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Geostatistical inverse modeling for super-resolution mapping of continuous spatial processes

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ABSTRACT

The increasing availability of satellite images derived from multiple sensors creates opportunities for broader spatial and temporal coverage but also methodological challenges. We present a geostatistical inverse modeling (GIM) approach for merging coarse-resolution images with variable resolutions and for super-resolution (i.e., predictions at the sub-pixel level) mapping of continuous spatial processes. GIM can explicitly account for the differences in spatial supports of multiple datasets. The restricted maximum likelihood method was used for parameter estimations associated with the change-of-support problem. We used GIM to produce both spatial predictions of a target image and prediction uncertainties, while preserving the values of original measurements. GIM is totally data driven, and covariance parameters for a target resolution can be directly derived from measurements. We also developed a moving-window GIM approach to accommodate spatial nonstationarity and reduce computational burden associated with large image data. First, we demonstrated GIM and moving-window GIM on synthetic images. Aggregated synthetic images with variable resolutions were merged to produce a single resolution image. The results show that the two approaches can produce accurate spatial predictions and generate prediction uncertainties. Second, we applied moving-window GIM for merging aerosol optical depth (AOD) data with variable resolutions, which were derived from two satellite sensors. The modeling results show that moving-window GIM can be applied for merging complementary AOD data from two sensors and for super-resolution mapping of global AOD distributions. Therefore, we can conclude that GIM is a practical solution for merging complementary coarse-resolution images and for super-resolution mapping of continuous spatial processes.

1. Introduction

Synthesizing complementary information derived from multiple sensors prompts the need to study rigorous data fusion algorithms. Data fusion is a process that integrates information derived from different sensors or different spectral bands of the same sensor and produces a single image that contains complementary information from multiple sources, while minimizing loss or distortion of the original data (Hall, 2004; Pohl & Van Genderen, 1998). In this work, we focus on statistical algorithms for merging measurements derived from multiple coarse-resolution sensors. Statistical data fusion combines statistically heterogeneous samples from marginal distributions to make statistical inference about the unobserved joint distributions or functions of them (Braverman, 2008). Statistical data fusion, including those based on geostatistics, can produce spatial predictions of pixel values (Atkinson, Pardo-Iguzquiza, & Chico-Olmo, 2008). Recently, several geostatistical algorithms, including fixed ranking kriging (Cressie & Johannesson, 2008; Shi & Cressie, 2007), fixed ranking filtering (Cressie, Shi, & Kang, 2010; Kang, Cressie, & Shi, 2010), spatial statistical data fusion (Nguyen, Cressie, & Braverman, 2012), space-time data fusion (Braverman, Nguyen, & Cressie, 2011), and moving-window kriging (Hammerling, Michalak, & Kawa, 2012), have been developed for mapping global distributions of environmental variables, such as aerosol optical depth (AOD) and carbon dioxide (CO_2), with sparsely distributed remotely sensed data. The numerous algorithms for merging measurements from different spectral bands (e.g., pan-sharpening) are beyond the scope of this paper.

Measurements from remote sensing sensors are constantly influenced by factors like atmospheric conditions, electronic noise of sensors, and changes in illumination. In order to build geostatistical models of sensor measurements contaminated with measurement errors, we take a stochastic view of remote sensing images. We regard the true spatial process of interest (i.e., spectral radiance) as a random field, i.e., a spatial random process with a set of random variables that have certain probability distributions. Then, a remote sensing image covering an area can be conceived as a realization of the random field. In this work, we adopt the Gaussian random field model, which involves

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a set of Gaussian probability density functions for random variables. For remote sensing measurements, the values of continuous spatial processes of interest are regularized to discrete pixels by a weighted average process, with the spatial weights determined by point spread functions (PSFs) of sensors (Jupp, Strahler, & Woodcock, 1988). The effective instantaneous field of view (EIFOV) of the sensor is an area over which measurements are averaged. EIFOV defines the spatial support of sensor measurements. Spatial support is a geostatistical concept that means the shape, size, and orientation of measurements (Gotway & Young, 2002, 2005). The value assigned to a pixel represents the average radiance arriving at the sensor from the EIFOV (Jupp, Strahler & Woodcock, 1988). Sensors with different sizes of pixels have different EIFOVs. As a result, measurements from these sensors have different spatial supports.

Merging remote sensing images with variable resolutions usually involves the change-of-support problem (Curran & Atkinson, 1999; Gotway & Young, 2002, 2005). Several geostatistical algorithms have been developed to solve the change-of-support problem. Area-to-point kriging was developed for downscaling areal data to point support (Kyriakidis, 2004; Kyriakidis & Yoo, 2005). Goovaerts (2008) developed a practical semivariogram deconvolution algorithm to derive point support variogram parameters from areal data. This algorithm solved one of the key problems in the practical application of area-to-point kriging. Moreover, a parallel computing algorithm has been developed for speeding-up the computations involved in the practical application of area-to-point kriging (Guan, Kyriakidis, & Goodchild, 2011). Area-to-point kriging has the potential for downscaling remote sensing data. Nguyen et al. (2012) developed a spatial statistical data fusion approach, which integrates a change-of-support model into fixed rank kriging for multi-resolution data fusion. It was applied for merging variable-resolution AOD images derived from the Multi-angle Imaging Spectroradiometer (MISR) and the Moderate Resolution Imaging Spectroradiometer (MODIS) sensors. Sales, Souza, and Kyriakidis (2013) applied a Kriging with external drift (KED) method for increasing 500-m resolution (bands 3–7) MODIS images to 250-m resolution.

The spatially varying dependence structure of random variables (i.e., spatial nonstationarity) is another problem to be dealt with when working with remote sensing images covering large geographic areas. In geostatistics, a fundamental assumption of most models is that random fields are second-order stationary, i.e., in a relatively small region the mean values of random variables are constant and the covariance between the values of random variables only depends on the distance between them (Chilès & Delfiner, 1999). However, for spatial data covering large geographic areas, this assumption may not be true because remote sensing images covering large geographic areas usually include spatial nonstationarity. In this work, we differentiated two types of spatial nonstationarity: one is spatial nonstationarity in the mean values of regionalized variables, and the other is spatial nonstationarity in the covariance structure. The need to address spatial nonstationarity has been discussed in the field of geostatistics over the past decades. Universal kriging is one way to address spatial nonstationarity in the mean values of regionalized variables. Hass (1990) applied a moving-window kriging approach to model acid depositions. In the moving-window kriging model, measurements in local-windows are used for both parameter estimations and spatial predictions. This approach is simple to be implemented, and it alleviates the problem of spatial nonstationarity. Because of local fitting and computing, moving-window kriging is also computationally efficient. One caveat of the local-window approach is that there is no consistent covariance function over the whole study domain. Higdon, Swall, and Kern (1999) convolved spatially varying kernels to give a nonstationary version of the squared exponential stationary covariance function. This approach has been applied in modeling remote sensing images (D'Hondt, López-Martínez, Ferro-Famil, & Pottier, 2007). Although this method can produce a consistent covariance function over the whole prediction domain, the Gaussian kernel applied in this method is too smooth for real spatial processes.

Besides spatial nonstationarity, the problem of computational burden also needs to be solved when applying geostatistical models for dealing with large spatial data. The local-window approach (e.g., moving-window kriging) is one way to solve the problem of computational burden. Data dimension reduction is another way to reduce computational burden associated with large spatial data (Wikle, 2010). Cressie and Johannesson (2008) developed a spatial mixed effects model (i.e., fixed rank kriging) with a flexible family of nonstationary covariance functions. For this approach, kriging can be done exactly, and the computational complexity is linear to the size of the data. Moreover, Cressie et al. (2010) developed a spatial–temporal random effect model (i.e., fixed rank filtering), which integrates fixed rank kriging and Kalman filter for dealing with large spatial–temporal data. Fixed rank kriging and fixed rank filtering are both approaches of data dimension reduction. These methods eliminate or reduce some components of spatial variability to improve computational efficiency.

In this work, we present a geostatistical inverse modeling approach for merging coarse-resolution remote sensing images with variable spatial supports. The geostatistical inverse model was designed to be statistically principled, and it can produce the best predictions (i.e., minimizing the squared errors between predictions and measurements) and prediction uncertainties, while honoring the original data (i.e., preserving the values of original measurements) (Kitanidis, 1995; Michalak, Bruhwiler, & Tans, 2004). In the geostatistical inverse modeling framework, the restricted maximum likelihood method was used for estimating covariance parameters related to the change-of-support problem. Moreover, we contributed a moving-window geostatistical inverse modeling approach to accommodate spatial nonstationarity and reduce computational burden associated with large spatial data. Following the introduction, we introduce the geostatistical inverse modeling methodology in Section 2. In Section 3, we illustrate the computer experiments using synthetic and real images. The modeling results are presented in Section 4. Finally, we discuss possible model improvements and summarize the major findings of this work.

2. Methodology

2.1. Geostatistical inverse modeling

Geostatistical inverse modeling (GIM) follows a Bayesian approach, and it is based on the principle of combining the prior information (i.e., spatial and/or temporal autocorrelation) with the information from available measurements (Michalak, Bruhwiler & Tans, 2004). Spatial and/or temporal autocorrelation can provide information about the structure of the data that can be used to reduce prediction uncertainty. GIM has been applied in ground water systems (Kitanidis, 1995), contaminant sources identification (Snodgrass & Kitanidis, 1997), estimating surface fluxes of atmospheric trace gases (Gourdji, Mueller, Schaefer, & Michalak, 2008; Michalak, Bruhwiler & Tans, 2004), characterizing attribute distributions in water sediments (Zhou & Michalak, 2009), and merging remote sensing images with variable resolutions (Erickson & Michalak, 2006). There remain unrealized opportunities in applying GIM for image scaling (i.e., downscaling and up-scaling) and multi-resolution data fusion. In comparison with area-to-point kriging, which also deals with predicting point values from areal data, the covariance parameters in the GIM framework can be inferred directly from measurements by the restricted maximum likelihood algorithm. Moreover, measurements with variable spatial supports can also be merged to produce a single resolution image using GIM.

We only present the key equations of GIM here. Readers are referred to Michalak et al. (2004) for an in-depth discussion about GIM. The spatial prediction problem of GIM can be expressed as

$$z = h(s, r) + v \tag{1}$$