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Spatial Downscaling of Remote Sensing Precipitation Data in the Beijing-Tianjin-Hebei Region

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Abstract

Precipitation is an important part of the global hydrological cycle. The large-scale, high-precision continuous precipitation data obtained by satellite remote sensing detection technology has become an important source of spatial precipitation data. However, because the spatial resolution of remote sensing precipitation data is still low, it is difficult to meet the needs of hydrological research, which restricts their application in drought and flood analysis, hydrological simulation, etc. In response to this problem, this paper takes the Beijing-Tianjin-Hebei region as the research area, downscaling the TRMM data and the GPM data space of the continuation plan, and increasing the spatial resolution of the data to 1 km. Compared with the original data, spatial downscaling data not only greatly improves the spatial resolution, but also increases the accuracy of the data, which has better applicability.

Keywords

TRMM, GPM, Spatial Downscaling, Geographically Weighted Regression

1. Introduction

Nowadays, global climate change research is receiving extensive attention from all walks of life, and precipitation is one of the core researches. Precipitation is an important part of the global hydrological cycle, and an important part of research fields such as meteorology, climate, biology, hydrology, and agriculture.

Obtaining precipitation data with long time series, high temporal and spatial resolution and high precision is of great significance to many fields.

The traditional source of precipitation data is the precipitation measured by ground meteorological stations. The precipitation data obtained through the direct measurement of weather stations is the most accurate and the most widely used data. However, the distribution of weather stations is sparse and uneven, and precipitation is a spatial distribution phenomenon. If you want to obtain a continuous spatial distribution of precipitation results, you need to perform spatial interpolation on the precipitation data of the weather station. There is a problem of substituting points for areas, and the results are obtained by interpolation. There are certain uncertainties in precipitation data. Satellite remote sensing precipitation observation breaks through the limitations of traditional observation methods, and realizes the conversion of precipitation observation from point to surface. It has the advantages of high temporal and spatial continuity, wide coverage, and less limited by the underlying surface. It has become an important part of spatial precipitation data source [1].

Commonly used satellite precipitation data include Global Precipitation Climatology Project (GPCP) [2], Global Satellite Mapping of Precipitation (GSMaP) [3], Tropical Rainfall Measuring Mission (TRMM) [4], and Global Precipitation Observation Plan (Global Precipitation Measurement, GPM) [5] and Fengyun series satellites [6]. However, the spatial resolution of these data is low. The most widely used TRMM data has a spatial resolution of up to 0.25˚, and its follow-up product GPM data has a spatial resolution of up to 0.1˚. In the application of local climate and hydrological simulation in small areas, remote sensing precipitation data can hardly reflect the spatial variability of precipitation and cannot meet research needs. Aiming at the problem of low spatial resolution of remote sensing precipitation data, it is an effective method to use spatial downscaling to improve the spatial resolution of remote sensing precipitation data.

2. Experimental Area and Experimental Data

2.1. Experimental Area

This article takes the Beijing-Tianjin-Hebei region as the research object of this study. The Beijing-Tianjin-Hebei region encompasses the two municipalities directly under the Central Government of Beijing and Tianjin and Hebei Province, and is known as my country's "Capital Circle". The Beijing-Tianjin-Hebei region is mainly located in the semi-humid and semi-arid regions of my country. It belongs to the warm temperate zone, semi-humid and semi-arid continental monsoon climate, with four distinct seasons, concentrated rainfall, obvious dryness and wetness, and rain and heat in the same season [7]. The changes in precipitation in the Beijing-Tianjin-Hebei region are related to seasons, latitudes, and topography, and have obvious regular changes. The time change of precipitation in the Beijing-Tianjin-Hebei region is relatively significant. The precipitation is mainly distributed in the period from May to September, and the precipitation in July is significantly higher than the other four months. The study of precipitation in the Beijing-Tianjin-Hebei region and obtaining precipitation data with long time series, high temporal and spatial resolution and high precision are of great significance and value (**Figure 1**).

2.2. Experimental Data

1) Measured precipitation data from ground stations

The measured precipitation data from the ground stations used in this paper comes from the National Oceanic and Atmospheric Administration of the United States (https://gis.ncdc.noaa.gov/maps/ncei). The data was filtered to filter out the sites with missing data, and finally the data of seven sites were selected for analysis. The latitude and longitude information of the ground station is shown in **Table 1**.

2) Remote sensing precipitation data

The Tropical Rainfall Measurement Mission (TRMM) is a remote sensing precipitation monitoring mission jointly developed by NASA and the Japan Aerospace Exploration Agency (JAXA) for the purpose of studying rainfall for

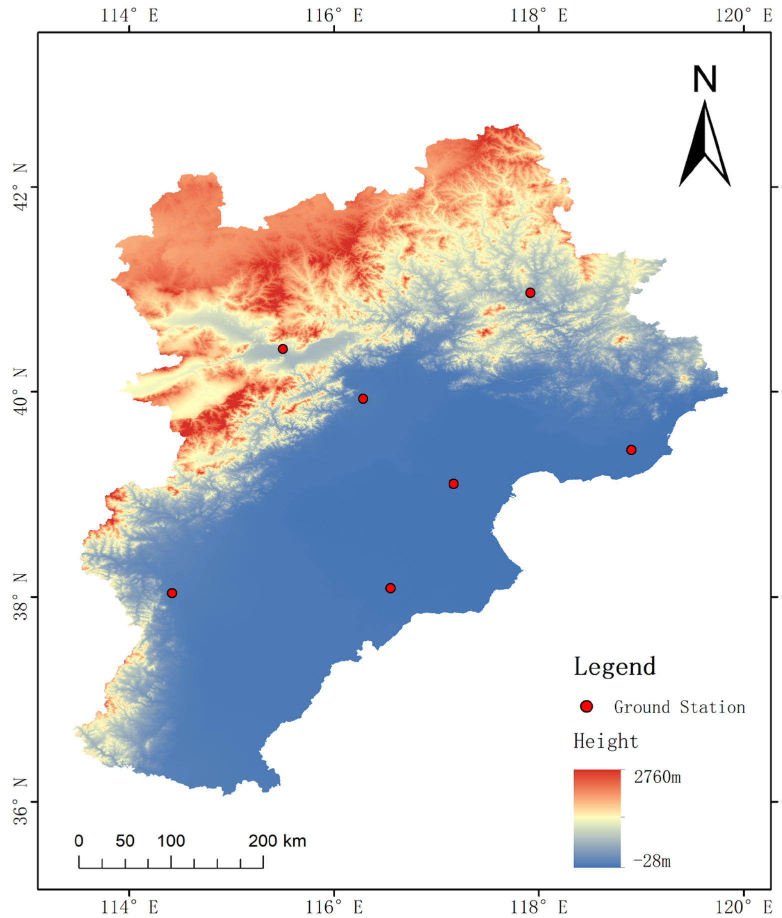

Figure 1. Beijing-Tianjin-Hebei region.

Table 1. Ground station information in the experimental area.

	Station Name	Longitude	Latitude
1	Potou	116.55	38.083
2	Leting	118.9	39.433
3	Tianjin	117.167	39.1
4	Huailai	115.5	40.417
5	Shijiazhuang	114.417	38.033
6	Beijing	116.283	39.933
7	Chengde	117.917	40.967

weather and climate research. The satellite was launched into space on November 28, 1997, with a designed orbital inclination of 35˚, an orbital height of 350 km, and orbiting the earth 16 times every 24 hours. TRMM carries 5 sensing devices, including Precipitation Radar (PR), TRMM Microwave Imager (TMI), Visible and Infrared Scanner (VIRS) three precipitation observation devices And lightning imaging sensor (Lighting Imaging Sensor, LIS), cloud and the earth radiant energy system (Clouds and the Earth Radiant Energy System, CERES) two related equipment [8]. The Global Precipitation Observation Program GPM is an extension of TRMM and is the follow-up satellite precipitation observation program of TRMM. It includes a core precipitation observation satellite and ten cooperative satellites [9]. The designed orbital inclination of the GPM satellite is 65˚, and it orbits the earth 16 times every 24 hours. Compared with TRMM satellites, the observation range of GPM satellites has been extended to 90˚N - 90˚S, and the highest spatial resolution has reached 0.1˚ × 0.1˚. The TRMM data used in this study is TRMM 3B43 v7, which belongs to the third-level product of TRMM. The data is downloaded from NASA's Earth DATA database (https://disc.gsfc.nasa.gov/), the time scale is 1 month, the spatial resolution is 0.25˚ × 0.25˚, and the time range is from February 2000 to 2014 December. The data used in this study is the GPM IMERG data provided by NASA. The specific data model is GPM_3GPROFGPMGMI_CLIM 05. The data source is the GMI microwave imaging meter carried by GPM, which belongs to the GPM Class III product. The time range is from January 2015 to December 2018.

3) NDVI data

The NDVI data used in this study is the MOD13A3 product released by the Land Product Distribution Center (LPDAAC) jointly established by the United States National Geological Survey (USGS) and the National Aeronautics and Space Administration. The spatial resolution of the data is 1 km and the time resolution is 8 Day, the data format is HDF. In this study, MRT batch processing tools are used to process mosaic, splicing, format conversion, projection, etc., to obtain rasterized NDVI data every 8 days, and on the basis of this data, obtain the monthly NDVI data value of each year. Because vegetation growth may have a certain lag relative to precipitation [10], in order to analyze whether this phenomenon exists in the Beijing-Tianjin-Hebei region, the relationship between NDVI and precipitation in the current month and one month lag is analyzed, and it is found that it is relative to the one month lag. In the situation, the correlation between the current month's NDVI and the precipitation is higher, and highly relevant areas also account for more, so the current month's NDVI is selected to participate in the downscaling of the data space (**Figure 2**).

4) DEM data

The DEM data used in this study is SRTM DEM, which is jointly obtained by NASA and the National Bureau of Surveying and Mapping of the Department of Defense. SRTM DEM provides two kinds of data with 30 m resolution and 90 m resolution, called SRTM1 and SRTM3 respectively, covering the world between 60˚N - 56˚S. This study uses SRTM3 DEM data with a spatial resolution of 90 m, and the data is obtained from the geospatial data cloud (http://www.gscloud.cn/), and the downloaded data is spliced, cropped, and projected to transform to obtain the required experiments DEM data for the Beijing-Tianjin-Hebei region.

3. Spatial Downscaling Model Based on Geographically Weighted Regression

Among the existing remote sensing precipitation data products, the spatial resolution of TRMM data and GPM data is higher than other data, and the coverage is wide, so they are favored by researchers at home and abroad. However, in the research of hydrology, climate, ecology and other fields in small and medium-sized regions, the spatial resolution of TRMM and GPM data is still low [11] [12] [13]. This chapter considers spatial heterogeneity, uses the relationship between TRMM data, GPM data and NDVI to construct a GWR regression model, downscaling the original resolution TRMM data and GPM data to obtain 1 km resolution spatially downscaled precipitation data.

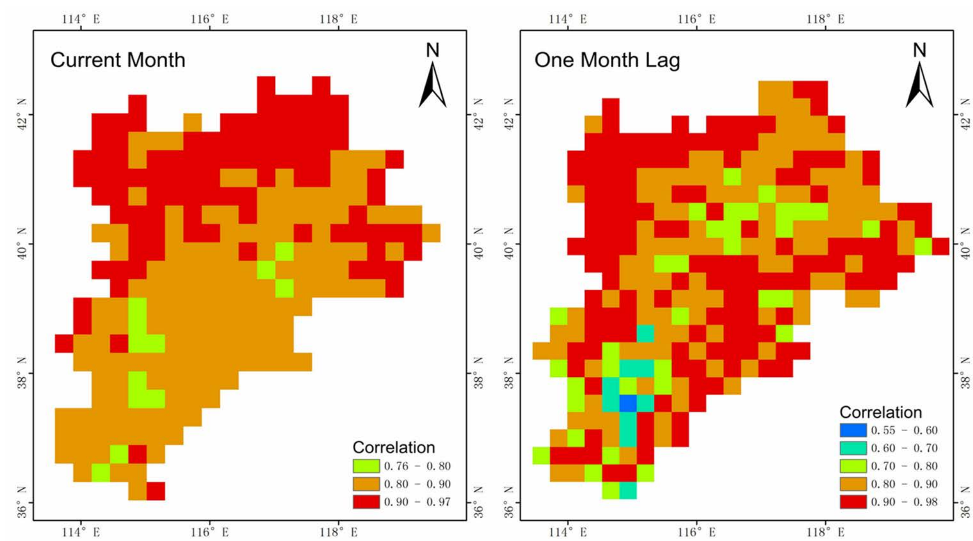

Figure 2. Correlation of NDVI and precipitation.

3.1. Predictor Selection

Precipitation is a complex weather phenomenon and will be affected by many factors. Downscaling needs to choose appropriate predictive factors, these factors need to have a close relationship with precipitation, and can predict or invert the precipitation law to a certain extent. In this paper, the following factors are selected as the predictive factors for spatial downscaling of remote sensing precipitation data:

1) Elevation

Elevation is one of the common downscaling predictors, and there is a relatively obvious correlation between precipitation and elevation. The northeast part of the Beijing-Tianjin-Hebei region is the North China Plain, the west is the Taihang Mountains, and the north is the Zhangbei Plateau. The precipitation is gradually decreasing from low-lying areas to high-lying areas. In order to reflect the changes in elevation in the Beijing-Tianjin-Hebei region, this study selects a digital elevation model as one of the predictive factors for downscaling.

2) Slope and aspect

The precipitation in the Beijing-Tianjin-Hebei region is affected by the monsoon. The warm and humid air current is blocked and forced to rise on the windward slope, the temperature decreases and the water vapor saturation increases, and it is easy to condense to form rainfall, which is called topographic rain. The air sinks on the leeward slope, the temperature rises and the precipitation decreases, which is called the rain shadow area. Windward slopes tend to be rainier than leeward slopes. In this study, the terrain slope aspect is selected as one of the downscaling predictive factors, which are extracted from DEM.

3) Geographical location

Geographical location can be expressed by latitude and longitude, and both in the Beijing-Tianjin-Hebei region affect the temporal and spatial distribution of precipitation. Latitude determines the amount of solar radiation received, which further affects the atmospheric circulation. The location of the sea and land is also one of the factors that affect precipitation. The coastal area is affected by water vapor from the ocean, and the amount of precipitation is larger. The farther away from the ocean, the more difficult it is to affect the ocean water vapor. The east coast of the Beijing-Tianjin-Hebei region has higher precipitation than the northwest. In this study, longitude and latitude are selected as the factor to characterize the geographic location, and as the predictive factor for downscaling, extracted from DEM.

4) NDVI

In the Beijing-Tianjin-Hebei region, precipitation is the main source of soil water and surface water. The growth of vegetation is affected by water. If there is more precipitation, the soil will have more water, while the growth of plants will be more luxuriant. If there is less precipitation, the growth of vegetation will be poor. Therefore, the growth of vegetation can be used as an important reflection condition of precipitation changes. The normalized vegetation index is an index that quantifies vegetation by measuring the difference between the near-infrared band and the red band, and can reflect the growth of regional vegetation. In this study, the normalized vegetation index was selected as a factor to characterize vegetation growth and as a predictor of downscaling. The Equation (1) is the calculation formula of NDVI:

$$\mathrm{NDVI} = \frac{\mathrm{NIR} - \mathrm{Red}}{\mathrm{NIR} + \mathrm{Red}}. \tag{1}$$

Among them, NIR and Red are the reflectivity of the near-infrared band and the red band, respectively. The value of NDVI is between −1 and 1. The larger the value, the greater the amount of vegetation.

3.2. Geographically Weighted Regression Model

The spatial downscaling analysis of remote sensing precipitation data needs to select suitable model variables to obtain better downscaling results. Commonly used downscaling models include general linear regression models and geographic weighted regression models. General linear regression models focus on the overall situation and cannot reflect local features. Geographically weighted regression emphasizes local features and is therefore widely used in geographic research and hydrometeorological research.

Geographically weighted regression model is a regression model proposed by Brunsdon, Fotheringham and others of the University of Newcastle, UK in 1996 [14]. It considers spatial heterogeneity based on the idea of local smoothing. The basic principle of GWR is to embed the spatial position of the data into the regression parameters, and use the local weighted least squares method to estimate the point-by-point parameter, where the weight is between the geographic spatial position of the regression point and the geographic spatial position of other observation points. Distance function. GWR is an extension of the ordinary linear regression model. The core is the spatial weight matrix, which expresses different understandings of the spatial relationship between data by selecting different spatial weight functions. In this study, the GWR regression model was used to downscale the remote sensing precipitation data. The regression formula established is shown in Equation (2):

$$Y_j = \beta_0\left(\mu_j, v_j\right) + \sum_{i=1}^{p} \beta_i\left(\mu_j, v_j\right) X_{ij} + \xi_j. \tag{2}$$

In the equation, $\beta_i\left(\mu_j, v_j\right)$ and $\beta_0\left(\mu_j, v_j\right)$ are the slope and intercept of the regression model established by GWR at the *j*-th point, *p* represents the number of predictors; ξ_j is the regression residual at the *j*-th point, $\left(\mu_j, v_j\right)$ represents the spatial position of the *j*-th point.

According to the relationship between precipitation and predictive factors, a geographically weighted regression model between remotely sensed precipitation data and predictive factors is established. Resample DEM and NDVI to make the spatial resolution the same as remotely sensed precipitation data, fit remotely sensed precipitation data with factors at low spatial resolution to estimate precipitation, and calculate the residual between the estimated precipitation and remotely sensed precipitation data, Interpolate the residual to obtain a residual with a resolution of 1 km. Combine the precipitation estimated through the geographically weighted regression model with the residual error to obtain the final down-scaled remote sensing precipitation data. The above process is completed by ArcGIS, where the geographic weighted regression model estimation uses the GWR module in ArcGIS.

4. Spatial Downscaling Results

4.1. Spatial Distribution of Precipitation

By constructing a GWR-based spatial downscaling model, the TRMM data and GPM data were spatially downscaled, and the precipitation raster data with a spatial resolution of 1 km in the Beijing-Tianjin-Hebei region from 2000 to 2018 was obtained. **Figure 3** shows the data comparison in August 2008. It can be found that the spatial distribution trends of the two types of data are consistent, which can better show the large amount of rainfall in the southwest and the small amount of rainfall in the east. Compared with the original resolution of remote sensing precipitation data, the spatial resolution of the downscaled data is increased to 1 km, and the trend of precipitation from high to low is smoother, showing more details of the spatial distribution of rainfall.

Figure 4 shows the results of the annual and monthly average precipitation distribution. The monthly average precipitation distribution in the study area shows a trend of more in the south and east. The monthly precipitation distribution in the study area is uneven. January has the least precipitation and July has the most precipitation. The precipitation is mainly concentrated from June to August. The maximum precipitation in these months can reach more than 150

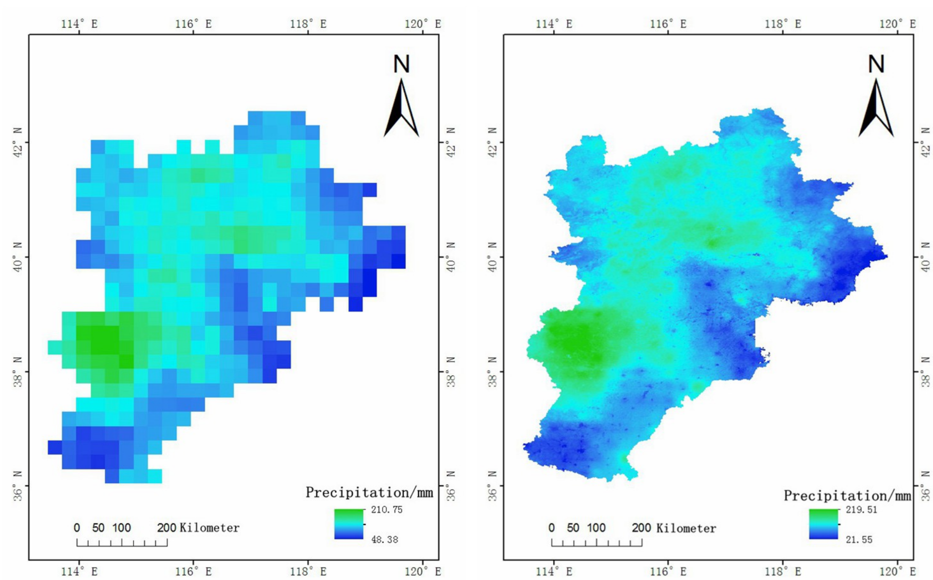

Figure 3. Comparison of spatial downscaling results.

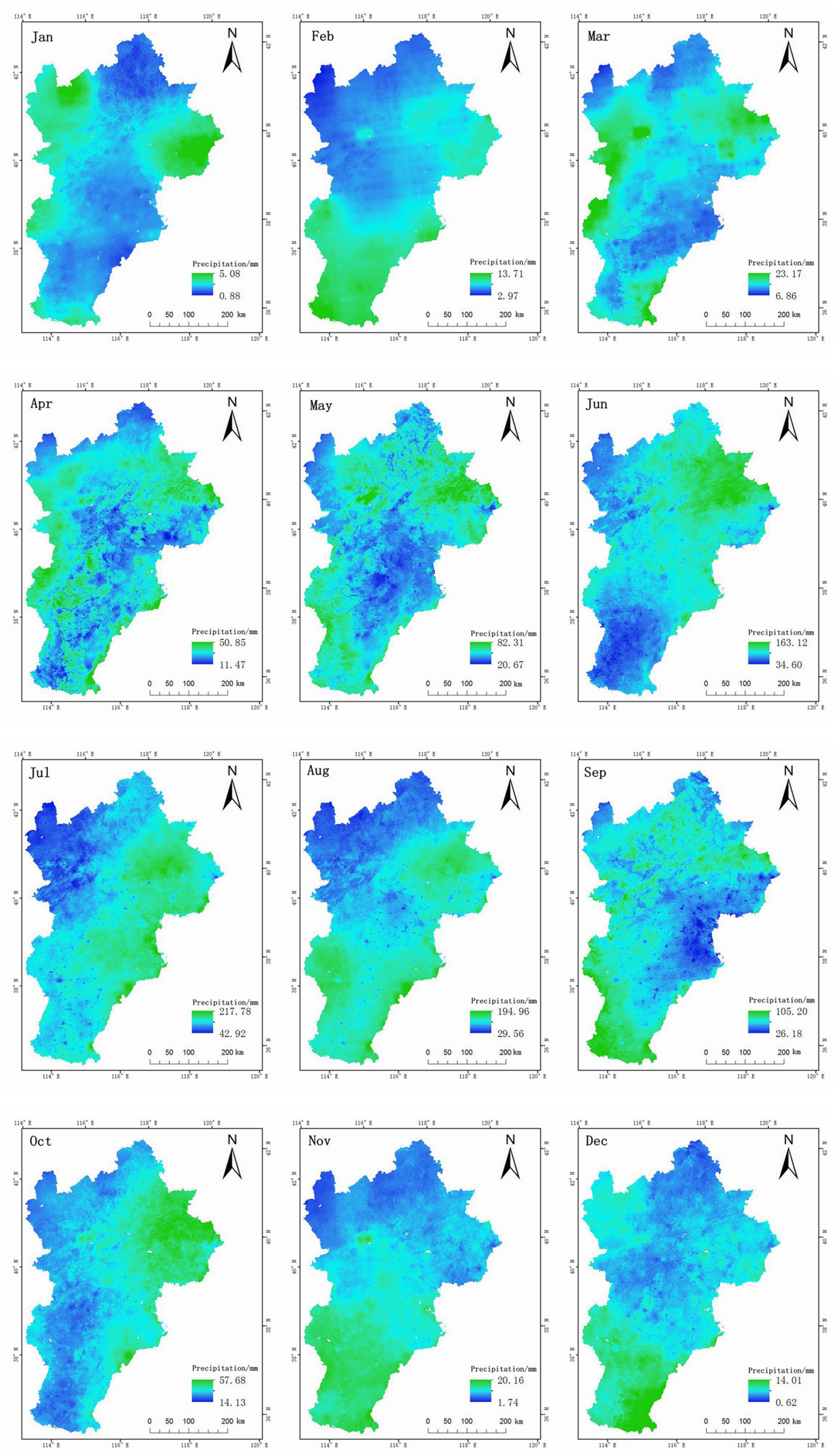

Figure 4. Monthly average precipitation distribution.

mm, and the maximum precipitation in January does not exceed 10 mm.

4.2. Result Accuracy Analysis

In order to evaluate the accuracy and applicability of remote sensing precipitation data in the Beijing-Tianjin-Hebei region, this paper uses the correlation coefficient R (Correlation Coefficient), the standard error RMSE (Root Mean Square Error) and the relative error BIAS as indicators.

Use ArcGIS to extract the corresponding grid value of the ground station as the remote sensing precipitation observation measurement of the station, and compare it with the actual measurement result of the ground station. After calculation, the average R^2 of the original spatial resolution remote sensing precipitation data and the measured precipitation is 0.970, indicating that there is a good agreement between the two. The average value of standard error RMSE is 56.18 mm, and the average value of relative error BIAS is 0.15. On the whole, the remote sensing precipitation data with the original resolution overestimated the actual precipitation. Compared with the original resolution data, the accuracy of the spatial downscaling data has improved. R^2 increased from 0.970 to 0.975, RMSE decreased from 56.18 to 53.74, and BIAS decreased from 0.15 to 0.09, indicating that the downscaling model based on geographically weighted regression is feasible in experimental area. The accuracy verification results of each site are shown in **Table 2**.

5. Conclusion

Aiming at the problem that the spatial resolution of TRMM data and GPM data is low, and it is difficult to meet the application of hydrological simulation in small and medium-sized areas, this paper conducts a spatial downscaling study of remote sensing precipitation data in the Beijing-Tianjin-Hebei region. Based on the response relationship of NDVI to precipitation, combined with terrain elements, the paper establishes a geographically weighted regression model to spatially downscale the original spatial resolution TRMM data and GPM data to 1 km, which improves the spatial resolution and data of TRMM data and GPM

Table 2. Accuracy verification results.

Station Name	Original resolution data R^2	Spatial downscaling data R^2	Original resolution data RMSE	Spatial downscaling data RMSE	Original resolution data BIAS	Spatial downscaling data BIAS
Potou	0.984	0.984	72.19	64.42	0.102	−0.075
Leting	0.999	0.998	70.35	67.62	−0.010	−0.041
Tianjin	0.966	0.971	41.49	36.30	0.277	0.144
Huailai	0.975	0.971	48.83	47.80	0.425	0.112
Shijiazhuang	0.969	0.975	52.78	48.94	0.030	−0.060
Beijing	0.939	0.957	40.72	54.20	−0.052	0.074
Chengde	0.960	0.967	60.63	56.93	0.187	0.098

data Accuracy can more finely describe the precipitation distribution characteristics of the Beijing-Tianjin-Hebei region, and provide high-resolution, continuous surface rainfall raster data for the Beijing-Tianjin-Hebei region.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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