Downscaling of GPM Satellite Precipitation Data: A Case Study of Shaanxi Province (Postprint)

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Abstract

Measurement data from 33 ground meteorological observation stations in Shaanxi Province in 2019 were used as ground truth to validate the accuracy of GPM (Global Precipitation Measurement) satellite precipitation data using multiple statistical analysis indicators including correlation coefficient (CC), root mean square error (RMSE), and relative error (BIAS). Topographic factors were introduced as spatial reference elements, and a Geographically Weighted Regression (GWR) model was employed to conduct downscaling research on the GPM precipitation data. The results indicate that: (1) At the interannual scale, GPM precipitation data exhibits a significant correlation with observed precipitation data, with favorable correlation (CC=0.89) and low relative error (BIAS=-0.45); (2) At the seasonal scale, the CC values between the downscaled GPM precipitation results and observed precipitation data are 0.92 and 0.80 for spring and summer, respectively, and 0.93 for autumn; (3) The downscaled precipitation results demonstrate a significant negative correlation with elevation, with precipitation decreasing relatively as altitude increases. Overall, the GWR downscaled precipitation data exhibits good accuracy within Shaanxi Province and can relatively accurately reflect the precipitation distribution across the province.

Full Text

Downscaling Study of GPM Satellite Precipitation Data: A Case Study of Shaanxi Province

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Abstract

Using ground-based meteorological observation station data in Shaanxi Province as reference values, this study evaluates the accuracy of Global Precipitation Measurement (GPM) satellite precipitation data through multiple statistical indicators including correlation coefficient (CC), root mean square error (RMSE), and relative error (BIAS). A digital elevation model (DEM) is introduced as a spatial reference factor, and the Geographically Weighted Regression (GWR) model is employed to downscale GPM precipitation data at interannual scales. The results demonstrate: (1) GPM satellite precipitation data exhibits significant correlation with measured precipitation data, with strong correlation coefficients (CC = 0.89) and low relative errors (BIAS = -0.45); (2) At seasonal scales, spring and summer show CC values of 0.92 and 0.80 respectively, while autumn reaches 0.93; (3) Downscaled precipitation results demonstrate a pronounced negative correlation with elevation, with precipitation decreasing as altitude increases. Overall, the downscaled GPM precipitation data achieves good accuracy in Shaanxi Province and can accurately reflect precipitation distribution patterns within the region.

Keywords: Global Precipitation Measurement (GPM); precipitation; downscaling; Geographically Weighted Regression model (GWR)

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1. Introduction

Precipitation continuously influences global water-heat cycles and human production activities, making its study crucial for regional water cycle analysis, water resource management, economic development, and ecological environmental governance. Currently, due to high spatiotemporal variability in precipitation, traditional ground-based meteorological observation stations struggle to accurately capture precipitation distribution patterns. The rapid development of satellite remote sensing and geographic information technologies has enabled new precipitation detection methods, yielding numerous satellite-based precipitation products.

The Global Precipitation Measurement (GPM) satellite represents a new generation of precipitation observation platforms with enhanced spatiotemporal resolution and improved detection capabilities for light and solid precipitation. The Integrated Multi-satellite Retrievals for GPM (IMERG) product provides continuous precipitation information, offering new data sources for high-resolution hydrological research. However, GPM precipitation data still faces limitations in hydrological applications, as its coarse resolution fails to meet the demands of high-precision hydrological studies.

High spatiotemporal resolution precipitation data facilitates research on regional precipitation variability characteristics. Therefore, downscaling GPM data holds significant practical importance. Spatial downscaling methods can further improve data quality, among which the Geographically Weighted Regression (GWR) model has been widely applied in geographic sciences. Using GWR for precipitation downscaling yields higher spatial resolution precipitation data, refining the spatial scale of precipitation estimation and providing robust support for regional hydrological and water resource management studies.

Previous studies have demonstrated the effectiveness of GWR-based downscaling approaches. Immerzeel et al. established exponential relationships between satellite precipitation and Normalized Difference Vegetation Index (NDVI) at low spatial resolutions for downscaling, revealing enhanced precipitation detail in results. Jia et al. introduced DEM as a spatial variable correlated with precipitation to downscale TRMM data in the Qaidam Basin, achieving 1 km resolution. However, most research has focused on TRMM downscaling, with limited studies on GPM satellite downscaling, primarily concentrating on applicability assessments.

Shaanxi Province, located in central-western China and topographically constrained by the Qinling Mountains and Loess Plateau, exhibits significant regional climate differences. Consequently, evaluating precipitation spatiotemporal patterns in Shaanxi is essential. This study selects Shaanxi Province as the research area, using ground meteorological station data as reference values to verify GPM accuracy and employing GWR modeling with DEM as a topographic factor to downscale GPM precipitation data. The methodology is further extended to monthly scales to obtain higher-resolution GPM monthly precipitation data and analyze topographic impacts on satellite precipitation product accuracy.

1.1 Study Area Overview

Shaanxi Province is located in the southeastern section of northwestern China, between 105°29 ~111°15 E and 31°42 ~39°35 N, covering an area of 2.05\$×10^{5}\$ km^2. The terrain is characterized by high elevations in the north and south with low-lying central regions [Figure 31: see original paper]. The northern region comprises the Loess Plateau, the central area features the Guanzhong Plain, and the southern region encompasses the Qinba Mountains. Significant north-south climate differences exist, with climate types transitioning from temperate sub-arid monsoon in the north, to warm temperate sub-arid humid monsoon in the center, and subtropical humid monsoon in the south. Annual precipitation decreases from south to north, markedly influenced by mountainous terrain. The primary dry seasons occur in winter-spring and autumn-winter, while rainy seasons occur in summer-autumn, with frequent heavy rainfall events in northern and southern summers, making precipitation monitoring critically important [Figure 1: see original paper].

1.2 Data Sources

This study utilizes GPM Version 04 monthly precipitation products (IMERG) with global coverage at 0.1°$×$0.1° spatial resolution, obtained from NASA’ s Precipitation Measurement Missions website (https://pmm.nasa.gov/precipitation-measurement-missions). The dataset records monthly average hourly precipitation (mm/h) in NetCDF format, integrating information from all microwave sensors, geostationary satellites, and ground stations.

Ground observation data were obtained from the China Meteorological Data Service Center (http://data.cma.cn/) daily dataset, serving as reference values for precipitation verification during 2019. The spatial distribution of 33 meteorological stations is illustrated in [Figure 1: see original paper]. DEM data were acquired from the Heihe Plan Data Management Center (http://westdc.westgis.ac.cn) with 1 km$×$1 km spatial resolution for GWR model downscaling analysis.

1.3 Methods

The evaluation metrics for GPM precipitation data and downscaled results include Pearson correlation coefficient (CC), relative bias (BIAS), and root mean square error (RMSE), calculated as follows:

$$CC = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 \sum_{i=1}^{n}(y_i - \bar{y})^2}}$$

$$BIAS = \frac{\sum_{i=1}^{n}(x_i - y_i)}{\sum_{i=1}^{n} y_i} \times 100\%$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - y_i)^2}$$

where n represents the number of stations; i indexes the precipitation data; x denotes satellite precipitation estimates; y represents ground-measured precipitation; $\bar{x}$ is the mean satellite rainfall; and $\bar{y}$ is the mean ground rainfall.

To further compare the matching between measured station precipitation and GPM data, the coefficient of determination (R^2) evaluates linear fitting goodness-of-fit:

$$R^2 = 1 - \frac{\sum_{j=1}^{n}(y_j - \hat{y}_j)^2}{\sum_{j=1}^{n}(y_j - \bar{y})^2}$$

where $\hat{y}_j$ represents fitted values; y_j denotes observations; $\bar{y}$ is the observation mean; and n is the total number of comparison records. R^2 approaching 1 indicates better data fitting.

1.3.1 Geographically Weighted Regression (GWR) Model The GWR model, proposed by Brunsdon et al., is a commonly employed statistical method in spatial data analysis. Its fundamental concept involves establishing regression models by estimating parameters for relevant and explanatory variables at each given location within the study area. The model formulates the relationship as:

$$y_i = \beta_0(u_i) + \beta_1(u_i)x_{i1} + \cdots + \beta_k(u_i)x_{ik} + \varepsilon_i$$

where y is precipitation at location i; x variables are explanatory factors; β coefficients are location-specific parameters; u represents spatial coordinates; and is the error term.

1.3.2 Downscaling Method The downscaling procedure involves: (1) Resampling DEM data to match GPM resolution; (2) Using GPM and DEM data at 0.1°$×0.1°*resolutionasinputvariablestoconstructtheGWRmodel*; (3)*Extractingconstantterms*, *DEMcoef*
km spatial resolution using ordinary Kriging; (6) Calculating final 1 km GPM precipitation data through downscaling computation.

2. Results

2.1 GPM Precipitation Data Accuracy Validation

Prior to downscaling, GPM data accuracy was validated using measured precipitation data from meteorological stations while ensuring scale consistency. Linear regression analysis was performed using annual observations from 33 meteorological stations as independent variables and corresponding annual GPM data as dependent variables [Figure 2: see original paper]. Validation metrics (CC, RMSE, BIAS) indicate strong correlation and consistency between GPM satellite and measured annual precipitation (CC = 0.89). However, correlation coefficients only reflect data relationships and cannot objectively quantify differences between satellite and measured data. Further calculations reveal relative error (BIAS = -0.45) and root mean square error (RMSE = 252.82), indicating systematic underestimation of precipitation in GPM monthly data.

2.2 Site-Specific Accuracy Validation

To further verify GPM satellite precipitation accuracy, statistical analysis was conducted comparing GPM data with 33 measured precipitation stations across Shaanxi Province. Error statistics for individual stations are presented in . Analysis reveals that most stations demonstrate good correlation between GPM and measured annual precipitation (CC > 0.75), indicating strong consistency and overall good data precision. However, CC exhibits spatial heterogeneity among stations, with locations such as Yulin, Dingbian, Zhenba, Liuba, Changwu, Foping, Ningqiang, and Shangnan showing BIAS > 0, suggesting GPM underestimation in these areas. Based on station geographic locations, lower-altitude regions exhibit smaller errors than higher-altitude areas. Overall, GPM precipitation data errors relative to measured data are small enough to meet regional hydrological application requirements, providing a scientific basis for subsequent downscaling.

2.3 GWR Downscaling Results and Validation

2.3.1 Annual Downscaling Results Annual GPM data were downscaled using the GWR model [Figure 3: see original paper]. Post-downscaling spatial resolution improved to 1 km, revealing more detailed spatial precipitation characteristics. Original GPM precipitation ranged from 338.82–1260.84 mm, while downscaled results showed reduced range though high precipitation values remained concentrated in southern Qinba Mountains. Enhanced spatial resolution provides stronger spatial detail representation, though further validation is required to confirm reliability.

2.3.2 Annual Downscaling Validation Downscaled results were validated using 33 ground meteorological stations. Validation metrics (RMSE and BIAS) demonstrate that annual downscaling improved the coefficient of determination ($R^2 = 0.81$) while maintaining correlation coefficient (CC = 0.90), indicating that systematic errors and correlation levels were preserved through the downscaling process. Relative error (BIAS = -0.45) decreased slightly, improving downscaling accuracy and enabling better representation of actual precipitation patterns [Figure 4: see original paper].

2.3.3 Seasonal Downscaling Results and Validation Shaanxi exhibits pronounced seasonal precipitation differences. To analyze seasonal impacts on downscaling, GPM data were aggregated by season (spring: March–May, summer: June–August, autumn: September–November) and validated using CC, RMSE, and BIAS metrics . Autumn shows the highest correlation (CC = 0.93), while summer exhibits the lowest (CC = 0.80) but largest RMSE (115.06 mm). Spatial distribution of seasonal downscaled precipitation reveals gradual south-to-north decrease across all seasons, with significant differences. Precipitation in areas south of the Qinling Mountains substantially exceeds that in the northern Loess Plateau, with maximum precipitation concentrated in southern regions. Summer maximum precipitation reaches 644.95 mm, autumn maximum 512.02 mm, and spring maximum 290.18 mm [Figure 5: see original paper].

Monthly-scale validation was performed using 2019 data (excluding winter). Scatter trend analysis of 33 observation stations shows R^2 values primarily between 0.46–0.76, with lower R^2 corresponding to lower precipitation, consistent with established research patterns. Monthly correlation coefficients remain generally high, with the best linear fit occurring in August (CC > 0.75). Monthly relative errors align with original low errors, indicating closer approximation to measured data at higher spatial resolution [Figure 6: see original paper].

2.4 Spatial Distribution of Precipitation in Shaanxi

Post-downscaling GPM satellite precipitation data exhibits substantially improved spatial resolution with enhanced spatial detail representation. Measured precipitation data, GPM data, and downscaled results share similar spatial distribution patterns, with precipitation decreasing from south to north and higher precipitation in mountainous areas compared to basins. Maximum precipitation concentrates in southern mountainous and central basin regions, while northern areas remain relatively dry [Figure 7: see original paper].

2.5 Impact of Elevation on Data Accuracy

To analyze spatial error distribution patterns between satellite and ground observation data, measured annual precipitation was interpolated to examine differences between pre- and post-downscaling distributions. Regression analysis was performed using station elevation as the independent variable and downscaled annual precipitation and absolute error (|BIAS|) as dependent variables [Figure 8: see original paper]. Results demonstrate negative correlation between elevation and precipitation, with precipitation decreasing as altitude increases, consistent with actual conditions in Shaanxi. Polynomial regression analysis of elevation versus |BIAS| indicates that |BIAS| initially decreases, slightly increases, then decreases again with rising elevation.

3. Conclusions

This study analyzes GPM precipitation data and ground-measured rainfall data accuracy in Shaanxi Province, introducing DEM data to downscale GPM precipitation using the GWR model. Key findings include:

1. GPM satellite precipitation data demonstrates good accuracy at annual and station spatiotemporal scales, with certain adaptability in the study area. GWR-based downscaling substantially improves spatial resolution while exhibiting stronger spatial detail representation capabilities.
2. Downscaled results correlate well with measured precipitation data (CC = 0.90 at annual scale). Seasonal scale CC values are 0.92 (spring) and 0.80 (summer), with autumn reaching 0.93. Monthly-scale correlations are also generally high with good accuracy, meeting precipitation research data requirements. Overall, GWR downscaled values are higher than original GPM data.
3. Downscaled precipitation shows significant negative correlation with elevation, decreasing as altitude increases. The GWR downscaling model is satisfactorily applicable to GPM precipitation data downscaling in Shaanxi Province, improving data spatial resolution.

This study provides important data for hydrological research and enhances simulation accuracy. However, the GWR model construction used easily obtainable topographic factors while neglecting other variables; future research should incorporate additional downscaling methods to further improve GPM product accuracy. Although the study area contains numerous meteorological stations, only 33 observation points were obtained through public channels. With more observational data, results could be further improved.

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