



Assimilation of In-Situ Measurements into Gridded Data Products using State-Space Estimation: Application over Central Africa

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The advent of satellite remote sensing and numerical weather prediction has led to an unprecedented ability to capture the spatial properties of meteorological variables at high spatial resolutions. However, due to imperfect instrumentation, methods, and input data, these products have biases and spurious trends. These uncertainties can be minimized through the assimilation of in-situ measurements. In an effort to provide high-quality data for flood-forecasting, drought management, and hydrologic modeling, geostatistical theory is used to devise a method to optimally merge in-situ measurements into gridded products for use over data-sparse regions.

Assuming an error-free station value's spatial coverage matches that of its collocated grid cell, the departure at each time step for the collocated grid cell from the station is calculated. Experimental semivariograms are assembled from these errors by using all error values in a given radius. In data-sparse regions, monthly climatologies of model semivariograms are assembled by trading space for time. The derived spatial correlation models are used to optimally interpolate the errors using state-space estimation. For each time step, each interpolated error field is superimposed on the background field to arrive at an optimal gridded field that includes the accuracy of the stations and the spatial properties of the background field.

The method has been validated in Oklahoma, USA using the high density MESONET network and NL-DAS. It has also been used to develop a high-resolution data over Central Africa by bias-correcting the downscaled Princeton University (PU) forcing data set with the gap-filled Global Summary of Day (GSOD) station global network. Results from the validation over Oklahoma and the Central African data set will be presented. The resulting algorithm is highly computationally efficient and can be applied to enhance the quality of currently available global high-resolution hydrological and meteorological data sets.