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Improving radar rainfall estimation by merging point rainfall measurements within a model combination framework

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ABSTRACT

While the value of correcting raw radar rainfall estimates using simultaneous ground rainfall observations is well known, approaches that use the complete record of both gauge and radar measurements to provide improved rainfall estimates are much less common. We present here two new approaches for estimating radar rainfall that are designed to address known limitations in radar rainfall products by using a relatively long history of radar reflectivity and ground rainfall observations. The first of these two approaches is a radar rainfall estimation algorithm that is nonparametric by construction. Compared to the traditional gauge adjusted parametric relationship between reflectivity (Z) and ground rainfall (R), the suggested new approach is based on a nonparametric radar rainfall estimation method (NPR) derived using the conditional probability distribution of reflectivity and gauge rainfall. The NPR method is applied to the densely gauged Sydney Terrey Hills radar network, where it reduces the RMSE in rainfall estimates by 10%, with improvements observed at 90% of the gauges. The second of the two approaches is a method to merge radar and spatially interpolated gauge measurements. The two sources of information are combined using a dynamic combinatorial algorithm with weights that vary in both space and time. The weight for any specific period is calculated based on the error covariance matrix that is formulated from the radar and spatially interpolated rainfall errors of similar reflectivity periods in a cross-validation setting. The combination method reduces the RMSE by about 20% compared to the traditional Z-R relationship method, and improves estimates compared to spatially interpolated point measurements in sparsely gauged areas.

1. Introduction

Accurate rainfall estimates are of great importance in hydrology. Rain gauges and weather radars are the two most widely used sensors for rainfall measurement (Severino and Alpuim, 2005; Habib et al., 2001; Berne et al., 2005). Rain gauges are a simple and cheap technology providing relatively accurate measurements at a point location. In contrast, weather radars provide estimations of rainfall over large geographic areas with the benefit of repeated measurements at high frequency (García-Pintado et al., 2009). Radar measures the strength of electromagnetic waves backscattered by the atmosphere, termed as 'Reflectivity' . Conventionally, a power law relationship often referred to as the Z-R relationship ($Z = AR^b$) is used to relate the radar reflectivities (Z) to ground rainfall rates (R) (Krajewski and Smith, 2002; Mapiam et al., 2009). In most situations, the process of radar rainfall estimation involves (1) the measurement of reflectivity, (2) the removal of errors caused during its measurement, (3) the conversion of estimated reflectivity into rainfall, and 4) an adjustment depending on gauge rainfall measurements (Chumchean et al., 2006a). Uncertainties are associated with each of these steps. In practice, when considering long duration rainfall periods and/or multiple storm types, steps (1) and (2) can be affected by phenomena such as ground clutter, beam blockage, anomalous propagation, hail, bright band, attenuation, range-dependent bias, range degradation, vertical profile of reflectivity, temporal and spatial sampling errors (Chumchean et al., 2006; Villarini and Krajewski, 2010). There are also errors introduced by rainfall variability and precipitation drift as well as the uncertainties of relating point rainfall measurements to radar measurements across a gridded domain. Our aim is to address the uncertainties in converting the radar reflectivity to rainfall rates that have

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hampered the widespread use of radars in hydrology (Villarini and Krajewski, 2010).

It has been shown that improved rainfall estimates can be achieved through a combination of radar and gauge measurements by exploiting their strengths and correcting for their shortcomings (Schiemann et al., 2011; Burlando et al., 1996; Krajewski, 1987). This paper proposes two innovative methods for improving radar rainfall estimation by combining gauge and radar measurements. The idea of merging radar and gauge measurement is not new and a number of different methods have been developed. Previous studies were mostly concerned about the application of gauge data for correcting systematic errors in radar rainfall estimates. The most common application is Mean Field Bias (MFB) correction of radar rainfall estimates (Chumchean et al., 2006a; Seo, 1998). It considers a multiplicative adjustment factor estimated as the ratio of the accumulated radar rainfall and the accumulated gauge rainfall (Kitzmiller et al., 2013). Though MFB correction improves radar data quality (Rabiei and Haberlandt, 2015), it is known to underestimate rainfall in some situations (Chumchean et al., 2006). Seo and Breidenbach (2002) suggest a method to correct spatially varying non-uniform bias in radar estimates by considering a small bin within the radar domain. The authors termed this method as a local bias correction method where locally varying bias is corrected instead of MFB (Seo et al., 2003). Based on the number of rain gauges and their distance from the radar, Chumchean et al. (2006a) present a method to update the current MFB estimate by applying a Kalman filter.

The application of bias correction depends mostly on the availability and quality of gauge data (Seo et al., 2003). In real time, the number of rain gauges available are often very small. Therefore, spatial averaging with gauged locations is required to apply this method to the ungauged region (Seo and Breidenbach, 2002; Steiner et al., 1999; Smith and Krajewski, 1991). Several radar and gauge merging methods have been proposed, such as ordinary kriging, cokriging, kriging with external drift (KED) (Berndt et al., 2014; Velasco-Forero et al., 2009; Sideris et al., 2014; Creutin et al., 1988), kriging with radar error (KRE) (also known as conditional merging) (Sinclair and Pegram, 2005) and wavelet analysis (Kalinga and Gan, 2012). Among all tested kriging techniques, KED often yields the best results (Haberlandt, 2007; Delrieu et al., 2014; Jewell and Gaussiat, 2015). The common assumption in all these techniques is that the gauge rainfall is the primary true source and the radar data is auxiliary information that can be used to improve the spatial interpolation (Rabiei and Haberlandt, 2015; Goudenhoofdt and Delobbe, 2009). This assumption is generally required because of the uncertainties and errors that result from converting the radar reflectivity to rainfall intensity. It is commonly accepted that the most useful information from the radar is the spatial pattern of the rainfall intensity rather than its magnitude (Méndez-Antonio et al., 2009). Rain gauges are more accurate, but conversely their measurements are only representative of a very small area (Goudenhoofdt and Delobbe, 2009; Martens et al., 2013). Furthermore, even if there are uncertainties in radar rainfall estimates, it does contain useful information about the temporal distribution of rainfall (Martens et al., 2013; Shucksmith et al., 2011). In this paper, we argue that if the errors in the rainfall field derived from gauges and radar can be accurately quantified, this information can be used to efficiently combine the two products without discarding the intensity information from the radar. This paper presents a method for combining spatially interpolated gauge rainfall with a radar rainfall estimate. Such combination is accomplished without making assumptions on the relationship between radar reflectivity and gauge rainfall. Furthermore, it considers the dependence between the radar and gauge estimates and thereby shows improvement over either the radar or gauge estimates taken individually.

In merging the radar and gauge products, there are parallels with recent work in combining multiple climate models or seasonal forecasts (Chowdhury and Sharma, 2009). One of the important findings from these studies is that dynamic weighting of the models (i.e. where the combination weights change with time) provides superior performance compared to static weighting schemes (Chowdhury and Sharma, 2010; Devineni and Sankarasubramanian, 2010). We therefore propose dynamic weighting to merge the radar and gauge data, which to our knowledge is a new contribution to the field. Dynamic weighting requires estimates of the error in each of the models at every location and every time step. The proposed method weights two different sources of information (radar and gauge estimates) based on their temporal distribution of errors without giving priority to one over another. We therefore propose an improved radar-rainfall relationship that calculates the uncertainties for different rainfall intensities.

Radar-rainfall relationships are very complex. The Z-R relationship depends on the drop size distribution of the rainfall as well as the rainfall regime and geographical location (Lee and Zawadzki, 2005; Steiner et al., 2004; Hazenberg et al., 2011). For example, Marshall and Palmer (Marshall and Palmer, 1948) found that, theoretically, reflectivity and rainfall intensity should be proportional to the 6th and 3.7th moments of the raindrop diameter respectively. Hence, radar reflectivity is more sensitive to rain drop diameter than to rainfall rate. Moreover, it has been observed that the Z-R relationship can be non-injective, such that a reflectivity value can correspond to samples having different drop size distributions and rainfall intensities (Ochou et al., 2011; Uijlenhoet, 2001). While DSDs obtained by disdrometers can be used for obtaining the Z-R relationship (Prat and Barros, 2009; Verrier et al., 2013), these measurements are not available in many parts of the world (Mapiam et al., 2009; Hasan et al., 2014) and statistical calibration of the Z-R relationship is required. The commonly used power-law, with only two free parameters (A and b), is unable to capture this complexity. To circumvent this limitation and make the best use of available records of radar reflectivity and ground rainfall, we propose a nonparametric method to model the full complexity of the Z-R relationship.

Nonparametric methods have been found to be efficient in a number of hydrologic applications including streamflow simulation (Sharma et al., 1997; Sharma and O'Neill, 2002) and synthetic rainfall generation (Oriani et al., 2014). Villarini et al. (Villarini et al., 2008) calculated nonparametric radar rainfall uncertainties in a study involving a dense gauge network and radar measurements. They formed a conditional expectation function to estimate the expected areal averaged ground rainfall for a given radar rainfall estimate. It was found that the nonparametric approach had similar performance to copula-regression estimates with the advantage of being able to better adapt to local variations in the data. A downside is the sensitivity to outliers, particularly at the smallest timescales (5–60 min) where there was a lot of variability in the data. A nonparametric method for converting radar reflectivity into rainfall was proposed by Calheiros and Zawadzki (1987). It assumes the same probability for gauge measured rainfall and radar-derived estimates (Rosenfeld et al., 1993; Seed et al., 1996). This probability matching method (PMM) overcomes limitations related to the sampling volume. In addition, PMM also eliminates collocation and timing errors because it does not consider the actual timing when the Z-R pair occurred (Piman et al., 2007). Later, the Window Probability Matching Method (WPMM) (Rosenfeld et al., 1994) was developed, which alleviates limitations of the PMM method by considering homogeneous rainfall regions. In the WPMM, the probability distribution of reflectivity is matched with gauge rainfall over small spatial extents and time windows. Finally, the Window Correlation Matching Method (WCMM) (Piman et al., 2007) was developed by introducing a space window to correct timing