Precipitation products are currently available from various sources at higher spatial and temporal resolution than any time in the past. Each of the precipitation products has its strengths and weaknesses in availability, accuracy, resolution, retrieval techniques and quality control. By merging the precipitation data obtained from multiple sources, one can improve its information content by minimizing these issues. However, precipitation data merging poses challenges of scale-mismatch, and accurate error and bias assessment. In this paper we present Optimal Merging of Precipitation (OMP), a new method to merge precipitation data from multiple sources that are of different spatial and temporal resolutions and accuracies. This method is a combination of scale conversion and merging weight optimization, involving performance-tracing based on Bayesian statistics and trend-analysis, which yields merging weights for each precipitation data source. The weights are optimized at multiple scales to facilitate multiscale merging and better precipitation downscaling. Precipitation data used in the experiment include products from the 12-km resolution North American Land Data Assimilation (NLDAS) system, the 8-km resolution CMORPH and the 4-km resolution National Stage-IV QPE. The test cases demonstrate that the OMP method is capable of identifying a better data source and allocating a higher priority for them in the merging procedure, dynamically over the region and time period. This method is also effective in filtering out poor quality data introduced into the merging process.

1. Introduction

Precipitation information is valuable for a wide range of earth science research and applications with practical benefits for society. Knowledge of temporal and spatial precipitation distributions is crucial for modeling and analysis of the water and energy cycles. Unfortunately, it is difficult to measure precipitation on the ground everywhere at all times because of limited resources, its extremely heterogeneous character, and the difficulty of accurately modeling precipitation. Direct gauge and radar observations are limited by poor spatial and temporal coverage. Space-borne precipitation measurements offer the means to monitor global precipitation. However, it is difficult to directly validate satellite precipitation products using surface measurements due to scaling issues.

Despite these difficulties, several high resolution precipitation products (HRPPs) are readily available from gauge, radar, satellite and numerical weather models. Each of the precipitation products has its own strengths and weaknesses. It seems plausible to obtain better precipitation estimates by judiciously merging the different rainfall estimates and optimizing the strengths of more than one precipitation product. The merged product is likely to retain the combined strengths of the individual HRPPs while minimizing their weaknesses.

Currently, several different approaches and methods are used for merging precipitation data. A typical merging exercise can be seen in the techniques for correcting rainfall estimates derived from the observations of ground-based radars, in which measurements from a network of ground-based rain gauges are used to adjust the biases in rainfall estimates derived from radar reflectivity [e.g., Wilson and Brandes, 1979]. Similarly, gauge adjustment [e.g., Gjørtsen et al., 2003] is used for operational radar to improve

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precipitation retrieval. Other examples of precipitation merging techniques include the cokriging method [Krajewski, 1987; Azimi-Zonoiz et al., 1989], probability matching method [Rosenfeld et al., 1994], statistical objective analysis [Pereira et al., 1998], correlation matching method [Piman et al., 2007], Bayesian correction filters [Todini, 2001], and Kalman filters [Chumchean et al., 2006; Seo and Breidenbach, 2002]. Most of these methods are developed for correcting errors in radar observed precipitation that is marred with problems like non-uniform profile of reflectivity, improper Z-R relationship and other contamination from electronic noise and radar range effects.

Satellite images have also been merged with radar observation to map precipitation patterns [Bellon et al., 1980]. Merging efforts are also found at the core of retrieval algorithms for satellite precipitation estimates [e.g., Bidwell et al., 2002; Joyce et al., 2004; Kummerow et al., 2001]. Most satellite-derived precipitation products use merging algorithm to take advantage of high infrared sampling from geostationary satellites and lower microwave errors from earth orbiting satellites. These methodologies sometime take advantage of other ancillary data such as radar, model output or gauge observations. Gourley et al. [2002] calibrated infrared data from the Geostationary Operational Environmental Satellite (GOES) using reflectivity derived rain rates from a WSR-88D radar. Todd et al. [2001] combined satellite passive microwave and infrared data to account for limitations in both data types. Joyce et al. [2004] also used passive microwave data to improve the precipitation data quality. Adler et al. [2000] merged rain gauge data with Tropical Rainfall Measuring Mission (TRMM) adjusted GOES precipitation index (AGPI) to provide fine scale pentad and monthly analyses. Grimes et al. [1999] merged satellite and rain gauge data assigning weights according to uncertainty given by their estimation variance. Most of the widely used high resolution precipitation products analyses, for example the Global Precipitation Climatology Project (GPCP) [Huffman et al., 1995, 1997], the Climate Prediction Center (CPC) Merged Analysis of Precipitation (CMAP) [Xie and Arkin, 1996, 1997], NOAA CPC Morphing Technique (CMORPH) [Joyce et al., 2004], and Naval Research Laboratory (NRL) [Turk and Miller, 2005] also use different merging methodologies. The popular multi-sensor precipitation estimates (MPE), based on the U.S. Next generation weather radar (NEXRAD), also use techniques to blend gage measurements [Young et al., 2000].

Merging and refining of satellite data are intended to improve the estimate quality [Chiang et al., 2007; Boushaki et al., 2009; Vila et al., 2009]; however, the satellite-derived HRPPs are still not as reliable as desired. Artificial neural networks (ANN) and other data fusion techniques are also used for combining information from different rainfall estimates in order to derive a combined product. The Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks (PERSIANN) approach involves adaptively calibrating IR measurements from geostationary satellites using the instantaneous rain rates estimated from the TRMM Microwave Imager (TMI) [Sorooshian et al., 2000]. The PERSIANN algorithm was further refined and augmented using a sophisticated Cloud Classification System (PERSIANN-CCS) to extract, classify, organize and calibrate cloud features using intelligent methods [Hong et al., 2004]. Chiang et al. [2007] used a linear model in conjunction with a recurrent neural network to merged satellite rainfall estimates with in-situ measurements for a flash flood forecasting application. Recently, Turlapaty et al. [2010] have used a technique based on ANN and vector space transform to fuse different satellite-based HRPPs; and the merged product, validated against gage measurements, demonstrated improved performance during the spring, summer and fall seasons in south-central United States.

Merging two or more HRPPs sounds conceptually straightforward; but the challenge lies in having a sound methodology that identifies the relative strengths. A merging method must consider varying data-quality over space and time as well as varying scale or resolution, which makes this a non-trivial exercise. As discussed in the afore-mentioned literatures, most of the precipitation merging techniques uses observational gauge and radar-network, satellite images, error correction methods, and numerical tools such as ANN and probabilistic adjustment method. These tools provide multi source multi sensor precipitation data sets, however, there is no accepted operational tool to merge them and produce an accurate and coherent precipitation dataset at needed resolutions for environmental and hydrological applications. Precipitation data merging has critical problems of different spatial and temporal scales resolved by different observing platforms, temporal and spatial gaps in data coverage, and uncertainties reflected in discrepancies between the data sources.

This study is motivated by the need for precipitation information at suitable scales and quality to produce reliable hydrologic prediction. Developing such a method poses a number of challenges including evaluating techniques for extracting useful information from multiple input features, performing sophisticated mapping in a multidimensional input–output space, and better utilization of existing multi-sensor precipitation products. The “Optimal Merging of Precipitation (OMP) algorithm”, developed in this paper, use optimized merging weights obtained from Bayesian analysis and performance trend traced in space and time windows. The objectives of OMP are to (1) function as a multi-scale precipitation filter for hydrological and land surface applications through explicit coupling of the OMP with hydrological and land surface models; and (2) facilitate uncertainty assessment of the various precipitation products obtained from both ground-based and space-borne platforms. The experiments in this study use the 12-km resolution precipitation products from the North American Land...
Data Assimilation System (NLDAS) project, the 8-km resolution CMORPH products and the radar-based 4-km resolution National Stage-IV QPE, representing a range of multiscale and multi-sensor precipitation sources. The quality of merged precipitation estimates depends upon accurate characterization of the precipitation dynamics in space and time, and their scale of representation. Hence, our goal is to provide an objective framework for multiscale optimal merging in an operational environment such that it enables rapidly processing of large multi-sensor, multi-source precipitation datasets at desired scales, while automatically updating itself when new data are available. To demonstrate the OMP performance, we show comparisons from various merging test cases. Special attentions are paid to the issue of scale mismatch and uncertainty of precipitation datasets.

The paper is organized as follows: Section 2 presents the OMP algorithm formulation. Section 3 discusses the experimental data. Section 4 discusses parameter calibration. In section 5, we evaluate the merging method including its numerical accuracy and scaling consistency, followed by a comparison with a benchmark merging method without involving the OMP algorithm. Finally in Section 5, we present our conclusions and future directions.

2. Formulation of the OMP Algorithm

Precipitation data merging has been practiced in many ways, including the interpolation of point measurements to spatial grids. The conventional method of simple averaging, and Thiessen Polygon methods are used widely to convert point-scale precipitation data into spatially gridded data and also to merge data from different sources. Additional merging methods include the nearest neighbor method, various interpolation methods such as bilinear, cubilinear and spline and probability based merging methods. All these methods can be generalized as

\[ M = \sum W_i X_i \text{ for } i = 1, N \]  

where, \( M \) is the merged precipitation; \( X \) is the individual precipitation data sources used to produce merged precipitation; and \( W \) is the merging-weight assigned for each of the precipitation data sources. Taking an average of all data sources \( (X_i) \) is the simplest merging that use an equal weighting distribution (i.e., \( W_1 = W_2 = \ldots = W_N \)). More complex methods would distribute unequal weights (i.e., \( W_i \neq W_{ij} \) for all \( j = 1, N-i \)). Giving more weight for better and reliable data sources assure better merging of the precipitation. However, how we obtain the right \( W_i \) for a source \( X_i \) is the prime question. It is to be noted that \( W_i \) is a space and time-variant component, which could be strongly influenced by other factors including the precipitation retrieval system, geography, seasonal influences, precipitation type and climatic conditions.

The methodology developed here attempts to optimize a set of \( W_i \) for each source. This process is a combination of downscaling, tracing and optimization of the weights to produce a consistent outcome. This new methodology produces merging weights through an iterative procedure. The weights are dynamic in both space and time, and can be uniquely assigned to respective sources of precipitation data to obtain the merged precipitation product. The following subsections explain the merging weight estimation in detail.

2.1. Downscaling Precipitation Fields

Different sources of precipitation data sources used in the merging procedure could have mismatched scales. It is simpler to produce coarse scale precipitation data if the source data is of a finer time or space scale. A downscaling procedure to produce a finer scale field from a coarser scale data source would not be as straightforward as the upscaling procedure. It has been widely noted that basic downscaling techniques such as interpolation do not adequately produce a finer scale precipitation field because those simpler methods often fail to generate appropriate space-time variability in the downscaled precipitation.

The precipitation downscaling used in this study is based on a multiplicative random cascade method [Over and Gupta, 1996], which has been used to improve the spatial structure of the precipitation cells [Shrestha et al., 2005]. The coarse scale precipitation structure is converted into a finer scale by dividing each of the coarse grid cells into four sub-grids. The sub-grid values are assigned by multiplicative weights obtained from beta-lognormal model [Jothityangkoon et al., 2000; Shrestha et al., 2005]. The multiplicative weights follow the scaling laws of precipitation and provide constants that separate (1) the rainy and non-rainy zones, and (2) assign a weight to obtain sub-grid scale precipitation. Due to the cascade of multiplicative operation, the precipitation becomes more intense as the resolution gets finer. Multiplicative weight assignments are based on the spatial correlation field obtained from the coarser precipitation pattern. This method ensures the successful transition of the precipitation field across various scales, enabling merging at the required scale. This downscaling method preserves the finer scale precipitation pattern, generates a realistic precipitation intensity, distribution and successfully separates rainy and non-rainy cells.

2.2. Tracer Algorithm

The data source quality can be evaluated by checking the differences between the original data and the merged precipitation. An algorithm is developed to trace each data source performance in the merging process, which assigns a higher priority for the better data source and avoids inconsistencies in the continuous merging process. There are three criteria used to evaluate the performance based on (T1) how successful a source detects precipitation, (T2) the performance persistence and (T3) how closely the precipitation intensity matches the merged precipitation field.
These tracer evaluations enable checking local precipitation features in a pre-defined space-time window.

T1 is a spatial tracer index that accounts for the match between rainy and non-rainy cells separately for each of the precipitation sources. This is evaluated by

\[ \text{Match}_X = C(R_X R_M) + C(N_X N_M) \]  
1

\[ \text{MisMatch}_X = C(R_X N_M) + C(N_X R_M) \]  
2

\[ T1_{SX} = \frac{\text{Match}_X}{\text{Match}_X + \text{MisMatch}_X} \]  
3

\[ T1_X = T1_{SX} \left/ \sum_X T1_{SX} \right. \]  
4

where \( R_X \) and \( R_M \) represent rainy grids in the precipitation source \( X \) and merged precipitation dataset \( M \) respectively; \( N_X \) and \( N_M \) represent the non-rainy grids in the precipitation source \( X \) and merged precipitation dataset \( M \) respectively; and \( C \) is a counter function. The grid cells having very small precipitation (<0.0001 mm/hr) are treated as non-rainy grids. \( T1_{SX} \) evaluates standard index of match probability for source \( X \), and \( T1_X \) is the normalized index to account for the match probability of the source \( X \) with respect to the merged precipitation. Here, \( \text{Match}_X \) and \( \text{MisMatch}_X \) are analogous to the standard binary forecast verification metrics based on a 2 x 2 contingency table with counts observed vs. forecast instances [see Wilks, 2006, p. 261]. \( \text{Match}_X \) is equivalent to (hits + correct rejection) and \( \text{MisMatch}_X \) to (false alarm + miss). However, we use them iteratively in our tracer algorithm to obtain merging weights. The distinct usage here varies from their typical application in forecast verification. Hence, we have avoided using the standard terminology in equations (2) and (3).

T2 is a temporal tracer index that evaluates the historical match between the precipitation source and merged precipitation. The T2 keeps track of each grid’s performance, which is used to obtain coefficients indicating the priority of a precipitation source at different intensity bins. The priority is set based on counts of successful precipitation bin matches. In addition, T2 provides an estimated merging weight based on past event record extrapolation, which is the expected merging weight given the past record trend.

\[ P_{bx} = \frac{\text{Match}_{bx}}{C(\text{Match}_X)} \]  
5

\[ T2_{sx} = F(W_{xt}) \]  
6

\[ T2_X = T2_{sx} \left/ \sum_X T2_{sx} \right. \]  
7

\[ T3_{sx} = \sum_b \left[ Q_{bx} \text{Match}_{bx} / (\text{Match}_{bx} + \text{MisMatch}_{bx}) \right] \]  
8

\[ Q_{bx} = P_{bx} T2_x \]  
9

\[ T3_X = T3_{sx} \left/ \sum_X T3_{sx} \right. \]  
10

where, \( P_{bx} \) is the priority based on a proportional match count for bin \( b \) of precipitation source \( X \). The \( T2_{sx} \) estimates the standard index based on the extrapolation function \( F \) using \( W_{xt} \) which is the \( t \) number of past \( W \) records for the source \( X \). The Lagrangian polynomial is used as the extrapolation function. The \( T2_X \) is the normalized index to account for the extrapolated merging weight.

T3 is a local scale spatial tracer index that evaluates the probability based index similar to \( T1_X \) but it separates precipitation into different intensity-bins. The intensity-bins may be set at a regular or irregular intervals depending upon additional information available for the analysis such that the OMP algorithm detects the best-performing source. T3 allows setting different priorities for different precipitation intensities, which then adjusts the merging process based on local scale precipitation features. This feature is helpful in screen precipitation data source or a sensor at a range of intensities and regions. The process of setting priority is an automated process based on the historical data source performance, which is traced by the T2 tracer. The T3 tracer is given by

\[ T3_{sx} = \sum_b \left[ Q_{bx} \text{Match}_{bx} / (\text{Match}_{bx} + \text{MisMatch}_{bx}) \right] \]  
11

where, \( b \) is the bin interval, \( Q \) is the priority coefficient based on bin interval and the performance \( P \) of the precipitation source \( X \) over time, which is obtained from (6) and (8). \( T3_X \) is the normalized index to account for the bin-separated match probability.

### 2.3. Bayesian Merging Weights

Bayes’ theorem provides a means for updating previously existing estimates to account for new information; or alternatively, to combine information from different sources. Todini [2001] used this approach to create a filter using block-kriging and a Kalman filter for combining weather radar based rainfall estimates with rain-gauge measurements. Di Michele et al. [2005] used the Bayesian approach for improving a precipitation retrieval algorithm. Luo et al. [2007] used the Bayesian approach for merging multiple climate model forecasts. There are many other examples, which demonstrate the advantage of using the information from empirical learning based on the Bayesian approach, which computes the conditional distribution of the variable of the interest.

The calculation of a variable’s conditional distribution clarifies significant features of preexisting information. The updated (conditional) probability distribution reflects the
new level of confidence about the variable. For example, if the variable of interest is a quantity $R$ representing precipitation from source X at a specific location for a given time. Before it is actually observed, $R$ would be a random variable; and our knowledge on $R$ is a probability distribution, i.e., its probability density function (PDF) $p(R)$. If we have only one source, $p(R)$ would simply be the distribution of $R$ from the records available. With additional precipitation data sources, a forecast ($TR$) of this variable can be made. Given this new information, $TR$, the conditional distribution $p(R|TR)$ reflects our new confidence. Bayes’ theorem computes $p(R|TR)$ as:

$$p(R|TR) = \frac{p(R) \cdot p(TR|R)}{p(TR)}$$  \hspace{1cm} (12)

where $p(R)$ and $p(TR)$ are the unconditional distributions of $R$ and $TR$, $p(R)$ is also referred to as the “prior” distribution of $R$ (prior to the new information $TR$), and $p(R|TR)$ is the “posterior” distribution of $R$ (posterior to $TR$). $p(TR|R)$ is referred to as the likelihood function; and it measures how closely $TR$ is distributed around $R$, i.e., in this example, the skill of the source precipitation data. The focus of the Bayesian method is to construct the posterior distribution $p(R|TR)$ from the probability models for $p(TR|R)$, $p(TR)$, and $p(R)$. The likelihood function is a key step because it measures the discrimination between the two sources and thus determines how much information is provided by the source(s). Here the likelihood function is constructed within the sample space by evaluating the false precipitation detection. As time changes, the rate of false detection may change and the likelihood function may change accordingly. This allows the likelihood function to remain dynamic in space and time depending on the false alarm detection and compute the conditional probability accordingly. The new information $p(R|TR)$ denotes the probability of having actual precipitation when a cell is detected as a rainy cell in the merging procedure. This information from all sources are collected and normalized to obtain the Bayesian merging weights, which is given by

$$BW_X = \frac{\text{Pr}(R_X/\text{TR}_X)}{\sum_X \text{Pr}(R_X/\text{TR}_X)}$$  \hspace{1cm} (13)

where $BW_X$ is the Bayesian weight for source X, $\text{Pr}(R_X/\text{TR}_X)$ is the probability of rain conditional on the rainfall known to us or the merged rainfall, which is assumed to be the true rainfall.

2.4. Estimation of Merging Weights

The merging weights are obtained from the $T1$, $T2$, $T3$ and $BW$ scores. Each of these scores is multiplied by a factor to obtain a standard weight which is given by

$$W_{SX} = f \ast T1_X + h \ast T2_X + g \ast T3_X + e \ast BW_X$$  \hspace{1cm} (14)

where, $f$, $h$, $g$ and $e$ are parameters that assign the importance of different factors considered in the merging procedure. For this experiment, these parameters are obtained from a sensitivity test. $W_X$ is the normalized weight assigned to the individual precipitation data sources.

2.5. Optimization of Merging Weights

From the above procedures, an initial merged precipitation field is produced using the merging weights $W_X$. The merging weights provide an estimation of merged precipitation. This initial merging based on tracers and BayesIan approximation is likely to have statistical bias in the merging outcome due to poor sampling included in the estimation of tracers and Bayesian statistics. In order to minimize the statistical gain, the merging process is subjected to optimization of the merging weights. The objectives of the optimization process are to first obtain a set of weights that ensure robustness of the merged precipitation product, and then to achieve an adequate balance of merging weights based on Bayesian approach, tracer evaluation and consistent performance of the sources used in the merging process.

The optimization process uses an updated set of the tracer scores $T1$, $T2$, $T3$s and re-estimate a new set of merging weights $W'_x$. With the two sets of weights, optimize the optimization process is conducted by recursively updating the merging weights. This is given by

$$\min \phi : (W_x - W'_x)$$  \hspace{1cm} (16)

subject to:

$$W'_x = U(W_x),$$

$$(W_x - W'_x) > 0.1 \ast W_x,$$ and

$$\sum W'_x \leq 1$$

where, $\phi$ is the minimization function; $U(W_x)$ is the updating function that include all the process needed to calculate the initial merging weights for source $x$; and $W'_x$ is the updated merging weight.

2.6. Multiscale Optimal Merging

The above procedure produces merged precipitation datasets at scale $L_s$, which is the coarsest experiment resolution in this merging process. This is given by

$$M_{OL} = \sum W_{OL} X_L \text{ for } X = N, C, \text{ and } S$$  \hspace{1cm} (17)
where, \( M_{OL} \) is the optimally merged precipitation at scale \( L \) and \( W_{zl} \) is the optimal merging weights. For other smaller scales, say \( \lambda \), the \( M_{OL} \) is downscaled to obtain a new precipitation field that can then be used in the optimization process. This is given by

\[
P_l = D(M_{OL})
\]  

(18)

where, \( D \) is the downscaling function representing the downscaling model described in section 2.1. The same model is used to obtain finer resolution precipitation \((X_l)\) if the original products are coarse resolution and the precipitation is merged at the finer resolution.

The OMP algorithm begins from the coarse scale merger, which allows using both fine and coarse scale data. At coarser scale merging, any fine-scale data gets averaged to a coarser scale and then is used in the merger. At finer scales, the coarse scale data is downscaled and used in the merger with other available fine scale data. The OMP can also downscale the coarse scale merged product and use in the next finer scale merger and so on. Through this process, the possible stochastic bias gains of the downscaling operation may have accumulate and further influence the finer scale merger strongly. The downscaled precipitation used in this study has been forced to conserve the mass to avoid the effect of stochastic gains.

### 3. Experimental Data

The participating precipitation data for the study are taken from 2004 NLDAS, CMORPH and Stage IV precipitation over the mid-western USA covering 101W-94W longitude and 33N–37.5N latitude. These three different sources represent model-based precipitation, satellite estimates and radar-gauge-network composites, respectively. NLDAS provides hourly fluxes including precipitation at approximately 12-km resolution. Mitchell et al. [2004] have reported the details of NLDAS products. CMORPH provides 30-min interval precipitation based on satellite observed IR-data at approximately 8-km resolution. The CMORPH products are based on space-borne passive microwave (PMW) measurements, which are propagated using motion vectors derived using IR imagery from geostationary satellites. The high temporal resolution of CMORPH is achieved by a morphing process, which propagates the precipitation features between instances of the PMW observations [Joyce et al., 2004]. The Stage IV precipitation is hourly product, based on the CONUS radar-rain-gauge network, which has an approximately 4-km resolution [Lin and Mitchell, 2005]. All three datasets provide high quality precipitation estimates, but significant differences remain due to the nature of the observing systems, measurement strategies, retrieval algorithms and compositing methodology.

Due to these differences, it is difficult to claim superiority of a dataset among the selected sources and judge quality of one dataset versus another at a particular time, scale or location. Therefore, to properly evaluate the OMP algorithm, it is reasonable to prepare a new set of synthetic data, which captures the basic space-time variability of different data sources but with known errors and quality. A synthetic data set is prepared from the above mentioned datasets and treated as the reference for optimization and evaluation purposes. The coarser resolution data are first downscaled to finer resolution producing datasets of the same scale. Then the downscaled data are merged together to obtain the synthetic data, which is given by

\[
M_l = N_l + C_l + S_l
\]  

(19)

where, \( M \) is experimental precipitation, \( N, C, \) and \( S \) are the NLDAS, CMORPH and Stage IV precipitation scaled to \( \lambda \). This \( M \) field is used to obtain the error fields corresponding to the each of the sources separately, as given by

\[
\varepsilon_{zl} = M_l - X_l \text{ for } X = N, C, \text{ and } S
\]  

(20)

where, \( \varepsilon \) is the differences between \( M \) field and other precipitation sources \( X \) at scale \( \lambda \). For a different scale, say \( L \), the \( M \) and \( \varepsilon \) are upscaled such that,

\[
\varepsilon_{zl} = U_L(\varepsilon_{zL})
\]  

(21)

\[
M_L = U_L(M_l)
\]  

(22)

where \( U \) is an upsampling function for scale \( L \). The upsampling function may have various weighted averaging methods. In this experiment, we use a simple upsampling method that assigns equal weight to all sub-grids. The upscaled fields corresponding to source \( X \) at scale \( L \) are then given by

\[
X_L = M_L + \varepsilon_{zl}
\]  

(23)

This equation gives the synthetic precipitation field at desired scales, consistent with the NLDAS, CMORPH and Stage IV precipitation data. The precipitation error can be analyzed either as additive bias [e.g., Mandapaka et al., 2009; Molini et al., 2003; Nicholson et al., 2003] or as multiplicative bias [e.g., McCollum and Krajewski, 1998; Hossain and Anagnostou, 2006; Moradkhani and Meskele, 2009]. The multiplicative error models are generally used in precipitation-retrieval analysis, whereas the additive error models are generally used in precipitation structure analysis. Equation (23) is an additive error model used to compute synthetic precipitation corresponding to different sources, which uses the additive bias computed in equation (18). Note that the precipitation scales in equation (18) and equation (23) are different. A multiplicative error model, if used in equation (18), will result in precipitation using equation (23) that would have multiplicative gain. This would make the analysis inconsistent across the scale and would violate conservation of precipitation mass within the coarser grid.
4. Calibration of Parameters

The OMP algorithm requires a few parameters to be specified or calibrated to yield better results. The first set of parameters is the intensity-bins that are to be specified for tracers T2 and T3 in equations (6), (9), and (10). We have arbitrarily chosen intensity bins separated at 0.05, 0.5, 5, 20 and > 20 mm/hr.

The second parameters set are the $f$, $h$, $g$ and $e$ in equation (14). These parameters are calibrated by running the OMP algorithm at 12-km, 8-km and 4-km resolutions. The spatial window is set to approximately 50 X 50-km square and the time window is set to 72 past hourly events. A sensitivity test is conducted to obtain the values of $f$, $h$, $g$ and $e$ tracer parameters. The experimental design for the calibration test, evaluates the $f$, $h$, $g$, and $e$ parameter sensitivity, which is conducted by varying the parameter values one at a time, as shown in Figure 1. The best values obtained from the earlier experiment are kept for the next run of the sensitivity test.

The parameters $f$, $h$, $g$ and $e$ assign weights to each tracer used to obtain the merging weights. A thorough calibration experiment is needed to find parameter values. Also, the calibrated parameter may exhibit significant sensitivity with the precipitation resolution chosen for the calibration because of parameter nonlinearity with respect to the resolution.

An exhaustive parameter calibration test was conducted to investigate an optimal set of parameter values and to see the resolution-dependence. First, the OMP algorithm is run with the same parameter values for all three resolutions while varying only one parameter value at a time. The resulting merged precipitation field ($M_{OL}$) is compared with the reference precipitation field ($M_I$) to calculate the average error. Figure 2 shows the sensitivity test results.

The second calibration test allowed the parameter values to vary at one resolution, while keeping the parameter values at other resolutions constant. The sensitivity test results (similar to Figure 2) did not show significant difference compared to the test keeping constant value across the resolution. This consistent optimal parametric response across scales indicates that the contribution of the tracer is related to precipitation structure rather than the choice of the resolution. It is obvious that if the resolution is too coarse to preserve the features of precipitation structure, the parameters may need re-calibration. After the calibration test, the chosen values of these parameters for this experiment are $f = 0.4$, $g = 0.35$, $h=0.25$ and $e=1.0$, these being a lumped approximation for the entire analysis period. It is noteworthy to mention that they may vary on seasonal basis or in different regions due to different precipitation processes, season, or climate zone.

5. Evaluation of OMP Algorithm

The merging weight provided by OMP algorithm is spatially and temporally variable field, which provides the optimally merged precipitation field. Another set of merging weight is used to produce a benchmark merging for evaluation purpose, which is called benchmark merging field. The benchmark merging does not incorporate spatially/temporally variable field and it assigns equal-weight to all precipitation sources. The optimal merging and the benchmark merging are compared with the reference precipitation dataset.

5.1. Reproducing the Spatial Pattern

Figure 3 shows a typical input field example used in the merging experiment. The plots show the 12-km CMORPH, NLDAS and Stage IV precipitation data. This winter precipitation event was moving from south-west to north-east. The western half of the domain has remnants of very low intensity precipitation after a major storm. The eastern half is still subject to the active storm. The storm’s center has intense precipitation, which is seen at the eastern edge of the domain. The storm is recorded by all three satellite, radar and numerical model data sources. These illustrations are obtained from the reference field after adding the noise component corresponding to CMORPH, NLDAS and Stage IV precipitation data.
Figure 2. Parameters $f$, $h$, $g$ and $e$ sensitivity test results. The average error is estimated by comparing optimally merged precipitation with the reference precipitation used in the experiment.
Figure 3. 12-km resolution precipitation fields representing (top) CMORPH, (middle) NLDAS, and (bottom) Stage IV precipitation sources respectively, which are obtained from a reference field adding the noise components of corresponding data sources (Jan 4, 2004 at 3PM).
The noise components are scaled from a higher resolution analysis such that it preserves scale consistency in the multiscale merging.

Due to the differences in precipitation estimation process, the same event may be recorded differently resulting in variable precipitation fields. In Figure 3, CMORPH shows more precipitation in the southeast region, whereas NLDAS has no precipitation. The Stage IV precipitation also records precipitation in the region, but the structure of Stage IV is different from CMORPH. This is a typical example of precipitation differences obtained from multiple sources.

Figure 4 shows the rainfall fields obtained from the merging exercise and its comparison against the reference field. From the comparison of the benchmark merging (Figure 4, top) and optimal merging (Figure 4, bottom) against the reference field (Figure 4, middle), the OMP algorithm appears successful in capturing the spatial patterns of precipitation. The rainy and non-rainy area delineated by the OMP algorithm is quite similar in structure to that of the reference field. Although the spatial storm structures in the input fields (Figure 3) are different to each other, the OMP has merged them together producing spatial structure similar to the reference field. The benchmark merging (Figure 4, top) has a more wide-spread precipitation extent in the south eastern region, which is not present in the reference field (Figure 4, bottom).

The input fields (Figure 3) are synthetic experimental data obtained by adding source-specific noise components to the reference field. The benchmark merging is insensitive to the source-specific noise as it assigns equal and uniform weights to all sources. The OMP is sensitive to the source-specific-noise components and assigns varying merging weights to each of the sources. The Bayesian statistics includes the local precipitation probability in the merging weights that are crucial to detect rainy and non-rainy cells. Other tracers also contribute to the successful delineation of the rainy and non-rainy regions. These features enable the OMP to preserving the location of precipitated region as demonstrated in the result (Figure 4, bottom). It is obvious to expect an ideal merging to filter out the noise components as the OMP has done successfully in this example. The results shown in Figures 3 and 4 are one snapshot of precipitation event. More analysis comparing errors, spatial correlation of the merging results, scale dependency etc. is presented in subsequent sections.

5.2. Scale Dependency

The 12 km OMP algorithm result is unable to reproduce the intense precipitation at the storm center located at the eastern edge of the domain (Figure 4, bottom). This effect shall be attributed to the assignment of weights based on the temporal precipitation trend in the OMP algorithm. If the optimization process maximizes the temporal trend based weight, it may attempt to smooth the precipitation time series. In result, this optimization may adjust the storm when the precipitation trend is abruptly changed either by an erroneous intensity surge or a missing record. Similar phenomenon shall occur at the center of a moving storm, where it is likely to have continuously changing intensities and disrupting temporal trend. The OMP algorithm may treat such precipitation variability as an abrupt change trend and may discard the source or modify the intensity temporarily. This may result the lower intensity precipitation in the center of the storm. This feature is found to be a scale-dependent problem. At coarser resolution, the OMP algorithm is guided by the grids that have lower intensity precipitation, which are replaced by higher intensity precipitation at a higher resolution. This affects the local statistics and consequently the optimized values of merging weights. On the other hand, the higher resolution merging at 8-km and 4-km are found to increasingly recover the appropriate intensity at the center of the storm (see Figure 5). The recovery of precipitation intensity is an advantage of multiscale merging that overcame the drawback of trend-capture at coarser resolution. This also demonstrates the advantage of multiscale merging for higher resolution precipitation merging.

5.3. Distribution of Merging Weights

The spatial distribution of merging weights generated by the OMP algorithm at 12-km are shown in the Figure 6 for different input fields. The distributions corresponding to various precipitation sources reveal the dynamic allocation of merging weights based on the preferences as determined by the OMP algorithm. A similar plot for benchmark merging has no spatial variation as the benchmark merging allocates equal weights for all sources. The spatial variation of optimized weights shown in Figure 6 reveal how the priorities to difference precipitation sources are spatially varied in the merging process. Note that this result is for an hourly event observed by multiple precipitation products for the same storm system. Since the spatially varying weights are used to obtain the merged precipitation intensity, it helps understanding the process of dynamic adjustment while correcting local bias and improving the precipitation estimates through the OMP algorithm.

In the illustrated case, all the sources are basically ignored in the south-west part where it is almost dry. The CMORPH data is ignored at the north-west domain where lower intensity precipitation is dominant. The CMORPH data gets slightly higher weights in the north-east domain where lower intensity precipitation prevails. The NLDAS and Stage IV are found to be preferred precipitation sources by the OMP algorithm in these regions. The south-east region has the active storm where the NLDAS precipitation is mostly ignored. CMORPH and Stage IV are preferred in this region. It is interesting to note that CMORPH is found to have higher weights where the more intense precipitation is located. On the other hand, Stage IV dominates the region surrounding the intense storm. This demonstrates that the
Figure 4. Precipitation field comparison obtained from two different merging methods with the reference field at 12 km. (top) Result obtained from benchmark merging, (middle) the reference field, and (bottom) result obtained from optimal merging using the OMP algorithm.
Figure 5. Precipitation field comparison obtained from the OMP algorithm at various resolutions: (top) 4 km resolution precipitation, (middle) 8 km resolution precipitation, and (bottom) 12 km resolution precipitation.
Figure 6. Comparison of spatial distribution of the merging weights obtained from the OMP algorithm corresponding to (top) CMORPH, (middle) NLDAS and (bottom) Stage IV sources at the scales of 12 km.
OMP algorithm has the ability to identify the appropriate precipitation source, which can be extremely useful in filtering out poor quality data. These merging results are complex combination of the information content from the different sources through the optimized merging weights, which have their own spatial and temporal variations.

5.4. Precipitation Time Series

The precipitation time series is neither continuous nor smooth. It often contains intermittent events and sometime erroneous surges. It is difficult to obtain a smooth precipitation time series even if it is heavily filtered or averaged over a large spatial area. If precipitation from two or more data sources is compared, it is common to find missing events, a shift in the event peak, or differences in storm intensity and duration. Figure 7 (top) is a typical example where precipitation time series differences are clearly visible. When these time series are merged together, they tend to balance the offsets. Figure 7 (top) covers three storm events and shows the differences between benchmark merging and optimal merging based on the OMP algorithm. The

![Figure 7](https://example.com/figure7.png)

**Figure 7.** (top) Comparison of precipitation time series obtained from different sources CMORPH, NLDAS and Stage IV products, and merged outcome using OMP algorithm’s optimal merging and benchmark merging at a 4-km resolution pixel. (bottom) A section zoomed from Figure 7 (top) covering the precipitation event of Jan 25, 2004.
CMORPH data has an early surge in the Jan 25, 2004 storm event. The NLDAS data reports the surge approximately 3 hours late and the Stage IV data reports it approximately 4 hours later (see the zoomed section in Figure 7, bottom). The benchmark merging misses the storm peak due to a smoothening effect resulting from the shifted surges. The OMP algorithm is able to preserve the storm peak and shifts the peak following the timing of NLDAS and Stage IV while maintaining the CMORPH precipitation volume. This is a typical example of optimal merging. The OMP algorithm discarded the initial CMORPH surge, since the other two sources did not report such a storm surge. A lower merging weight for the CMORPH data produced a lower value of OMP outcome than the benchmark merging until 01 hour of Jan 25, 2004 (01Z 25Jan2004). The OMP algorithm allocated larger merging weight to NLDAS and CMORPH from 01Z to 05Z, and allowing the surge to be retained. At 06Z both NLDAS and Stage IV reported unusually low intensities whereas CMORPH estimated moderate intensity. The OMP algorithm discarded both the NLDAS and Stage IV intensities to yield high storm intensity. It seems that the OMP algorithm attempted to maintain the trend and rewarded the CMORPH at 06Z. The NLDAS surge at the next hour 07Z slightly elevated the intensity and then the storm receded. The OMP algorithm produced a slightly more gradual storm recession than the source data sets. There is approximately a 1-hour shift in the receding storm event.

The OMP algorithm is found to be successful in filtering surges (both positive and negative) and in preserving the storm characteristics. The Feb 2, 2004 NLDAS surge and the Feb 6, 2004 CMORPH surge are filtered out in the merged product (which can be seen in Figure 7, top). In contrast, the benchmark merging is unable to preserve the storm characteristics; it can only smooth the storm peaks by giving equal weight to all of them, which result in much lower storm intensities. The outcome of benchmark merging does not retain the storm event rise and fall, whereas the outcome of optimal merging is able to retain this feature. In the illustrated example, the optimal merging is found to maintain gradual rise and drop of precipitation intensities as a result of retaining temporal memory of precipitation. Since the OMP allocates weights dynamically and continuously correcting its priorities based on past performances evaluation, the OMP is expected to produce better results at later merging stages.

### 5.5. Overall Performance

Table 1 summarizes the errors obtained in the experiment at various resolutions. These values are obtained from 8760 realizations of the optimization process covering the entire study year. The column $E_{LB}$ in Table 1 shows the root mean square errors at scale $L$, which are obtained from the comparison between the optimally merged precipitation ($M_{OL}$) and reference precipitation ($M_L$) at scale $L$. The column $E_{LB}$ shows the root mean square errors obtained from the comparison between the benchmark merging ($M_{BL}$) and reference precipitation ($M_L$). These results clearly show that the $M_{OL}$ fields are quite close to the $M_L$ fields. The differences between $E_{LB}$ and $E_{LO}$ are noteworthy as it highlights how different merging methods could produce different results. The better OMP algorithm performance not only shows good agreement between the merged and reference data but also demonstrates the efficacy of the optimal merging method.

These results also highlight the scale dependency of merging at different precipitation resolutions. At 12-km resolution, the benchmark merging yielded much higher error than the optimal merging method. The lower value of optimal merging error ($E_{LO}$ at $L=12$-km) than the benchmark merging error ($E_{LB}$ at $L=12$-km) indicates that the optimization process is able to better identify the precipitation information and assign merging weights accordingly.

At the 8-km scale, ($E_{LO}$ at $L=8$-km) the OMP error is slightly increased from the 12-km scale ($E_{LB}$ at $L=12$-km) but it is still much smaller than the error obtained from the benchmark merging ($E_{LB}$ at $L=8$-km). This error ($E_{LB}$ at $L=8$-km) is the time-space average error obtained from comparing the 8-km resolution reference and the 8-km resolution precipitation from benchmark merging. The lower $E_{LB}$ at $L=8$-km compared to that of the error at 12-km (i.e., $E_{LB}$ at $L=12$-km) shows improvements at higher resolution within the same merging method. In addition, the lower error $E_{LO}$ at $L=8$-km than $E_{LB}$ at $L=8$-km shows that the OMP is able to outperform the benchmark merging method. However, the increasing OMP error across scales (i.e., $E_{LO}$ at $L=8$-km > $E_{LO}$ at $L=12$-km) shows that this method struggles more at higher resolution, which is further confirmed by increased error at 4-km ($E_{LO}$ at $L=4$-km > $E_{LO}$ at $L=8$-km). On the other hand, the errors from benchmark merging ($E_{LA}$ at $L=8$-km and 4-km) decrease as the resolution is increased. This shall not be perceived as the strength of benchmark merging because this phenomenon is related to the diminishing effect of the scaled error field $e$ used in producing the synthetic source data for merging experiment. The columns $e_{LN}$, $e_{LC}$, and $e_{LS}$ summarize the mean values of these error fields compared to the merged precipitation at various scales. It is obvious to expect increasing errors at increasing resolution, as it is likely to increase both

| Table 1. Time-Space Average Errors Obtained in the Optimal Merging Experiment$^a$ |
|------------------|----------------|----------------|----------------|----------------|----------------|
| $L$ (km) | $E_{LO}$ (%) | $E_{LB}$ (%) | $e_{LN}$ (%) | $e_{LC}$ (%) | $e_{LS}$ (%) |
| 12 | 2.54 | 10.48 | 5.08 | 5.08 | 4.36 |
| 8 | 3.74 | 9.32 | 7.98 | 8.58 | 7.16 |
| 4 | 5.37 | 0 | 38.35 | 34.21 | 12.84 |

$^a$Average root mean square errors expressed in percentage. $E_{LO}$ is the average error obtained from the OMP algorithm for scale L; $E_{LB}$ is the average error obtained from the benchmark merging at scale L; $e_{LN}$, $e_{LC}$, and $e_{LS}$ are the mean values of error fields at scale L.
sample size and the magnitude of errors resulting a higher mean error. The mean error given by $e$ in Table 1 confirms this trend for all sources, however this trend is missing in the benchmark merging because the error fields vanish in the process of obtaining the reference data, which is confirmed from the zero error for $E_{L,B}$ at $L=4$-km. This is a known problem of performance analysis based on RMS error that is particularly affecting the analysis of benchmark merging results.

Additional analysis is conducted by evaluating spatial correlation of precipitation fields. Table 2 summarizes the spatial correlation statistics obtained from comparison of benchmark merging and optimal merging with the reference data, as well as the precipitation sources used for merging exercise. At 12-km resolution, the benchmark merging is found to have poor mean spatial correlation with the reference data than any of the individual precipitation sources suggesting that the merging is not a good option for improving the precipitation data. On the other hand, the optimal merging has improved the mean spatial correlation and decreased the variance of spatial correlation outperforming all the individual sources as well as the benchmark merging.

At a higher 8-km resolution merging, the optimal merging has slightly dropped mean spatial correlation and slightly increased the variance of spatial correlation, however it still outperforms rest of all sources and benchmark merging. The same trend continues for the further higher resolution (4-km) merging. The optimal merging has higher mean spatial correlation than the individual precipitation sources. The benchmark merging at 4-km resolution turns to be the same reference dataset, and thus showing perfect spatial correlation. The dynamics of RMS error in Table 1 and the dynamics of spatial correlation in Table 2 both confirm the diminishing effect of error fields in the benchmark merging.

The optimal merging is found to perform consistent and robust across the multiple scale of merging. The variance of spatial correlation is slightly elevated at increasingly higher resolution, which is apparently connected to the increased sample size and intensity distribution. Compared to the individual precipitation sources, the optimally merged precipitation has a lesser variance and a higher mean-spatial correlation, which confirms that the OMP algorithm is capable of selectively picking better precipitation source through the allocation of optimal weight in the merging exercise.

The merging weights provided by OMP algorithm and benchmark merging are further analyzed to understand merging performances. Table 3 provides the summary of the analysis from 12-km merger, which presents the average merging weights filtered for precipitation fields yielding spatial correlation higher than 0.8. A constant value of $W_b$ confirms the insensitive nature of benchmark merging to any kind of precipitation variability, whereas, the dynamic values of $W_o$ confirms the sensitivity of the optimal merging to the quality of precipitation data sources.

Table 3 shows that the Stage IV is assigned lesser priority compared to NLDAS and CMORPH for the 12-km merger. CMORPH has received higher merging weights during the summer months (May, Jun, Jul and Aug), whereas NLDAS received higher merging weights during the winter months (Dec, Jan, Feb). The merging weights indicate priority-assignment to selecting a particular source, which is consistent with the percentage of higher spatial correlation precipitation events. Upon careful comparison of the results in Table 3, it is clear that there is no direct relation between the $W_o$ and $p(\%)$ even though the trend of higher $W_o$ for higher $p(\%)$ is evident. This illustrates the complex nature of weights resulted from the OMP algorithm

6. Conclusions

Precipitation data often contain erroneous surges, bias, data-gaps and systematic errors due to scale-mismatch. Precipitation data obtained from multiple sources may be merged in such a way that the merged product encapsulates the strengths of the individual products while suppressing the weaknesses. This optimal merging process would require filling the gaps, improving resolution and accuracy in a range of space, time and precipitation intensity, performing needed scale conversions and assigning appropriate priorities to the precipitation sources. The Optimal Merging of Precipitation (OMP) algorithm carries out these tasks and provides better precipitation estimates, which is crucial for water resources decision support and other cross-cutting applications. This method integrates precipitation downscaling and merging weight optimization based on performances specific to participating data sources, which is found able to dynamically correct local bias and improve the precipitation estimates. This method assigns and optimizes

<table>
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<th>L (km)</th>
<th>$P_{L0}$ Mean</th>
<th>$P_{L0}$ Var</th>
<th>$P_{LB}$ Mean</th>
<th>$P_{LB}$ Var</th>
<th>$P_{LN}$ Mean</th>
<th>$P_{LN}$ Var</th>
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<th>$P_{LC}$ Var</th>
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*Here, $P_{L0}, P_{LB}, P_{LN}, P_{LC}$ and $P_{LS}$ are spatial correlation of the reference precipitation data with optimal merging, benchmark merging, NLDAS, CMORPH and Stage IV precipitation respectively at the scale $L$. 
the merging weights dynamically to enable the selection of appropriate precipitation sources. Case studies demonstrate that the OMP is capable of dynamically identifying a better data source and allocating higher priority for it over the given region and period of time. The OMP method is effective in automatic filtering of poor quality data stream(s). Some features lost at coarser resolution such as intense precipitation grids are recovered at higher resolutions. The optimized merging results are much better than benchmark merging and much closer to the reference data prepared for an ideal test case evaluation.

A number of further investigations are required to fully understand the scope and limitations of the OMP method. Immediate next steps include understanding the role of parametric values introduced in the optimal merging method across various climatic zones and precipitation system types. An extended inter-comparison with other precipitation merging techniques using geostatistical tools and bias correction methods would also be useful to fully understand the OMP’s relative performance strengths.

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References


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**Table 3.** Analysis of Monthly Spatial Correlation and Merging Weights for 12-km Merger*  

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<tr>
<th>Stage IV</th>
<th>Jan</th>
<th>Feb</th>
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<th>Apr</th>
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<th>Jun</th>
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<th>Aug</th>
<th>Sep</th>
<th>Oct</th>
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<td>42.5</td>
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<td>41.6</td>
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<tr>
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<td>28.6</td>
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<tr>
<td>ρN (%)</td>
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<tr>
<td>ρC (%)</td>
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*Here, Wo and Wb are average weight from optimal merging and benchmark merging respectively. ρS, ρN, ρC are the percentage of precipitation events yielding spatial correlation higher than 0.8 for Stage IV, NLDAS and CMORPH data respectively.


