Remote Sensing of Environment 215 (2018) 109–127

Contents lists available at ScienceDirect

Remote Sensing of Environment

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

Spatial downscaling of TRMM precipitation data considering the impacts of macro-geographical factors and local elevation in the Three-River Headwaters Region

Tao Zhang[a,b], Baolin Li[a,b,*], Yecheng Yuan[a], Xizhang Gao[a], Qingling Sun[a,b], Lili Xu[c,d], Yuhao Jiang[a,b]

[a] State Key Laboratory of Resources and Environmental Information System, Institute of Geographic Sciences and Natural Resources Research, CAS, Beijing 100101, China
[b] University of Chinese Academy of Sciences, Beijing 100049, China
[c] Key Laboratory for Geographical Process Analysis & Simulation of Hubei Province, Central China Normal University, Wuhan 430079, China
[d] College of Urban and Environmental Sciences, Central China Normal University, Wuhan 430079, China

ARTICLE INFO

Keywords:
Downscaling
Precipitation
TRMM
NDVI
DEM
Three-River Headwaters Region

ABSTRACT

Precipitation products with high spatial resolution are important for basin-scale hydrological and meteorological applications. Downscaling techniques commonly used with satellite-derived rainfall data build statistical regression relationships between the precipitation and land surface characteristics to obtain rainfall estimates with improved spatial resolution. However, these relationships tend to be extended mistakenly from the regional scale to the hill slope scale. This paper introduces a quadratic parabolic profile (QPP) model for downscaling precipitation. The proposed technique uses a quadratic parabolic equation to express the rule for changes of precipitation with elevation. It is assumed that precipitation is the primary factor restricting vegetation growth during the growing season. Therefore, an ordinary least square regression method is used to fit an "elevation–normalized difference vegetation index (NDVI)" function to determine the parameters of the QPP model. This method was implemented in the Three-River Headwaters Region (TRHR) during the growing seasons of 2009–2013 for both monthly and total precipitation. The results indicated that the precipitation estimates downscaled using the QPP method had higher accuracies than those of commonly used exponential regression, multiple linear regression, and geographically weighted regression models. The average root mean square errors (RMSEs) and mean absolute percent errors (MAPEs) of total precipitation during the growing season of the commonly used models were 17%–69% and 17%–92% higher, respectively, than those of the QPP model. Meanwhile, the precipitation downscaled using the QPP technique also had lower MAPEs and RMSEs than the PERSIANN-CCS, PERSIANN-CDR, GSMaP-RNL, and GSMaP-RNLG products. Downscaled precipitation estimates from the QPP model exhibited patterns with elevation that were more detailed and more reliable than from the commonly used downscaling methods and another four satellite products. In addition, the QPP model is insensitive to errors in the NDVI or elevation. These findings suggest the proposed approach could be implemented successfully to downscale both monthly and total precipitation of the Tropical Rainfall Measuring Mission (TRMM) 3B43 product throughout the growing season in the TRHR.

1. Introduction

Precipitation is an essential component of the global water cycle that has an important role in hydrological, meteorological, and ecological research (Langella et al., 2010). However, the lack of sufficient numbers of rain gauges makes it a challenge to determine accurate high-resolution spatial distributions of precipitation in mountainous areas (Henn et al., 2018). Satellite precipitation datasets offer a promising solution for this problem (Darand et al., 2017; Pombo and de Oliveira, 2015; Yang et al., 2017) and several regional- and global-scale satellite precipitation datasets have been developed. These include the Global Precipitation Climatology Project (Huffman et al., 1997, 2009, 2001), Climate Prediction Center Merged Analysis of Prediction (Xie and Arkin, 1997; Xie et al., 2003), Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks (PERSIANN) (Hsu et al., 1999; Hsu et al., 1997; Sorooshian et al., 2000),

* Corresponding author at: State Key Laboratory of Resources and Environmental Information System, Institute of Geographic Sciences and Natural Resources Research, CAS, Room 1308, Datun Road 11A, Chaoyang District, Beijing 100101, China.
E-mail address: libl@lreis.ac.cn (B. Li).

https://doi.org/10.1016/j.rse.2018.06.004
Received 11 May 2018; Accepted 5 June 2018

Tropical Rainfall Measuring Mission (TRMM) (Huffman et al., 2007; Kummerow et al., 1998), and Naval Research Laboratory-Blend satellite precipitation estimates (Turk et al., 2010).

The spatial resolutions of the above datasets are all equal to or coarser than 0.25° × 0.25°. Therefore, their use in hydrological or meteorological applications at local basin scales is inappropriate because these spatial resolutions are too coarse to reflect meso- and microscale variabilities in the precipitation distribution (Duan and Bastiaanssen, 2013; Immerzeel et al., 2009; Xu et al., 2015). One solution is to adopt full utilization of infrared data with high spatial resolution for integration with other satellite rainfall data, e.g., passive microwave and active microwave data. The PERSIANN-Cloud Classification System (PERSIANN-CCS) realizes this idea by adopting high spatial resolution infrared data (0.04° × 0.04°) to extract cloud structure parameters. These parameters are then input into an artificial neural network to build a relationship between temperature brightness and rainfall rate (Hong et al., 2004). The Climate Prediction Center morphing method uses high spatial resolution infrared data (0.07° × 0.07°) to detect both the direction of movement and the speed of cloud systems. The passive-microwave-derived rainfall is then propagated to adjacent times by adopting the same direction and speed as the cloud movements (Joyce et al., 2004). The Global Satellite Mapping of Precipitation (GSMaP) uses similar algorithms to obtain a product with spatial resolution of 0.1° × 0.1° (Kubota et al., 2007; Ushio et al., 2009). Of those listed above, the PERSIANN-CCS dataset has the highest spatial resolution of 0.04° × 0.04° (Hong et al., 2004). However, even this is still coarse for regional hydrological and meteorological applications.

Another solution is to develop spatial downscaling algorithms to downscale existing satellite precipitation estimates based on land surface characteristics using remote sensing data with higher resolution (Immerzeel et al., 2009). Many attempts have been made to establish an appropriate downscaling model for precipitation products. An exponential regression (ER) model was proposed to improve the resolution of annual TRMM precipitation data from 0.25° to 1 km. This method was based on the response relationship between the normalized difference vegetation index (NDVI) and precipitation (Duan and Bastiaanssen, 2013; Immerzeel et al., 2009). Considering the relationship between precipitation and multiple land surface characteristics, a multiple linear regression (MLR) model was introduced to downscale TRMM precipitation data to 1-km resolution (Fang et al., 2013; Jia et al., 2011; Zheng and Zhu, 2014). Both the ER and the MLR models are global regression techniques. They are suitable in specific geographic regions that have consistent spatial relationships between precipitation and land surface characteristics. However, the relationships between precipitation and various land surface characteristics are spatially variable and scale dependent (Foody, 2003). Therefore, the geographically weighted regression (GWR) model was introduced to downscale TRMM data (Chen et al., 2015; Chen et al., 2014; Xu et al., 2015). Recently, researchers have tried to construct MLR methods for several subregions with different land surface characteristics as explanatory variables (Ma et al., 2017; Ma et al., 2017; Zhu et al., 2018).

Generally, precipitation is affected by both macro-geographical factors and local elevation (Fu, 1983, 1984; Lin, 1995). The main problem with commonly used downscaling models is that the downscaled precipitation data cannot reflect precisely the vertical precipitation distribution with local elevation at the hill slope scale in mountainous regions. These models introduce statistical regression methods to extend directly the relationships between precipitation and land surface characteristics controlled by macro-geographical factors at the regional scale to the hill slope scale. If the observed relationship between precipitation and elevation at the regional scale is inconsistent with that detected at the hill slope scale, the downscaled precipitation will be misestimated. In the Three-River Headwaters Region (TRHR), precipitation generally decreases from southeast to northwest (Shi et al., 2016). Meanwhile, the regional elevation increases from southeast to northwest (Qin, 2014). Thus, based on these models, downscaled precipitation estimates will decrease as the elevation increases. Accordingly, the vertical distribution of the downscaled precipitation at the hill slope scale will reflect the trend of decreasing precipitation with increasing elevation. However, a number of studies have confirmed that precipitation at the hill slope scale can increase with increasing elevation and decrease when a specific elevation threshold is exceeded (Barry, 2008; Lin, 1995). The effects of macro-geographical factors at the regional scale and local elevation at the hill slope scale illustrate the different relationships between precipitation and elevation. Therefore, in contrast to the typical trends of precipitation at the hill slope scale, the commonly used models could indicate that precipitation in valleys might be greater than over neighboring slopes.

A second problem is that the NDVI, which is commonly employed in downscaling models, does not accurately encompass precipitation. Jia et al. (2011) utilized the local Moran's index (Anselin, 1995) to identify NDVI outliers that were not determined from precipitation. Xu et al. (2015) removed pixels with NDVI values that were below zero to exclude non-vegetation regions. They then used a noise reduction approach in a spatial neighborhood to identify NDVI outliers and to eliminate areas controlled mainly by non-precipitation factors. These methods can determine outliers caused by noise; however, areas controlled by non-precipitation factors cannot be differentiated because they are not distributed randomly. Plants located in valley plains or on concave-sloping landforms benefit considerably from groundwater and runoff. Therefore, NDVI values in such places are higher than on adjacent slopes. Consequently, these high NDVI values could lead to overestimation of downscaled precipitation in these areas.

To obtain rainfall products with enhanced spatial resolution and increased accuracy of spatial distribution, this study developed a quadratic parabolic profile (QPP) method that considers the effects of both macro-geographical factors and local elevation. This algorithm was implemented in the TRHR to downscale both monthly and total precipitation of the TRMM 3B43 product during the growing seasons (May–September) of 2009–2013. The performance of the QPP model was compared with the performances of three commonly used methods (i.e., the ER, MLR, and GWR models) and another four satellite-derived high spatial resolution precipitation products.

2. Study area

The TRHR is the source area of the Yangtze, Yellow, and Lantsang rivers. The region is located in southern Qinghai Province (China) on the central Tibetan Plateau (31°39′–36°16′N, 89°24′–102°23′E). The TRHR encompasses an area of approximately 350,000 km^2 (Fig. 1) and the area has a plateau continental climate. From southeast to northwest, the annual average temperature decreases from 3.8 to −5.6 °C, the annual average precipitation decreases from 772.8 to 262.2 mm, and the climatic zone changes from humid subtropical to semiarid (Qin, 2014). In addition, there are many large mountains covered with glaciers and many lakes situated in the lower plains (Guo et al., 2014; Wan et al., 2016). The TRHR is covered mainly by meadow (57.5%) and steppe (21.9%), although other vegetation types include alpine vegetation (10.0%; e.g., sparse vegetation and cushion vegetation), bush (5.7%), and forest (1.1%) (Fig. 1(c)).

3. Data and methodology

3.1. Datasets and processing

3.1.1. Satellite precipitation datasets

Five types of satellite precipitation product for the study area were obtained during the growing seasons of 2009–2013. The monthly precipitation estimates of TRMM 3B43 Version 7 (0.25° × 0.25°) were downloaded from https://trmm.gsfc.nasa.gov/. The monthly rainfall of