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Downscaling MODIS images with area-to-point regression kriging

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ABSTRACT

The first seven bands of the Moderate Resolution Imaging Spectroradiometer (MODIS) data have been used widely for global land-cover/land-use (LCLU) monitoring (e.g., deforestation over the Amazon basin). However, the spatial resolution of MODIS bands 3–7 (i.e., 500 m) is coarser than that of bands 1 and 2 (i.e., 250 m), and may be too coarse for a large number of applications. In this paper, a new geostatistical approach based on area-to-point regression kriging (ATPRK) is proposed for downscaling coarse spatial resolution bands 3–7 such as to produce a complete set of MODIS images at 250 m. ATPRK takes advantages of the fine spatial resolution information in bands 1 and 2 by regression modeling, and uses area-to-point kriging to downscale the coarse residuals from the regression. ATPRK was compared to four existing methods, including the principal component analysis, wavelets, high-pass filter and kriging with external drift (KED) methods for downscaling in two experiments on MODIS data from the Brazilian Amazon. Both visual and quantitative evaluations (in terms of the root mean square error, correlation coefficient, relative global-dimensional synthesis error, universal image quality index, spectral angle mapper and spectral information divergence) showed that ATPRK produced sharpened images with the greatest quality. In addition, ATPRK perfectly preserved the spectral properties of the original coarse data and was faster than KED. The results reveal the great potential of ATPRK applied to MODIS data for a wide variety of applications, including global monitoring of deforestation. The ATPRK proposed in this paper is an entirely new image fusion approach based on a new conceptualization.

1. Introduction

In the Amazon rainforest, deforestation processes have caused large impacts on the flow of water and energy in the global ecosystem. To study the future development of the Amazon basin, besides physical and atmospheric processes, land-cover/land-use (LCLU) change processes caused by human activities also require in-depth monitoring. Moderate Resolution Imaging Spectroradiometer (MODIS) images have become an increasingly important source of data for detecting deforestation processes over the Amazon area, and in near real-time (Anderson, Shimabukuro, & Arai, 2005). The MODIS sensor is a common source of remote sensing imagery used for global monitoring, due to its free availability, wide swath and regular revisit (near-daily frequency) capabilities. MODIS images are composed of 36 spectral bands, including two 250 m spatial resolution bands (bands 1 and 2), five 500 m bands (bands 3–7) and 29 1 km bands. The first seven bands have been used widely for LCLU monitoring.

When using MODIS data, it is always favorable to take advantage of all of the first seven bands to provide the richest spectral information possible for reliable LCLU monitoring. Bands 1 and 2 are related mainly to land/cloud/aerosol boundaries, while bands 3–7 are related to land/cloud/aerosol properties. The mismatch in the spatial resolution between bands 1–2 and bands 3–7 necessitates approaches to match the spatial resolution of the two groups of bands. There are two categories of schemes for this purpose. One is to upscale the two 250 m bands to 500 m to match bands 3–7, in which seven-band 500 m data are produced as a result. This is the common case; for example, the 500 m MODIS products published online. The other is to downscale bands 3–7 to 250 m, thereby generating the seven-band 250 m data. Land cover changes usually occur at a finer spatial resolution than 500 m. Using the seven-band 250 m MODIS data, more LCLU detail and LCLU change detail can be acquired by image analysis techniques such as LCLU mapping and change detection. It is of great interest to study the latter scheme (i.e., downscaling MODIS bands 3–7 to match bands 1 and 2) to provide finer spatial resolution (i.e., 250 m) LCLU information.

Downscaling MODIS images with bands of different spatial and spectral resolutions is a typical image fusion problem (Kim, Kang, & Lee, 2010; Sales, Souza, & Kyriakidis, 2013; Sirguey, Mathieu, & Arnaud, 2009). Image fusion is a technique for combining a fine spatial, but

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coarse spectral resolution image (e.g., MODIS image bands 1 and 2) with a coarse spatial, but fine spectral resolution image (e.g., MODIS image bands 3–7) to generate a fine spatial and spectral resolution image. For MODIS image downscaling, one band from bands 1 and 2 is selected as the fine spatial resolution image in general, which acts in the same way as the panchromatic (PAN) band in the well-known image fusion technique called PAN-sharpening. The PAN-like band in MODIS images can be decided according to the differences in the center wavelength of the bands (Sirguey, Mathieu, Arnaud, Khan, & Chanussot, 2008) or spectral similarity between bands (Kim et al., 2010). The known fine spatial resolution information is deemed to have great importance in decreasing the inherent uncertainty in the under-determined image downscaling problem. Various image fusion algorithms can be made available for downscaling MODIS images, including the intensity–hue–saturation (Chavez, Sides, & Anderson, 1991), Brovey (Gillespie, Kahle, & Walker, 1987), principal component analysis (PCA) (Shettigara, 1992), wavelet transformation (Nunez et al., 1999), high-pass filter (HPF) (Aiazzi, Alparone, Baronti, & Garzelli, 2002), support vector machine (Zheng, Shi, Liu, Zhu, & Tian, 2007), sparse representation (Wei, Bioucas-Dias, Dobigeon, & Tourneret, 2015) methods, and the automated statistics-based fusion method implemented in PCI Geomatica (Zhang, 2004). It is beyond the scope of this paper to conduct an explicit literature review on existing image fusion methods. Related reviews can be found in Bioucas-Dias et al. (2013), Pohl and Van Genderen (1998), Vivone et al. (2015), Wang, Ziou, Armenakis, Li, and Li (2005), and Zhang and Mishra (2014).

In MODIS image downscaling and even more general image fusion, an open issue is the capability to preserve the spectral properties of the observed coarse images. This means that if the downscaled image is upscaled to the original coarse spatial resolution, it should be identical to the original one across all bands. The recently developed geostatistical solutions are a family of image fusion methods able to retain the spectral properties and have received increasing attention in image downscaling (Atkinson, Pardo-Igúzquiza, & Chica-Olmo, 2008; Pardo-Igúzquiza, Chica-Olmo, & Atkinson, 2006; Pardo-Iguzquiza, Rodríguez-Galiano, Chica-Olmo, & Atkinson, 2011; Sales et al., 2013). Pardo-Igúzquiza et al. (2006) proposed a cokriging method to downscale Landsat images, taking each observed coarse band as the primary variable and the fine PAN band as the secondary variable and performing downscaling for each coarse band in turn. This interesting approach was extended by adopting a spatially adaptive filtering scheme (Pardo-Iguzquiza et al., 2011), in which the cokriging weights changed across the image, rather than being fixed in Pardo-Igúzquiza et al. (2006). Atkinson et al. (2008) extended the cokriging approach to cases where the pixel size to be predicted is smaller than that of all input variables (i.e., even smaller than that of the PAN). The cokriging approach, however, requires complex semivariogram modeling. That is, the auto-semivariogram and cross-semivariogram need to be estimated for each coarse band. The former accounts for the relationship between pixels in the primary or secondary variables, while the latter accounts for the relationship between pixels between the primary and secondary variables. This characteristic makes the cokriging-based downscaling approach computationally intensive and difficult to automate (Liu, Kyriakidis, & Goodchild, 2008). Alternatively, Sales et al. (2013) applied a kriging with external drift (KED) approach to downscale a MODIS image. KED requires only auto-semivariogram modeling for the observed coarse band and simplifies the semivariogram modeling procedure, which makes it easier to implement than cokriging. As mentioned in Sales et al. (2013), however, KED suffers from expensive computational cost, because KED needs to compute kriging weights locally for each fine pixel. The computing time increases linearly with the number of fine pixels.

In this paper, for the first time, a new geostatistical solution to MODIS image downscaling based on area-to-point regression kriging (ATPRK) is proposed. ATPRK consists of two parts: regression and area-to-point kriging (ATPK). ATPRK can be viewed as an extension of both regression kriging and ATPK (Atkinson, 2013; Goovaerts, 2008; Kyriakidis, 2004; Kyriakidis & Yoo, 2005). For the former, ATPRK is a newly developed regression kriging with ATPK for kriging interpolation, while for the latter, ATPRK incorporates fine spatial resolution ancillary data into ATPK for image downscaling by regression modeling. Regression kriging is a hybrid interpolation technique that uses regression on covariates and kriging to interpolate the residuals from the regression model (Hengl, Heuvelinkb, & Rossiter, 2004, 2007, Hengl, Heuvelinkb, & Stein, 2004). ATPK is distinguished from conventional centroid-based kriging which ignores the spatial support (treating it always as equivalent to the observation support). ATPK takes into account explicitly the size of support(s) and predicts variables from areal supports to points via semivariogram deconvolution to parameterize the Random Function model and kriging for prediction (Kerry, Goovaerts, Rawlins, & Marchant, 2012). Moreover, ATPK can precisely honor the observed areal data. In the proposed ATPRK approach, by regression on ancillary information (fine spatial resolution band 1 or 2, hereafter called fine band; the so-called secondary variable in cokriging) in advance, ATPK is performed for downscaling residuals in coarse bands 3–7 (primary variable in cokriging). The advantages associated with regression kriging and ATPK encourage the development of ATPRK for downscaling MODIS imagery in this paper.

ATPRK has shown its potential for disaggregation of data of irregular geographical units (i.e., data defined on complex polygon maps). Liu et al. (2008) proposed an ATPRK method to disaggregate population-density from irregular census units to the land-use zones within them, where the remote sensing image (i.e., IKONOS image) was used to obtain ancillary information. To the best of our knowledge, ATPRK has not been studied in remote sensing image analysis. In remote sensing images, the spatial support is fixed across a whole image as it is composed of regularly sized pixels that cover a positive finite area, producing a given spatial resolution (Wang, Atkinson, & Shi, 2015a). It is of great interest to develop an ATPRK approach for remote sensing image downscaling.

The remainder of this paper is organized as follows. Section 2 introduces the principles of the new approach ATPRK in detail, which includes two parts, that is, regression and ATPK. The experimental results are provided in Section 3 for validation. Section 4 further discusses the proposed approach, followed by a conclusion in Section 5.

2. Methods

2.1. Problem formulation

Let $Z_V^l(\mathbf{x}_i)$ be the random variable of pixel V centered at $\mathbf{x}_i$ (i = 1,…,M, where M is the number of pixels) in coarse band l (l = 3,…,7), and $Z_v^k(\mathbf{x}_j)$ be the random variable of pixel v centered at $\mathbf{x}_j$ (j = 1,…, MF^2, where F is the spatial resolution (zoom) ratio between the coarse and fine bands) in fine band k (k = 1,2). The notations v and V denote fine and coarse pixels, respectively. The task of the ATPRK-based MODIS image downscaling method is to predict $Z_v^l(\mathbf{x})$ for all fine pixels in all coarse bands. ATPRK contains two phases: regression and ATPK. It first performs regression of each coarse band on the fine band and then performs ATPK to downscale the band residuals from the regression model. The prediction of ATPRK is

$$Z_v^l(\mathbf{x}) = Z_{v1}^l(\mathbf{x}) + Z_{v2}^l(\mathbf{x}) \quad (1)$$

where $Z_{v1}^l(\mathbf{x})$ and $Z_{v2}^l(\mathbf{x})$ are the predictions of the regression and ATPK parts. The details regarding their calculation are given in the following sub-sections.

2.2. Regression between fine and coarse bands

The regression part in ATPRK is critical as it takes advantage of valuable fine spatial resolution texture information from ancillary