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A new satellite-based monthly precipitation downscaling algorithm with non-stationary relationship between precipitation and land surface characteristics

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ABSTRACT

Remote sensing is an important tool to monitor precipitation over regions with sparse rain gauge networks. To provide high-resolution precipitation estimates over un-gauged areas, great efforts have been taken to downscale low-resolution satellite precipitation datasets using the Normalized Difference Vegetation Index (NDVI) and the Digital Elevation Model (DEM) based on the assumption that precipitation can be simulated by vegetation and topography proxies at various spatial scales. However, the non-stationarity of the relationship between precipitation and vegetation or topography has not been appropriately considered when low-resolution satellite precipitation datasets are downscaled using NDVI and DEM in previous studies. To overcome this limitation, a new downscaling algorithm was proposed in this study by introducing a regional regression model termed as geographically weighted regression (GWR) to explore the spatial heterogeneity of the precipitation–NDVI and precipitation–DEM relationships. The performance of this new downscaling algorithm was assessed by downscaling the latest version of monthly TRMM precipitation datasets (referred to TRMM 3B43 V7) over the eastern Tibetan Plateau and the TianShan Mountains from 0.25° (about 25 km) to 1 km spatial resolution, and the downscaled precipitation datasets were validated against ground observations measured by rain gauges. The validation results indicate that the high-resolution precipitation datasets obtained through the new algorithm not only performed better than the traditional downscaling algorithms, but also had higher accuracy than the original TRMM 3B43 V7 dataset. Besides, we found that the performance of this new algorithm was largely dependent on the accuracy of the original TRMM 3B43 V7 data. We therefore recommend considering the non-stationarity of the precipitation–NDVI and precipitation–DEM relationships in the downscaling process, and demonstrate the possibility of downscaling satellite precipitation with NDVI and DEM at monthly temporal scale.

1. Introduction

As a key component of material exchange and energy balance, precipitation plays a significant role in hydrological, meteorological, and ecological research (Li & Shao, 2010; Wu & Chen, 2012). However, it is still a great challenge to acquire precipitation observations over mountainous and underdeveloped regions due to the sparse rain gauge network (Xie & Xiong, 2011). With the development of advanced meteorological satellites, remote sensing has become the main tool for estimating precipitation over areas lacking rain gauge networks (Mahesh, Prakash, Sathiyamoorthy, & Gairola, 2011). Since the 1980s, several satellite precipitation datasets have been developed, such as precipitation estimation from remotely sensed information using artificial neural networks (Hsu, Gao, Sorooshian, & Gupta, 1997), the Global Precipitation Climatology Project (Huffman et al., 1997), the Tropical Rainfall Measuring Mission (Kummerow, Barnes, Kozu, Shiue, & Simpson, 1998), and the Climate Prediction Center Morphing Method (Joyce, Janowiak, Arkin, & Xie, 2004). Although these satellite precipitation datasets provide more reliable estimates of precipitation over un-gauge areas compared with various interpolation methods, their spatial resolution (e.g., 0.25°–5°) is often too coarse to present the meso- and micro-scale variability of precipitation, which makes it impossible to derive hydrological and meteorological models at a local basin (Duan & Bastiaanssen, 2013; Immerzeel, Rutten, & Droogers, 2009; Tao & Barros, 2010).

Over the past decade, satellite observations of the land surface were found to be useful to downscale satellite precipitation datasets because (1) land surface can influence the occurrence and volume of precipitation through its thermal and dynamic forcing mechanisms (Richard & Poccard, 1998; Sokol & Bližňák, 2009), and (2) satellite observations about land surface characteristics can be obtained with high spatial resolutions (30 m–5 km). Consequently, great efforts have been made in

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recent years to improve the spatial resolution of satellite precipitation datasets using high-resolution satellite images of the land surface characteristics. Immerzeel et al. (2009) made the assumption that precipitation was correlated with vegetation at various spatial scales and proposed an algorithm which downscaled the satellite precipitation datasets using the exponential function between the precipitation and Normalized Difference Vegetation Index (NDVI) established at low spatial resolution. Jia, Zhu, Lű, and Yan (2011) revised this downscaling algorithm by introducing both NDVI and Digital Elevation Model (DEM) to regress the satellite precipitation datasets with multiple linear regression model, and downscaled the spatial resolution of Tropical Rainfall Measuring Mission (TRMM) precipitation datasets from 0.25° to 1 km over the Qaidam Basin. Duan and Bastiaanssen (2013) further improved the downscaling algorithm by introducing geographical differential analysis (GDA) and geographical ratio analysis (GRA) calibration methods to reduce the errors of the downscaled precipitation datasets. Independent validation indicated that the downscaled precipitation datasets could represent the detailed distribution of precipitation in space with similar or even higher accuracy compared with the original satellite precipitation datasets, suggesting that it is a promising approach to improve the spatial resolution of satellite precipitation datasets using NDVI and DEM.

Although great efforts have been made to advance the downscaling algorithms based on NDVI and DEM, there were still notable errors in the downscaled precipitation datasets. Immerzeel et al. (2009) pointed out that the downscaled satellite precipitation may be suffering from the errors inherent in the satellite precipitation datasets and NDVI caused by orbital drift, atmospheric conditions, and imperfect retrieval algorithms. In addition, Jia et al. (2011) indicated that the soil type, hydrological conditions, and human activities could seriously disturb the relationship among precipitation, NDVI and DEM, making it difficult to accurately predict precipitation NDVI and DEM. However, a potential source of errors in current downscaling algorithms that has not been considered until now is that the satellite precipitation datasets were predicted using a single multiple linear regression or exponential regression model, which assume that the relationship between the independent variable and the explanatory variables is constant in space. However, several studies have indicated that the relationship between precipitation and land surface characteristics is spatially varying and scale-dependent (Foody, 2003; Gao, Huang, Li, & Li, 2012), which contradicts the assumption of these regression models. This limitation can affect the predictability of the satellite precipitation datasets with NDVI and DEM over regions with complicated land–atmosphere interactions, leading to serious uncertainty in the downscaled satellite precipitation datasets.

Another notable problem is that previous researches have only downscaled yearly or the mean of multi-year satellite precipitation datasets (Immerzeel et al., 2009; Jia et al., 2011), while almost no investigation has been conducted to assess the performance of these downscaling algorithms at monthly temporal scale. Duan and Bastiaanssen (2013) suggested that it was not feasible to downscale monthly satellite precipitation datasets because the response of NDVI to precipitation usually lagged by two or three months. In comparison, Brunsell (2006) separated the land surface into four categories according to the relationships between precipitation and NDVI as well as precipitation and land surface temperatures, and the time lag of the precipitation–NDVI relationship for each category was investigated using lagged covariance. The results indicated that the strongest relationship between precipitation and NDVI could be observed with zero month lag for three categories, and only one month lag for one category, indicating that the precipitation–NDVI relationship is hardly time-lagged. As pointed by Brunsell (2006), vegetation could affect precipitation by changing the temperature and moisture of the air during the growing season. In such cases, the response of precipitation to vegetation tends not to be time-lagged or, at least, to be alleviated. Therefore, it might be possible to simulate precipitation with NDVI at monthly temporal scale, which could be quite beneficial to ecological models that are driven by monthly precipitation inputs (Wu, Gonsamo, Gough, Chen, & Xu, 2014).

In this study, a new downscaling algorithm is proposed by introducing a regional regression method termed as geographically weighted regression (GWR) model, which can be used to address the spatially heterogeneous relationships between various environmental factors (Foody, 2003; Li, Zhao, Miaomiao, & Wang, 2010). We applied this new algorithm to downscale the latest version of the TRMM satellite precipitation datasets (TRMM 3B43 V7) over the eastern Tibetan Plateau and TianShan Mountains with NDVI and DEM at monthly temporal scale. Using ground observations measured by rain gauges, the performance of this new algorithm is assessed and compared with the existing downscaling algorithms proposed by Immerzeel et al. (2009) and Jia et al. (2011). Besides, the main causes influencing the performance of the proposed downscaling algorithm were further investigated using the 70 monthly results in our tested areas. The objective of this study was to generate a reliable downscaling algorithm at monthly temporal scale over regions with complex precipitation–NDVI and precipitation–DEM relationships, and further provide quantitative information for improving the performance of the downscaling algorithms based on NDVI and DEM.

2. Study areas

Two mountainous regions in western China were selected as study areas, namely the TianShan Mountains and the eastern Tibetan Plateau. The TianShan Mountains are in the middle of Eurasia which is far from all the oceans, leading to relatively low precipitation over this area (Yuan & Li, 1999). The study area in the TianShan Mountains is located between 40.5°N–47.5°N and 79.5°E–87.5°E (Fig. 1(a)). The elevation of this area ranges from 183 m to 7053 m, with several large mountains in the southern part of this area (McVicar & Körner, 2013). The annual precipitation over this area is about 213 mm, and more than 60% precipitation happens between May and September. The land cover of this area shows great spatial heterogeneity. Several deserts are located in the southern and eastern parts of this area (about 23.9%), while the middle and northern parts are mainly covered by grassland (about 62.3%) and some forests (about 2.3%, including Evergreen Broadleaf, Evergreen Needleleaf, and Deciduous Needleleaf forests). It should be noted that the agriculture over this area is well developed because of the abundant water resource from the melted snow. There are many large croplands distributed over the southern and western parts of the area (about 7.4%), which could seriously disturb the relationship between precipitation and NDVI.

Tibetan Plateau is the source of several major rivers such as the Yangtze, Yellow, and LanCang rivers (Yin, Liu, Zhang, & Chung, 2004). This study focused on the eastern part of Tibetan Plateau between 30.5°N–35.5°N and 95.5°E–102.5°E (Fig. 1(b)), covering approximately 350,000 km^2. The annual precipitation observed by rain gauges is 591 mm, and most precipitation (about 488 mm) happens in summer (from May to September). The elevation of these areas increases from northeast to southwest, with several large mountains above 6000 m. The land cover over this area is much simpler than TianShan Mountains. Except some Evergreen Broadleaf forest in the western part (7.1%) and some snow cover (4.3%) in the southeast part, land surface of this area is governed by grassland.

3. Data and methodology

3.1. Data

3.1.1. Rain gauge data

The ground observations used in this study were provided by the Institute of Tibetan Plateau Atmospheric and Environmental Science. Due to the harsh environment and complicated topography, the rain gauge