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Multiple Radar Data Merging in Hydro-NEXRAD

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Abstract

The Hydro-NEXRAD merging algorithms include two options: (1) data-based merging; and (2) product-based merging. Data-based merging algorithm takes volume scan reflectivity data from all radars involved through preprocessing algorithm that performs volume data quality control, interpolates data to synchronize temporal scale between individual radars, and finally combines data onto a common geographic grid. Reflectivity values for a given location are assigned by a weighting function with respect to the distance from the radar. This single reflectivity field is then converted to rainfall amounts using a user-requested standard approach. In product-based merging algorithm reflectivity data from multiple radars are all converted to rainfall using the same, user-specified algorithm. These products are then combined into the final one using a weighting function that expresses the uncertainty of estimated rainfall amounts.

Introduction

Since their deployment in the 1990s, the national network of WSR-88Ds (Weather Surveillance Radar-1988 Doppler) has substantially contributed to weather forecasting and research, especially for severe weather (e.g. flash floods, severe storms, tornados, etc.) warning. Radar observations can be assembled over large domain with fairly high temporal and spatial resolution to provide quantitative rainfall estimates for various hydrologic applications. Different applications may require different resolution in space and time of the rainfall input. Although the operational WSR-88D rainfall estimation algorithm, called the *Precipitation Processing System* or *PPS* (Fulton et al. 1998), provides rainfall products for the purpose of the National Weather Service's warning and forecasting missions, such products are not always best suited for other applications.

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Numerous algorithms for radar data processing to estimate quantitative precipitation are mainly based on single radar data. Using single radar data for atmospheric and hydrologic applications is often subject to restrictions such as beam blockage, limited coverage, vertical gaps, etc. Some of these problems can be mitigated by combining data from two or more radars. Merging multiple radar data onto a common grid enables studies that need to cover much larger hydrologic units represented by watersheds or basins. However, numerous challenges associated with temporal and spatial synchronization, as well as calibration differences among WSR-88Ds, still remain to be solved.

A few schemes to consider and reduce temporal and spatial variability from multiple radar data have been studied. To figure out the variability in temporal sampling between radars to be merged Langston et al. (2007) have developed a temporal synchronization method represented by an exponential decaying scheme as a part of Four-Dimensional Dynamic Grid (4FFG). Lakshmanan et al. (2006) considered storm movement by advecting it to the location where it is expected to be at the common point in time. Zhang et al. (2005) showed that the nearest neighborhood and the maximum-valued methods are not always optimal to spatially combine multiple radar data. In the nearest neighborhood reflectivity discontinuities appeared along equidistance line between radars due to calibration differences. It is known that calibration differences among WSR-88Ds are often above 5 dBZ (Gourley et al. 2003). Although maximum reflectivity value in same field can mitigate the attenuation problem, the maximum-valued method may result in biased estimates from the radar that provides higher value due to the systematic bias (Smith and Krajewski 1991). Zhang et al. (2005) also tested two weighting schemes, called the flat and the steep exponentially decaying functions, and suggested the latter scheme to spatially combine reflectivity data from multiple radars due to beam spreading problem.

Since WSR-88D radars are calibrated individually, lack of cross-calibration is the most significant obstacle in merging multiple radar data. We present large sample statistics of the problem based on the collected four-dimensional matches of volume data and show mismatch problems. We also present preliminary results from comparison studies of the different merging approaches and rain gauge data to evaluate the capability of the Hydro-NEXRAD (Krajewski et al. 2007), a prototype software system that enables increased use of NEXRAD data in hydrologic research and applications. Due to nonlinear transformation involved in radar-rainfall estimation algorithms it is not clear what is the best sequence of data processing that leads to smallest uncertainty of the final products. The issue is compound by lack of adequate ground reference data and rigorous evaluation procedures (see Krajewski and Smith 2002 for discussion).

Merging Algorithms

Multiple radar data merging in the Hydro-NEXRAD involves two algorithms (1) data-based, and (2) product-based. By user's request both algorithms are connected with proper components of the system (Krajewski et al. 2007) that is, preprocessing, rain rate calculation, and rainfall accumulation to estimate quantitative rainfall amounts as shown in Figure 1. Multiple radar data are combined onto a common geographic grid to unify the spatial basis and then this common grid can be converted to other grids for follow-on hydrologic research and applications.

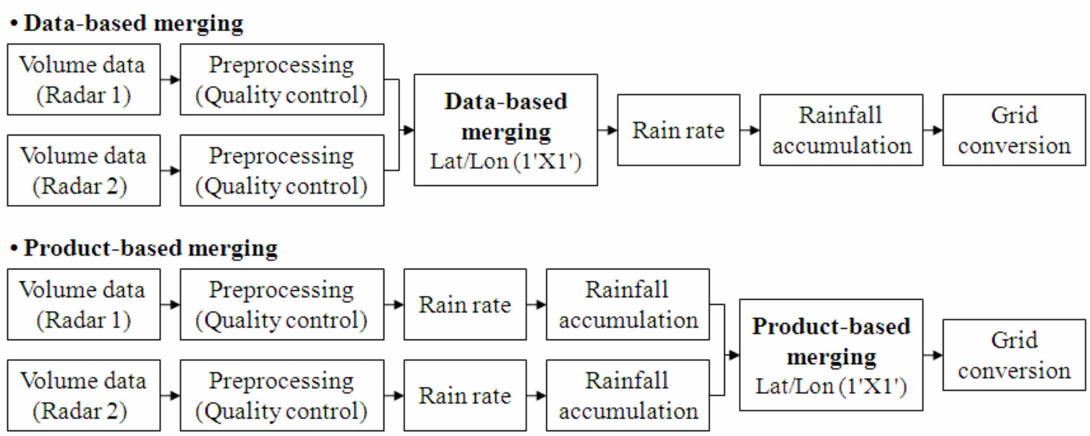

Figure1. Overview of the multiple radar merging algorithm in Hydro-NEXRAD.

1. Data-based merging.

The merging algorithm based on radar volume data takes volume scan reflectivity data from all radars involved through preprocessing that performs volume data quality control, generates data every 5 minutes to synchronize temporal scale between individual radar data to be merged, and finally combines data onto a common grid. Reflectivity values for a given location are assigned by a weighting function with respect to the distance from the radar. This single reflectivity field is then converted to rainfall amounts using a user-requested standard approach.

Common grid. The WSR-88Ds collect their raw observations based on spherical coordinate system represented by the range and azimuth plane. Since each single radar data cannot be combined with the spherical coordinates, a common framework that enables to merge individual datasets is needed. A few efforts (e.g. Zhang et al. 2005; Lakshmanan et al. 2006; Langston et al. 2007) to translate radar data to a Cartesian coordinate system have made it possible for multi-radar data to be merged. We define 1'×1' geographic coordinates as a reference common grid for the merging scheme in Hydro-NEXRAD since Cartesian coordinates might lead to distortions especially at the large scale domains. The advantage of using geographic coordinates is that all product maps can be easily transformed into any grid such as LDAS, HRAP (Fulton 1998; Reed and Maidment 1999), and S-HRAP (Krajewski et al. 2007) for atmospheric and hydrologic applications.

Temporal synchronization. An exponentially decaying weighting function is used to adjust temporal variations of multiple radar data:

$$w_t = \exp\left[-\left(\frac{t}{T}\right)^n\right] \tag{1}$$

where t is time difference between observations and synchronization moment (every 5 minutes) and T and n are adaptable parameters associated with decay rate. Figure 2 shows how the temporal weight for volume data varies with respect to the denominator values of the exponential function in equation (1) when $n = 2$. The time interval of consecutive volume scans is dependent on VCP (Volume Coverage Pattern) and is about 10 minutes for some VCPs. Therefore, one should consider the proper parameter value for those scan strategies because temporal weight does not exist for some T values when t value is close to 10 minutes (Figure 2). In addition, more experiments that show how the parameter T affects synchronization for a given time gap are needed. We use 5 minutes and second order as the typical values of the parameters in Hydro-NEXRAD merging algorithm.

Spatial merging. To consider spatial variability from multiple radar data one can allow closer ranges to have more contributions in determining spatial weight than farther ranges due to beam spreading (Zhang et al. 2005; Langston et al. 2007). Thus, smaller weights should be assigned to the reflectivity values at far range than those at close range. In addition, a steep weighting function (rapidly decreasing weight) with respect to the distance is necessary since reflectivity values at far ranges might smooth severe storm structure due to increasing sampling volume. Equation (2) is also the exponentially decaying weighting function to spatially combine multiple radar data:

$$w_s = \exp\left[-\left(\frac{r}{R}\right)^n\right] \tag{2}$$

where r is the distance from each individual radar and R and n are adaptable parameters associated with decay rate. The typical values for R and n are 25 km and 2, respectively.

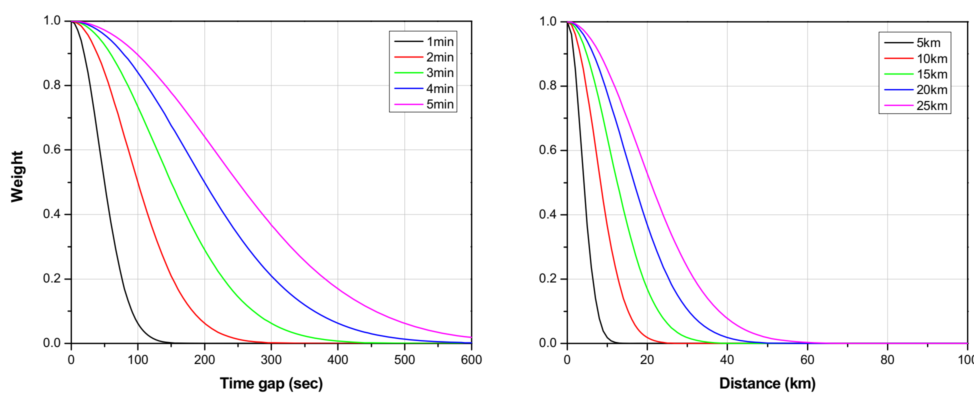

Figure 2. Weighting function examples with respect to temporal (left) and spatial (right) parameter values.

2. Product-based merging

Most of current multi-sensor algorithms produce deterministic precipitation fields (e.g. Zhang et al. 2005; Seo at el. 2005; Lakshmanan et al. 2006; Langston et al. 2007). It is well-known that rainfall estimates are notoriously uncertain due to high space and time variability of the relevant physical process and the limitation of the observational systems. However, those multi-sensed products do not provide any quantitative information on rainfall products uncertainty.

In product-based merging algorithm reflectivity data from multiple radars are all converted to rainfall using the user-specified algorithm. These products are then combined into the final one using a weighting function that expresses the uncertainty of estimated rainfall amounts (Ciach et al. 2007).

Results and Discussion

1. Four-Dimensional Match-up

As we stated above, radar calibration difference is a significant challenge in multiple radar data merging. As an approach to investigate calibration-caused differences without any operational information about it, we use volume data match-up that considers temporal and spatial coincidence in hope that this can show relative biases for common target locations. The most significant aspect of this approach is to maintain volume data spatial structure and information because the biases might be smoothed or distorted by spatial interpolation and grid conversion.

First of all, temporal coincidence should be satisfied to match two radar beams from different radars. One can obtain observation time for every elevation angle and the corresponding velocity of radar rotation. In other words, time for horizontal observations in a certain elevation angle can be obtained from volume scan information. An adaptable parameter, i.e. time difference between two radar beams, for this match-up is highly dependent on storm velocity. For spatial match-up one needs to take into account horizontal locations represented in spherical coordinates and vertical heights of radar sampling volumes. Since the geographic coordinates of each radar and the spherical coordinates of radar observations are known, the spherical coordinates that represent the center (C_2 in Figure 3) of a sampling volume from one radar can be easily transformed with respect to the other radar. The differences (dr, d , and dh in Figure 3) in azimuth, range, and height between two sampling volumes explain how close two radar sampling volumes are and how well those are matched. These three adaptable parameters could be expressed by the proportion over radar beam width, sampling bin size, and vertical beam width to consider the variability associated with radar sampling volume due to beam spreading. Although two centers are close enough as shown in the bottom of Figure 3, the locations of sampling volumes might be pretty much different. Therefore, matching zone should be confined to close range from equidistance line between radars.

We present large sample statistics of the problem based on the collected four-dimensional matchups of volume data from the Oklahoma City and the Tulsa WSR-

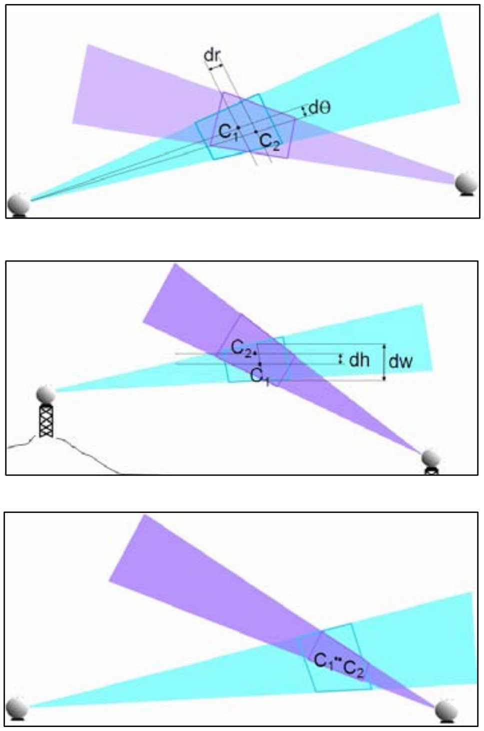

Figure 3. Spatial match-up of two radar sampling volumes in horizontal plane (top) and in vertical height (middle) and mismatched sampling volumes (bottom).

88Ds (KTLX and KINX) for 2006. To match sampling volumes from two radars four adaptable parameters (30 seconds for time difference and 95% agreement in azimuth, range, and height, respectively) were applied and only 419 matched pairs were obtained due to the elevation difference (166 m) between two radar sites. Figure 4 and Figure 5 show correlation between matched pairs, difference distribution, and the time series of daily averaged differences, respectively. Figure 4 demonstrate that the Tulsa radar is “hotter” than the Oklahoma City radar even for common targets and that they have calibration differences. Smith et al. (1996) also showed that hourly rainfall estimates from Tulsa were systematically greater than those from Oklahoma City. However, it is hard to say how much calibration difference there is since the variability of differences between matched pairs is very high as shown in Figure 5.

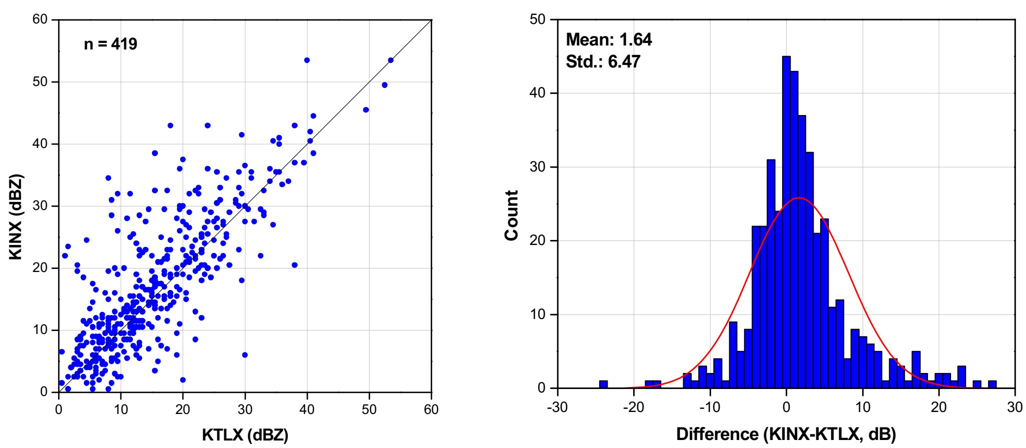

Figure 4. Large sample statistics (scatter plot and histogram of difference) based on 4-dimensional match-up.

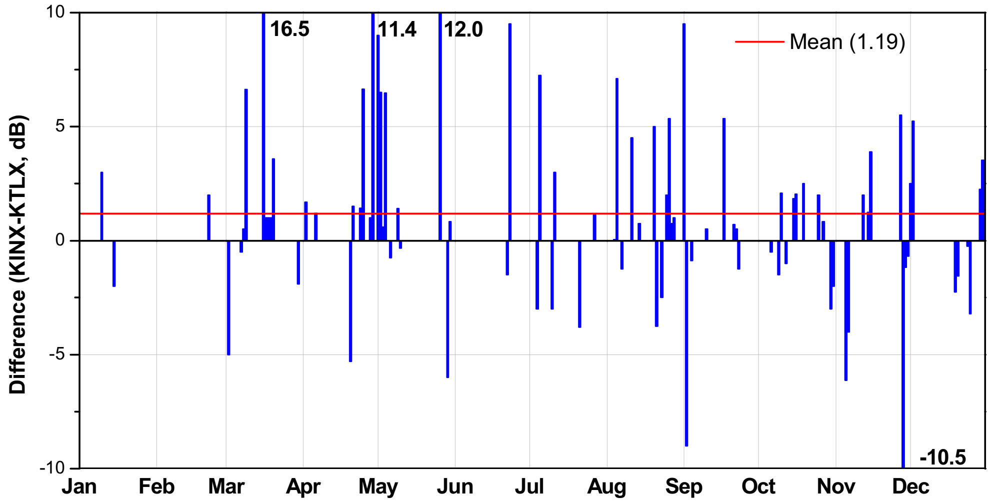

Figure 5. Daily averaged difference.

2. Algorithm Testing and Evaluation

In this section we briefly discuss the testing and evaluation for the rainfall estimates of Hydro-NEXRAD merging algorithm options as shown in Figure 1. Since a comprehensive testing and comparison of all the different options available in Hydro-NEXRAD is well beyond the scope of this short article, we present two comparison results (with radar-only merging product and with gauge data) for two short-term events. We show comparison results using NCEP/EMC U.S. gridded radar estimates and rain gauge data provide by NCAR/EOL and Oklahoma Mesonet, respectively. The data used in the comparison is hourly rainfall estimates based on HRAP grid for two events from lower Canadian River watershed in Oklahoma. The Hydro-NEXRAD rainfall estimates options used are the *Quick Look* and the *Hi-Fi* (see Krajewski et al. 2007) with two WSR-88Ds (KTLX and KINX) in Oklahoma City and Tulsa.

The radar-only products comparison (Figure 6) between the NCEP/EMC data and the data-based merging of Hydro-NEXRAD shows the scatter plots, correlation, and mean differences of hourly rainfall estimates for an event of October (2006). The gray scale on the top of Figure 6 corresponds to the number of pairs of rain values. The correlations between both products are fairly high except for the starting point of this event. It seems like that the *Hi-Fi* has higher correlation and smaller estimates than *Quick Look* because of radar data quality controls such as AP removal, range dependent bias correction, and advection correction. Figure 7 shows the comparison results between rain gauge data and four Hydro-NEXRAD merging options that can be arranged by user-requests. As shown in Figure 7, scatter plot and mean difference obtained by averaging each difference from three gauges located in lower Canadian River watershed demonstrate that the correlations is quite high even if radar estimates are a little higher than ground measurements for this event. Also, both the *Hi-Fi* options of data-based and product-based merging show better capability to estimate rainfall amounts than the *Quick Look*.

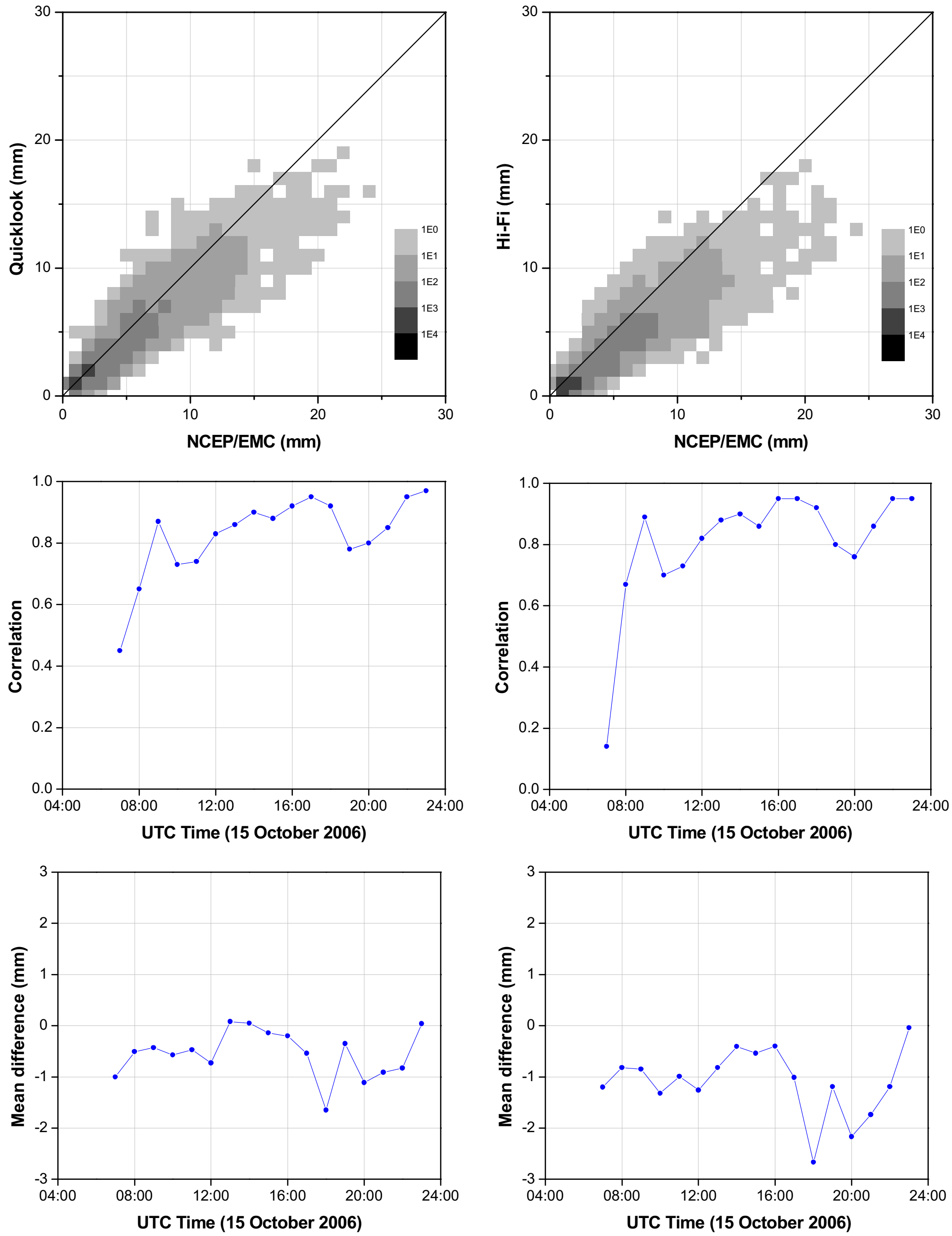

Figure 6. Radar-only products comparison between data-based merging of Hydro-NEXRAD and NCEP/EMC U.S. gridded radar estimates.

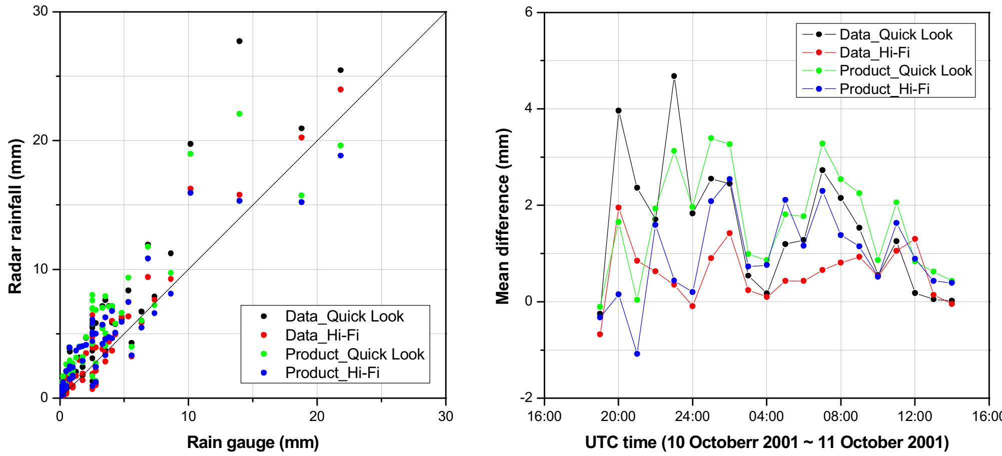

Figure 7. Example of Hydro-NEXRAD product comparison with Oklahoma Mesonet rain gauge data.

Summary

We present preliminary results of two different options for merging radar data from multiple radars. While far from being conclusive, the early results indicate that more complex radar-rainfall estimation algorithms that account for range correction and other improvements lead to better results of the merged product. Also, it seems that error reduction due to averaging radar reflectivity reduces the final uncertainty more effectively than the averaging at the level of the products.

In the coming months we will be conducting comprehensive, multi-year evaluation of all Hydro-NEXRAD products over some 40 radars included in its database. All products are radar-only but users can combine them with rain gauge data on their own. Perhaps the most significant challenge is that due to lack of information on the absolute calibration procedures and schedule for the WSR-88D radars. We hope that join community efforts, such as that described by Vasiloff et al. (2007) will be helpful to overcome this limitation.

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