Remote Sensing of Environment 214 (2018) 154–172

Contents lists available at ScienceDirect

Remote Sensing of Environment

journal homepage: www.elsevier.com/locate/rse

A new downscaling-integration framework for high-resolution monthly precipitation estimates: Combining rain gauge observations, satellite-derived precipitation data and geographical ancillary data

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ARTICLE INFO

Keywords:
Precipitation
TRMM
Geographically weighted regression kriging
Downscaling
Integration
Geographical factors

ABSTRACT

Deriving high quality precipitation estimates at high spatial resolution is of prime importance for many hydrological, meteorological, and environmental investigations. Rain gauge observations and satellite-derived precipitation data are two main sources of precipitation estimates. Gauge observations are accurate and reliable, but are heavily point-based and sparse in areas of rugged or complex terrains. Satellite-derived precipitation products can cover large areas, but they are generally characterized by inherent bias. To optimize the use of both datasets, we propose in this paper, a downscaling-integration framework to generate high quality monthly precipitation datasets at 1 km spatial resolution by merging rain gauge observations and TRMM 3B43 products. Firstly, an area-to-point kriging (ATPK) approach is used to downscale the original TRMM product to 1 km, so as to ensure a fair comparison with rain gauge data. Then, the downscaled TRMM precipitation datasets are integrated with the gauge observations using geographically weighted regression kriging (GWRK). The geographical factors (i.e. longitude, latitude and elevation) are also used as auxiliary variables in the GWRK model. Applying this approach to an experiment conducted at the middle and lower reaches of the Yangtze River in China from 2001 to 2014 shows that: (1) the downscaled monthly TRMM precipitation data by ATPK are more accurate than the original TRMM estimates; (2) the GWRK model employing the downscaled TRMM precipitation data and geographical factors provides better monthly precipitation estimates than the conventional ordinary kriging (OK) interpolation and the commonly used merging methods (i.e. geographical difference analysis, GDA and kriging with external drift, KED); (3) the GWRK method reduces the influence of the inaccuracy (bias) of satellite-derived precipitation data on the precipitation estimates compared to GDA. The approach presented in this study has provided an efficient alternative for solving the scale mismatch problem between point-based gauge data and low resolution satellite data, and producing improved precipitation data at high spatial resolution.

1. Introduction

Precipitation as a key driving force of the global water cycle, is critical in earth science, hydrology, climatology and agriculture (Goovaerts, 2000; Jia et al., 2011; Langella et al., 2010). However, acquiring accurate precipitation data at higher spatial and temporal resolution is still a challenging task (Fang et al., 2013; Karl and Easterling, 1999). As the most reliable source of precipitation information, rain gauge observations can provide accurate points measurements, but it is difficult to provide adequate and reliable spatial

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https://doi.org/10.1016/j.rse.2018.05.021
Received 20 November 2017; Received in revised form 12 April 2018; Accepted 13 May 2018

information of precipitation due to the limited spatial coverage especially in mountainous areas (Celleri et al., 2010). Additionally, limited spatial coverage of rain gauge observations is also apparent in most poor or developing countries where weather stations are sparsely distributed due to limited funds allocated to meteorological research.

With the development of remote sensing and geographic information technology, a series of rainfall datasets have been developed at both regional and global scales, for example, the Global Precipitation Climatology Project (GPCP) (Huffman et al., 1997), the Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks (PERSIANN) (Sorooshian et al., 2000), the Tropical Rainfall Measuring Mission (TRMM) (Huffman et al., 2007) and the Global Satellite Mapping of Precipitation (GSMap) project (Kubota et al., 2007). These satellite-derived rainfall products have been widely used in various parts of the world (Huffman et al., 2007; Nastos et al., 2016; Ochoa et al., 2014; Xue et al., 2013). However, precipitation estimates from satellite-based products contain significant uncertainty derived from retrieval algorithms, topographic features and insufficient sensitivity between electromagnetic signals and clouds (Adhikary et al., 2015; Aghakouchak et al., 2011; Chen et al., 2013; Kidd et al., 2003; Xie and Arkin, 1997). Furthermore, their spatial resolution is still too coarse to meet the requirements of hydrological and meteorological studies at local or watershed scales (Zheng and Bastiaanssen, 2013). Therefore, calibrating and downscaling procedures for satellite-derived rainfall products are necessary before application in hydrological and meteorological models at a local or basin scale.

Numerous statistical methods have been proposed for downscaling coarse resolution satellite precipitation products to fine resolution precipitation data by establishing statistical models between coarse precipitation and related environmental data with high spatial resolution such as topography and vegetation (Chen et al., 2015; Chen et al., 2014; Immerzeel et al., 2009; Jia et al., 2011; Park, 2013; Xu et al., 2015; Zheng and Bastiaanssen, 2013). These downscaled approaches greatly improve the spatial resolution of satellite data. However, the improvement of their accuracy is limited by the accuracy of the original satellite precipitation datasets.

To improve the accuracy of precipitation estimates, many studies have developed various local statistical merging schemes that combine satellite-derived rainfall data with rain gauge observations, including statistical objective analysis (Boushaki et al., 2009; Rozante et al., 2010), optimal interpolation techniques (Shen et al., 2014; Xie and Xiong, 2011), conditional merging (Sinclair and Pegram, 2005), double kernel smoothing (Li and Shao, 2010) and geographical difference analysis (Baik et al., 2016; Verdin et al., 2016; Xu et al., 2015). These statistical merging approaches focus on the difference between satellite-retrieved precipitation datasets and rain gauge observations. The satellite-retrieved precipitation datasets are usually used as background fields due to their continuous spatial coverage. Though these merging methods substantially improve the accuracy of precipitation estimates, there are still some limitations. Firstly, most of these precipitation merging methods directly combine spatial data measured over different supports (e.g. rain gauges and satellite data). However, a coarse pixel value of satellite precipitation product (e.g. TRMM 3B43) is the areal average precipitation within it, while rain gauge data are point measurements. The scale difference issue derived from point-based rain gauges versus satellite pixels is present here, which will inherently include some errors (Atkinson and Tate, 2010; Park et al., 2017; Verdin et al., 2016). Li and Shao (2010) have pointed out that the direct merging of precipitation datasets to fine spatial resolution would produce significant bias around the areal boundary of the grid cell of the original satellite precipitation data because of the discontinuity of background fields (i.e. original gridded data). Some studies have attempted to solve the scale mismatch issue to some extent by using the average value of multiple rain gauges within a coarse pixel as the ground truth (Chokngamwong and Chiu, 2008; Kenawy et al., 2015; Yong et al., 2010). However, this method can only be used in regions where high density gauge network are available. Kyriakidis (2004) proposed a generally unifying framework for interpolating point values from available areal data using the area-to-point method. The area-to-point kriging has been proven to be effective in combining point- and areal-support data in the fields of soil science and medical geography (Goovaerts, 2010; Kerry et al., 2012), and in downscaling remote sensing images (e.g. MODIS images) (Wang et al., 2015; Zhang et al., 2017). However, it was seldom utilized in downscaling satellite-derived precipitation datasets. Secondly, merging approaches using satellite-based precipitation as background field would generally transform inherent systematic errors from satellite data to the resulting rainfall estimates (Verdin et al., 2016). One of the main assumption for some residual-based merging methods is that the satellite products are unbiased estimators of the precipitation background field over the regions (Shen et al., 2014; Verdin et al., 2016; Xie and Xiong, 2011), while satellite estimates generally have large biases which are spatially varying, temporally changing, and range-dependent (Hong et al., 2007; Hu et al., 2014; Tian et al., 2009).

Recently, Zheng and Bastiaanssen (2013) developed an integrated downscaling-calibration procedure to obtain improved annually and monthly precipitation estimates at a 1 km × 1 km scale using the Version 7 TRMM 3B43 precipitation product at a spatial resolution of 0.25°. The TRMM 3B43 annual precipitation was downscaled with annually averaged NDVI at fine spatial resolution and calibrated with rain gauge observations by geographical differential analysis (GDA) and geographical ratio analysis (GRA). The downscaling-calibration procedure was mainly implemented at annual scale, while the fine 1 km monthly precipitation datasets were generated by disaggregating the final annual precipitation estimates. Furthermore, there was no comparison of the performance of the finely disaggregated monthly precipitation data with the original TRMM monthly precipitation data, and the direct interpolated results of rain gauge data to demonstrate the superiority of the proposed method. Park et al. (2017) proposed another downscaling and integration approach to integrate coarse resolution satellite precipitation data and rain gauge data for mapping precipitation at fine spatial resolution. In their approach, ATPK was selected to downscale monthly TRMM 3B43 data and three multivariate kriging algorithms including simple kriging with local means (SKLM), kriging with an external drift (KED) and conditional merging (CM), were used to integrate the downscaled TRMM precipitation and rain gauge data. They concluded that the multivariate kriging algorithms yielded more significant improvements than original kriging (OK) when rain gauges are sparse. However, other environmental variables (e.g. longitude, latitude and elevation) related to precipitation were not considered in the estimation of precipitation, and there was no comparison of final predictions obtained by downscaling and integration approach and direct integration approach, respectively, in their study.

The objective of this study is to develop a downscaling-integration framework for fine resolution mapping of precipitation with high quality at a monthly temporal scale, and investigate the error sources of various precipitation estimates using long time-series experiments for better spatial precipitation prediction. Similar to Park et al. (2017), the coarse resolution pixels of TRMM precipitation datasets (TRMM 3B43 V7) are first downscaled to 1 km using area-to-point kriging (ATPK) for better comparison against individual rain gauges. Then, another nonstationary geographical method i.e. geographically weighted regression kriging (GWRK), that incorporates external variables, is used to combine rain gauge observations with the downscaled satellite estimates. Other geographical auxiliary data (i.e. DEM, longitude, latitude) are also included in the GWRK model. The two-step strategy (geostatistical approach) is applied to each monthly precipitation from 2001 to 2014 over the middle and lower reaches of the Yangtze River in China. The final estimated results are assessed using rain gauge data and compared with the interpolation results of ordinary kriging (OK) interpolation as well as the commonly used merging methods (i.e. geographical difference analysis, GDA and KED). Besides, factors that influence the