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Geo-spatial grid-based transformations of precipitation estimates using spatial interpolation methods

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ABSTRACT

Geo-spatial interpolation methods are often necessary in instances where the precipitation estimates available from multisensor source data on a specific spatial grid need to be transformed to another grid with a different spatial grid or orientation. The study involves development and evaluation of spatial interpolation or weighting methods for transforming hourly multisensor precipitation estimates (MPE) available in the form of $4\times4\,\text{km}^2$ HRAP (hydrologic rainfall analysis project) grid to a Cartesian $2\times2\,\text{km}^2$ radar (NEXt generation RADar:NEXRAD) grid. Six spatial interpolation weighting methods are developed and evaluated to assess their suitability for transformation of precipitation estimates in space and time. The methods use distances and areal extents of intersection segments of the grids as weights in the interpolation schemes. These methods were applied to transform precipitation estimates from HRAP to NEXRAD grids in the South Florida Water Management District (SFWMD) region in South Florida, United States. A total of 192 rain gauges are used as ground truth to assess the quality of precipitation estimates obtained from these interpolation methods. The rain gauge data in the SFWMD region were also used for radar data bias correction procedures. To help in the assessment, several error measures are calculated and appropriate weighting functions are developed to select the most accurate method for the transformation. Three local interpolation methods out of six methods were found to be competitive and inverse distance based on four nearest neighbors (grids) was found to be the best for the transformation of data.

1. Introduction

The availability of continuous precipitation data without any gaps is critical for studies that require reconstruction of past climate and hydrological history of a site for hydrologic design, modeling, and management of water resources systems. Radar (NEXRAD)-based precipitation estimates (Vieux, 2001) provide data that have a significant spatial resolution compared to point rain gauge measurements. Availability of radar (NEXRAD)-based rainfall data also provides benefits to many studies that involve in-filling missing precipitation records. Precipitation being an essential input for many hydrological simulation models has a direct bearing on the management of water resource systems at different spatial and temporal scales. The importance of rainfall as the most sensitive input to the simulation models was stressed by many researchers (e.g., Larson and Peck, 1974; Vieux, 2001; Xu and Singh, 1998). Xu and Singh (1998) indicate that the accuracy of any streamflow simulation model primarily depends on how well the variability of the rainfall can be defined. In-filling of historical precipitation data that are missing due to a variety of reasons is an important task that relies on availability of data from monitoring networks and computationally tractable interpolation methods that are conceptually sound and robust. Spatial interpolation methods ranging from conceptually simple weighting techniques to methods using artificial intelligence (AI) paradigms are now available for generation of rainfall fields for distributed hydrologic models and estimation of missing precipitation data (Teegavarapu, 2009). In the current study use of geo-spatial interpolation methods for creating a continuous spatially gridded precipitation data set is of interest. Since precipitation data are generated or estimated at fixed grid points using precipitation observations available from surrounding control points in space, the problem handled in this study is exactly similar to estimation of missing precipitation data. The following section provides a brief review of spatial interpolation methods used for estimating point precipitation data.

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2. Spatial interpolation of point precipitation data

Spatial interpolation of precipitation data is generally accomplished by traditional weighting methods (Smith, 1993), distance-based weighting methods (Simanton and Osborn, 1980; Wei and McGuinness, 1973; ASCE, 2001a, b), nonlinear deterministic and stochastic variance-dependent interpolation methods (e.g., kriging) (Teegavarapu, 2007; Zimmerman et al., 1999), and regression and time series analysis methods (Salas, 1993). Comparative analysis of rainfall estimation methods can be found in studies by Singh and Chowdhury (1986), Tabios and Salas (1985), and Tung (1983). Variants of regression models incorporating meteorological and variables that change in spatial domain (i.e., elevation) were proposed by Daly et al. (1994, 2002). Models incorporating locally weighted polynomials reported by Loader (1999) are conceptual improvements over traditional weighting methods in which the number of neighbors and polynomial functions are objectively chosen. The inverse distance weighting (IDW) method recommended by Handbook of Hydrology ASCE (1996) is the most commonly used method for estimating missing data in the fields of hydrology and geographical sciences. Recent studies of Teegavarapu and Chandramouli (2005) and Tomczak (1998) provided several variants of the IDW method. Lu and Wong (2008) modified weights used in the IDW method using distances based on decay parameters that relate to the diminishing strength of spatial autocorrelations.

Spatial interpolation methods are also used for estimation of missing precipitation data (Teegavarapu and Chandramouli, 2005; Teegavarapu, 2009). Teegavarapu (2009) used an association rule mining (ARM) approach to improve estimates of missing precipitation data. Global interpolation methods that use trend surface analysis with polynomial equations of spatial coordinates (Wang, 2006) and regression are also applicable for spatial interpolation. However, selection of the appropriate functional form to model the trend poses a major problem due to the large range of candidate functions (O'Sullivan and Unwin, 2010). Also, thin-plate spline methods tend to generate steep gradients in data-poor areas leading to compounded errors in the estimation process (Chang, 2010). Improvement in interpolation can be achieved with a variant of the above method referred to as thin-spline with tension. Xia et al. (1999) used inverse distance, normal ratio, single best estimator, and multiple regression methods for estimation of missing climatological data. The regression method was proven to be the most accurate of all the methods investigated in their study. In another study, Xia et al. (2001) reported the use of thin-splines, closest station, multiple linear regression, and Shepards' method (Shepard, 1968) for estimation of daily climatological data. They indicated that the thin-splines method was the best among all the methods investigated. Ramos-Calzado et al. (2008) proposed a new approach for estimating missing precipitation data considering the rainfall measurement uncertainty. Improvements were achieved in the estimation of precipitation data when the stations with lowest measurement uncertainty were selected in the interpolation process.

Variance-dependent stochastic surface interpolation methods, belonging to the general family of kriging, have been applied to spatial interpolation problems (Vieux, 2001; Grayson and Bloschl, 2001) in hydrological sciences. Kriging in various forms has been used to estimate missing precipitation data as well as to interpolate precipitation from point measurements (Dingman, 2002; Vieux, 2001; Ashraf et al., 1997). Cokriging of radar and rain gauge data has been employed by Krajewski (1987) to estimate mean areal precipitation. Seo et al. (1990a, b) and Seo (1996) described the use of cokriging and indicator kriging for interpolating rainfall data. Seo and Smith (1993) employed a Bayesian approach for short-term rainfall prediction using radar data in conjunction with rain gauge data. Real-time estimation of rainfall fields using radar and rain gauge data was discussed by Seo (1998). The use of ordinary kriging along with universal function approximation-based kriging for estimating missing daily precipitation data was reported by Teegavarapu (2007). This modified version of kriging provided improved estimates compared to ordinary kriging.

Regression and time series models used for estimating missing rainfall data require the functional forms of the relationships among dependent and independent variables a priori. Empirical models derived using evolutionary and biological principles, namely genetic algorithms (GAs), artificial neural networks (ANNs), and genetic programming (GP) have found numerous applications in the development and application of inductive models. Applications of artificial neural networks (ANNs) in the fields of hydrology and water resources (ASCE, 2001a, b; French et al., 1992; Govindaraju and Rao, 2000; Teegavarapu and Chandramouli, 2005) are not new. Teegavarapu (2007) demonstrated the use of universal functional approximation within a stochastic variance-dependent interpolation technique for estimation of missing precipitation data. Recent work of Teegavarapu et al. (2009) focused on the development of optimal functional forms for estimating missing precipitation data using genetic algorithms. The methods using optimal forms provided better estimates compared to those by traditional distance-based methods. Many of the interpolation methods discussed in this section are applicable to the problem addressed in the current study. However, grid-based spatial interpolation is a special case that requires techniques that can benefit from information about spatial sizes and orientation of grids. Also, grid-based interpolation for large spatial extents with different format of grids poses computational challenges and can be handled by techniques routinely used in digital image processing studies.

3. Grid-based spatial interpolation

Spatial interpolation using point precipitation data to generate precipitation fields or surfaces is an essential task in distributed hydrologic modeling. Also, the generation of precipitation data sets confined to a fixed tessellation (grid of specific size) is generally the final product of any processed radar data. Radar data available as gridded data can be used for estimation of missing precipitation data at a rain gauge using local filters (Lloyd, 2007) with appropriate focal functions to derive the value of a cell using values from a nearest group of cells. Moving window approaches using focal operators (Lloyd, 2007, 2010) are common in image processing problems. The moving window approach was adopted in a recent study (Teegavarapu and Pathak, 2008) in which pixels (grids) with radar-based precipitation estimates surrounding a rain gauge are used to estimate missing data at that gauge. Spatial interpolation involving grid operators such as local, focal, zonal, and global functions (Chou, 1997) are generally used to process grids for spatial segmentation and classification. Spatial domain filters (Mather, 2004) are used in remotely sensed image processing studies, which use moving average windows to reduce the variability of images. These spatial filters adopt different forms of focal operators (Smith et al., 2007) where the value of any given cell (grid, or pixel) is a function of values from the surrounding pixels. However, no optimization formulations are generally incorporated into these filters. Concepts of spatial filters are adopted for grid-based transformation of precipitation estimates in this study. These methods are discussed in Section 5.

4. Geometric transformation of HRAP (4×4 km^2) grid to NEXRAD (2×2 km^2) grid

Spatial weighting and interpolation methods are used for transformation of hourly precipitation estimates from the HRAP