fisher estimation. There are many fusion techniques available (see, e.g., Castanedo, 2013, for a review). Our choice for Fisher estimation and Fisher-like estimation using the conditional bias-penalized variant stems from two considerations. The first is that Fisher estimation has been used extensively for precipitation analysis for many years as explained above. As such, it provides a natural starting point for multiscale estimation (see, e.g., Ebtehaj and Foufoula-Georgiou, 2013). The second is that it is arguably the most fundamental method in estimation theory and hence is more likely to yield insight and foresight for advancing multiscale estimation. Note that, in a broad sense, Fisher estimation includes optimal estimation, kriging, and Kalman filter, among others. For evaluation, we compared the fused precipitation estimates with rain gauge observations in the DFW area.

The main contributions of this work are: development and comparative evaluation of different procedures for fusing multiple radar-based precipitation products, advancing understanding of precipitation fusion and the relationships among the different procedures, and evaluation of multiple radar QPEs in the DFW area. The rest of this paper is organized as follow. Section 2 describes the approach used to arrive at the four fusion procedures. Section 3 describes the procedures in detail. Section 4 describes the study area and data used. Section 5 describes estimation of the statistical parameters. Section 6 describes the evaluation experiments. The results are presented in Section 7. Finally, the conclusion and future research recommendations are given in Section 8.

2. Approach

Below, we describe the four procedures used in this work in the context of fusing the MPE and Q2 estimates which have nominal spatiotemporal resolutions of 1 h and 4×4 km^2, and 5 min and 1×1 km^2, respectively. The rain gauge data used in this work for parameter estimation and validation are available only at a 15-min resolution. As such, we chose 15 min and 1×1 km^2 as the target resolution for fusion, rather than 5 min and 1×1 km^2. Because we are interested in precipitation estimation at the highest possible resolution, fusion is performed at the highest spatial and temporal resolutions among all ingredient QPEs. It is possible that the spatiotemporal grid sizes of ingredient QPEs (however many there may be) may not be integer multiples of the smallest grid size. In theory, QPE products of any spatiotemporal resolution can be included in fusion by defining the spatiotemporal support associated with each datum in the ingredient QPEs in the observation equation (see below). In the real world, however, the detailed bookkeeping and covariance modeling necessary for such an approach would be too complex to be practical, and approximations to render the larger grid size(s) to be integer multiples of the smallest grid size would be necessary. Fig. 1 illustrates the data flow for the MPE and Q2 products, and the fusion of the two QPEs. Once the techniques are comparatively evaluated for fusion of MPE and Q2 QPE, we apply the best performing procedure for fusion of MPE and CASA QPE as well. The nominal resolution of the CASA QPE is 1 min and 500×500 m^2. The target resolution for fusion of the CASA and MPE products is 15-min and 500×500 m^2. Before we describe the procedures in some detail, we first explain the rationale and motivation for their formulations below.

In the first approach, the observation vector, Z, is made of a single MPE estimate at 1-h 4-km resolution and all 64 (=4^3) Q2 estimates at 15-min 1-km resolution within the sampling volume of the MPE estimate. The state vector, X, denotes the true unknown precipitation at the 15-min 1-km resolution, which is then solved for via Fisher estimation (Schweppe, 1973; Bras and Rodriguez-Iturbe, 1985) under the linear observation equation, $Z = HX + V$, where H denotes the structure matrix and V denotes the observation error vector. This approach is referred to as Direct Estimation (DE) as the procedure represents direct estimation of precipitation at the target resolution using observations at multiple scales. Because the Fisher solution does not impose non-negativity constraints on the estimates, DE may produce negative estimates particularly in areas of light or no precipitation. It is possible to impose non-negativity constraints and solve constrained minimization via, e.g., the Lagrange method (Szidarovszky et al., 1987). Such an approach, however, is suboptimal and may compromise effectiveness of the procedure particularly for estimation of large precipitation amounts, and hence is not considered here. In this work, all negative DE estimates are reset to zero.

In the second approach, the observation vector remains the same, but the state vector is made of multiplicative adjustment factors for the Q2 estimates at 15-min 1-km resolution, and the