Spatial downscaling of monthly precipitation based on TRMM satellite in Ya’an

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Abstract. In the study of precipitation in ya’an with complex terrain, a statistical downscaling algorithm based on the monthly precipitation data of TRMM 3B43 from 2000 to 2008, digital elevation model (DEM) and normalized difference vegetation index (NDVI) was presented. The precipitation fields from TRMM 3B43 were downscaled to 1 km × 1 km resolution simulated precipitation by constructing multiple linear regression equation and using regression model and residuals method. Combined with the observation values obtained from 8 weather stations in the study area, the downscaled precipitation was tested in the two aspects of overall accuracy and single station. On this basis, the spatial and temporal distribution characteristics of monthly precipitation in recent 9 years in the study area were analyzed. The results showed that: The correlation coefficients of TRMM before and after downscaling and observation values were 0.863 and 0.854, and the biases were -0.08 and -0.12. The correlation and accuracy of the two types of data were basically consistent on the whole. 75% of the stations had a high correlation with the downscaling results, and the absolute value of the bias of each station was no more than 0.35, which showed that the data accuracy was high, the data was suitable for the precipitation analysis in the research area. The distribution of monthly precipitation in 8 stations over the years showed that the precipitation in the middle of ya’an was concentrated in January and November to December. From February to April and July to August the north received more precipitation than the south, while the opposite was true from May to June and September to October, and the August in the main flood season reached the heaviest rainfall of the year.

1. Preface
Precipitation, as the most active meteorological element in the process of hydrological cycle, climate change and ecosystem balance, has a strong driving force, and its amount plays a key role in the water vapor distribution and heat balance of the region and even the whole world[1-2]. Atmospheric movement, underlying surface conditions and geographical location act on precipitation, which makes precipitation have strong spatial and temporal heterogeneity[3-4]. Therefore, high spatial resolution continuous distributed precipitation data plays an important role in constructing regional hydrological and meteorological models and analyzing regional precipitation characteristics[5-6]. In the past,
researchers spatially interpolated based on the data from the dot-form meteorological observatory to obtain regional precipitation data. This traditional method is usually limited by the observation range and topography of monitoring instruments [5], and has advantages in areas with high-density meteorological observatory network. Although many observation stations have been set up in Ya’an area, which are located in the western Sichuan plateau, the number of stations is still very limited. The precipitation is greatly affected by the local special topography and complex climate. Therefore, the density of stations can not meet the needs of regional precipitation research. Different from point rainfall, area rainfall is based on the whole research area or basin, which has the advantages of high data continuity and wide coverage. Therefore, other methods with high feasibility and accuracy can be used to obtain surface distributed precipitation data for precipitation research.

The rapid development of RS and GIS provides a new way for precipitation research [7]. In the late 1990s, TRMM (Tropical Rainfall Measuring Mission), a remote sensing satellite developed jointly by the United States and Japan, carried a detector with the function of precipitation measurement. Through space-time detection and inversion of tropical and subtropical rainfall [8], it was obtained that the spatial resolution of precipitation data with strong spatial-temporal continuity, large coverage area and small geographical constraints is as high as 0.25° × 0.25° [9]. At present, a large number of studies have shown that TRMM data and meteorological observation data have good consistency and high applicability [10-11]. However, when constructing hydrological and meteorological models, the accuracy of data often can’t meet the demand, and regional precipitation analysis is limited to some extent. Therefore, it is necessary to downscale TRMM precipitation data in order to obtain higher precision spatial distribution precipitation.

Many domestic and overseas scholars have used statistical downscaling method to construct the linear function relationship between TRMM 3B43 precipitation data and other underlying surface elements to study the regional precipitation distribution characteristics. The two types of underlying surface factors that are often taken into account are terrain and normalized difference vegetation index (NDVI). Topography is an important factor affecting local climate. Considering the influence of topography on precipitation, we can start with specific factors such as elevation, slope, aspect and so on, and concretize complex elements. However, there are some limitations for the lack of consideration of other underlying surface factors. For example, Ma JH [5] and Yang WY [6], taking into account the complex topographic conditions, extracted five types of topographic elements from DEM, including elevation, aspect, slope, longitude and latitude, and established a multiple linear regression equation between TRMM 3B43 annual average precipitation data and extracted topographic elements. Satellite precipitation data in the study area in the past 10 years was obtained from 0.25° (the low resolution) to 1 km (the high resolution), which reflected the basic characteristics of local precipitation better. Based on the principal component-stepwise regression method, Fan XW [12] reduced the dimension and eliminated the insignificance of seven types of topographic factors extracted from the study area, deepened the multivariate linear regression analysis method, established the annual and seasonal downscaling model, and found that the precision of precipitation data with 1 km resolution was higher, which provided a methodological reference for the study of spatial precipitation in arid areas. There will be some limitations if only the influence of NDVI is considered. Immerzeel [13] only considered NDVI as a factor, and constructed a polynomial regression equation between TRMM precipitation and NDVI. Because of the absence of relevant geographical factors, the 1 km high resolution data could not meet the needs of research. Some scholars took the NDVI factor into account while considering the topographic impact. Based on Immerzeel’s research and considering NDVI and DEM factors simultaneously, Park and Jia SF [14-15] obtained the simulated precipitation distribution with a high resolution of 1 km in the study area. Li J [16] took the middle part of Tianshan Mountains as the research area. Based on the correlation among TRMM 3B43 precipitation and NDVI, DEM, aspect, longitude and latitude, the multivariate linear regression equation was constructed to obtain higher resolution spatial distribution data 250 m × 250 m, which was suitable for precipitation research in Tianshan Mountains. Zheng J [17] obtained high-precision monthly precipitation data with resolution of 1 km by further analyzing the lag of
NDVI factor to precipitation response and eliminating the data with weak correlation. The addition of NDVI factor on the basis of considering topographic influence not only improved the spatial variability of regression model, but also improved the coupling degree between variables. However, it had the shortcoming of imperfect analysis of the spatial characteristics of NDVI itself.

Most of the previous studies focused on downscaling study and spatiotemporal analysis of annual precipitation data, but the time scale has not been significantly improved, and there was no analysis of the spatial characteristics of the introduced NDVI factor. Considering the complex topography and vegetation coverage in ya’an, based on the analysis of the spatial correlation of NDVI, combined with longitude latitude, elevation, aspect and NDVI factors, this paper studied the spatial downscaling of monthly precipitation data from 2000 to 2008 in the study area, used the measured data of eight meteorological stations in the study area to test the accuracy, and then carried out the precision test. The spatial and temporal distribution of monthly precipitation in the study area was analyzed to provide an effective data basis for the construction of meteorological and hydrological models in ya’an.

2. Survey and data processing of research areas

2.1 Survey of research areas

Ya’an, located in the western margin of Sichuan Basin, belongs to the upper reaches of the Yangtze River. Its geographic coordinates range from 28°51′-30°56′ north latitude, and 101°56′-103°23′ east longitude. The study area is adjacent to the western Sichuan plain in the East and the western Sichuan plateau which is the eastern part of the Qinghai-Tibet Plateau in the east. It is located at the southeastern edge of the western Sichuan plateau. As a transitional zone from Sichuan-Chongqing Basin to the western Sichuan Plateau, the mountain ranges are crisscrossed and the relief degree is relatively large (Figure 1 (a)). The overall topography is higher in the north, West and south, lower in the middle and East (Figure 1 (b)), and uneven distribution of precipitation in the north and south. The unique topography of “windward slope” and “trumpet mouth” in ya’an makes it easy for water vapor to rise and condense in the circulation process, forming precipitation. The local climate type is subtropical monsoon humid climate, with more rainfall and high humidity. The annual rainfall is about 1000-1800 mm, it is the most rainfall area in Sichuan province[18]. In ya’an, there are two main river systems, Dadu River and Qingyi River. The river network has high density, large drop, rapid flow and abundant hydropower resources. Ya’an forest is widely distributed, and its vegetation coverage is as high as 50.97%. Influenced by the special topography and landform, complex climatic characteristics, dense river network distribution and high vegetation coverage in ya’an, the interaction between the air flow from the western plateau and the warm and wet air flow from the basin has formed the precipitation characteristics of ya’an with more rainy days, longer rainy hours and larger rainfall. The spatial distribution of 8 basic meteorological stations selected in this study is shown in figure 1 (b).
2.2 Data source and preprocessing

2.2.1 Remote sensing data. The remote sensing data products used in this paper include TRMM 3B43 satellite precipitation data set, MODIS data product NDVI data, and data of digital elevation model.

The spatial resolution of TRMM 3B43 data is 0.25°, the temporal resolution is 1 month, and the precipitation unit is mm/h. The data comes from the DAAC (Distributed Active Archive Center) of NASA Goddard in the United States, which is available free of charge through the NASA website (http://trmm.gsfc.nasa.gov/). In this study, we used MATLAB program to read the precipitation matrix data of TRMM 3B43 in HDF format from 2000 to 2008, and converted it into point and surface files in vector format through ARCGIS.

The NDVI data of the same period is MODND1M, which is synthesized in China. It comes from MODIS synthesized products in China. It is calculated by monthly maximum synthesis method. The spatial resolution is 500 m and the temporal resolution is 1 month. Considering the lag of vegetation response to precipitation, this study covered the period from February 2000 to January 2009. A total of 108 NDVI images were downloaded, which could be obtained free of charge through the geospatial data cloud website (http://www.gscloud.cn/). Through projection conversion, resampling and mask processing of ARCGIS, NDVI data with spatial geographic information at resolutions of 0.25° and 1 km were obtained, which served as the data basis for vegetation precipitation hysteresis analysis, multiple linear regression model construction, and downscaling precipitation data calculation.

DEM data comes from the GDEM data set, which is processed from the data of the first edition of ASTER GDEM (V1). It is a digital elevation data product with global spatial resolution of 30 m × 30 m. According to the latitude and longitude of the study area, 12 DEM data covering the study area were downloaded. The geospatial data cloud website (http://www.gscloud.cn/) could download the data for free. Preprocessing of DEM was the same as NDVI, and aspect of corresponding resolution were extracted at the same time.
2.2.2 Meteorological station data. Meteorological station data includes daily precipitation data of 8 rainfall stations in Baoxing, Lushan, Ya’an, Xingjing, Hanyuan, Shimian, Mingshan and Tianquan. This data comes from Sichuan Meteorological Bureau. After strict quality control and inspection, the quality is good. In this study, the daily precipitation (unit: 0.1mm/day) of the stations was calculated, and the monthly precipitation (unit: mm/month) was obtained. The average monthly precipitation of each station was calculated year by year, which served as the test data basis for the downscaling precipitation results.

3. Research method
3.1 Introduction and analysis of NDVI factor
3.1.1 Time lag analysis of vegetation response to precipitation. The vegetation growth status and coverage area are greatly affected by precipitation. It takes a long time from rainfall to the ground, through vegetation interception and absorption, vegetation growth and coverage expansion. During this period, NDVI showed a lag to precipitation [19]. Zheng J studied the correlation between the monthly NDVI value and the precipitation of the same month, the previous month and the previous two months in the western Sichuan Plateau from 2001 to 2013, and obtained that the lag period of vegetation relative precipitation in the study area was about one month [17]. Ya’an is in the western Sichuan plateau, which satisfies this conclusion. Therefore, the NDVI value of vegetation in the next month was selected as the vegetation factor corresponding to the monthly precipitation when constructing the multi-linear regression downscaling model.

3.1.2 Spatial autocorrelation analysis of vegetation. (1) Global Moran’s index
The spatial distribution of vegetation is affected to some extent by the spatial distribution of precipitation. In this part, the global Moran’s index was introduced to illustrate the spatial autocorrelation of the normalized vegetation index NDVI. The formula is as follow:

$$I = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{S^2 \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}}$$

(1)

In the formula, $w_{ij}$ is a spatial weight matrix (used to measure the degree of influence between pixels I and j), $x_i$ and $x_j$ are the NDVI values of spatial pixels i and j, and $S^2$ is the variance of NDVI samples. $S^2 = \frac{\sum_{i=1}^{n} (x_i - \bar{x})^2}{n}$, $\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}$ is the sum of all spatial weights, $n$ is the number of spatial pixels.

The value range of global Moran index is [-1, 1]. When the global Moran’s I is greater than 0, the data shows positive spatial correlation, and the greater the spatial correlation is, the more obvious the spatial correlation is; when the global Moran’s I is less than 0, the data shows negative spatial correlation, and the smaller the value is, the greater the spatial difference is, then the NDVI factor is not used as the influencing factor to construct the downscaling model. When equal to 0, the space is random. In this paper, the global Moran’s I index was calculated by GeoDa software.

(2) Local Moran’s index
Influenced by human factors, there was an unreasonable correlation between regional precipitation and vegetation cover. In order to eliminate the abnormal values in NDVI, local Moran’s index was introduced on the basis of global Moran’s index, which could reveal the correlation between current spatial pixels and their adjacent spatial pixels, identify the degree of spatial dispersion and reflect the spatial variability of vegetation. The concrete calculation formulas are as follow:

$$I = \frac{n^2 \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} (x_i - \bar{x}) \sum_{j=1}^{n} (x_j - \bar{x})}{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} \sum_{j=1}^{n} (x_j - \bar{x})^2}$$

(2)

When the local Moran’s I is greater than 0, the NDVI aggregation is relatively concentrated, and
the positive spatial correlation is relatively strong; when the local Moran’s I is less than 0, the NDVI aggregation is relatively discrete and the positive spatial correlation is relatively weak. If the index is less than a certain value, the part of NDVI value should be excluded in the construction of downscaling model. In this paper, ARCGIS software was used to calculate the local Moran’s I.

3.2 Construction of spatial downscaling model

3.2.1 Principle of statistical downscaling. Statistical downscaling is a common empirical downscaling method. The linear or non-linear function relationship between large-scale and low-resolution meteorological change elements and regional small-scale and high-resolution meteorological change elements is constructed by using the statistical empirical data collected by satellites, so as to realize the transformation of spatial scale and obtain small-scale. On the basis of statistical downscaling method, this paper chose multivariate linear regression method to construct a downscaling model suitable for the study area.

3.2.2 Downscaling steps. (1) Taking the study area as the boundary, a buffer with a distance of 25 km was established by using the neighborhood analysis method, which included and superimposed the original area. The monthly precipitation, NDVI and Dem data areas of TRMM 3B43 at 0.25° resolution in the study area were obtained by using the established buffer as the clipping boundary. The central positions of each data pixel correspond one by one.

(2) The monthly precipitation and five kinds of independent variables were extracted from the grid center at 0.25° resolution, and the multiple linear regression model was constructed. Namely:

\[ P_{LR} = aX + bY + cN + dD + eA + C \]  

In the formula, \( P_{LR} \) is the predicted monthly precipitation with resolution of 0.25° × 0.25°, mm; \( X \) and \( Y \) are longitude and latitude respectively, °; \( N \) is normalized difference vegetation index; \( D \) is elevation, m; \( A \) is aspect, m; \( C \) is constant; \( a, b, c, d \) and \( e \) are linear regression simulation fitting coefficients.

(3) Calculated the \( \Delta TRMM_{LR} \) of precipitation residual caused by various topographic factors and vegetation coverage at a resolution of 0.25°.

\[ \Delta TRMM_{LR} = TRMM_{LR} - P_{LR} \]  

In the formula, \( TRMM_{LR} \) is the original monthly precipitation value at a resolution of 0.25°, mm. The precipitation residual \( TRMM_{HR} \) at 1 km high spatial resolution is extracted by spline interpolation.

(4) The regression coefficients at 0.25° × 0.25° and the corresponding factors at 1 km resolution were substituted into equation (3) to obtain the predicted monthly precipitation value (\( P_{HR} \)) at high resolution. Using the method of “regression model + residual”, the monthly simulated precipitation (\( TRMM_{HR} \)) of each year in the study area under 1 km × 1 km was obtained. Namely:

\[ TRMM_{HR} = P_{HR} + \Delta TRMM_{HR} \]  

3.2.3 Precision testing index of downscaling result. For the scale-down results of 108 months from 2000 to 2008, the measured data of time and space at 8 rainfall stations in the study area were tested. The results were validated by the following three indicators: correlation coefficient (R), bias (BIAS) and root mean square error (RMSE):

\[ R = \frac{\sum (H_i - \bar{H})(M_i - \bar{M})}{\sqrt{\sum (H_i - \bar{H})^2} \sqrt{\sum (M_i - \bar{M})^2}} \]  

\[ B = \frac{\sum M_i}{\sum H_i} - 1 \]  

\[ RMSE = \sqrt{\frac{n}{\sum (H_i - M_i)^2}} \]  

Among them, \( Hi \) is the measured precipitation at the rainfall station, \( Mi \) is TRMM 3B43
precipitation or precipitation at downscales, i is the rainfall station, and n is the total number of data. In practice, the coordinates of TRMM monthly precipitation grid unit at 0.25° and 1 km resolution were calculated according to the longitude and latitude position of the meteorological station, and then the monthly precipitation at the center of the pixel was extracted as the value of \( M_i \). R is used to measure the linear relationship between \( H_i \) and \( M_i \). The value range is \([-1, 1]\). The closer R is to -1 or 1, the higher the consistency of data is. Bias and RMSE are used to describe the deviation or deviation between TRMM monthly precipitation and downsampling results and observed monthly precipitation values. The closer Bias approaches 0 or RMSE is, the higher the accuracy of TRMM monthly precipitation or downsampling results is.

4. Result and discussions

4.1 Overall accuracy test

TRMM 3B43 precipitation data was downscaled to obtain simulated precipitation with high resolution. To verify its effectiveness, monthly measured precipitation at eight precipitation stations in ya’an from 2000 to 2008 was used to verify the downsampling results from January to December. The monthly precipitation from the corresponding location of each rainfall station and the monthly precipitation from TRMM 3B43 data were extracted separately. The measured precipitation from each rainfall station was taken as an independent variable, and a linear regression analysis was made. The correlation coefficient R was used to reflect the correlation between variables. Bias (B) and RMSE were calculated to test the accuracy of the data. Figure 2 shows the scatter plots and error statistics of the observed monthly precipitation and TRMM 3B43 monthly precipitation (a) and downscaled monthly precipitation (b) in ya’an.

From figure 2, it can be seen that: (1) The correlation coefficient between downsampling simulated precipitation and observed monthly precipitation at rainfall station is 0.85, which is close to that of TRMM 3B43. The correlation degree between the two types of data and observed monthly precipitation data is basically the same. (2) Compared with the original data, the deviation value of the downscaled simulated precipitation data is slightly higher, which indicates that the downsampling results are slightly lower as a whole. However, the deviation values of the two types of data are low, indicating that the deviation degree has not changed significantly. (3) RMSE is sensitive to very large or very small outliers in predicted data. When there is a big difference between predicted and measured values, RMSE will be very large. By comparing the RMSE values of the two types of data in the graph, we can find that the RMSE values of the two types of data are close, which shows that the accuracy of the two types of data is basically the same. The data correlation and accuracy of downsampling simulated precipitation results are slightly lower than that of TRMM 3B43 data. The main reason is that TRMM satellite is affected by atmospheric circulation, complex terrain and underlying surface coverage differences in the study area, which results in some errors in data inversion results. This study combines five factors with TRMM 3B43 data to reduce the scale. Degree model construction, considering factors have certain representativeness and limitations, will produce certain errors in the process of model construction. But on the whole, the correlation and accuracy of the two types of data are not very different. The downsampling model in this paper still has certain reliability, and can reflect the spatial and temporal characteristics of precipitation distribution in ya’an more comprehensively.
4.2 Accuracy test of single station

Based on the measured precipitation data and downscaling simulated precipitation data from 2000 to 2008, taking the monthly precipitation at 8 stations as independent variable, and the corresponding downscaling monthly precipitation at the corresponding location as the dependent variable, the linear regression analysis was carried out. The linear relationship and error statistics between the monthly precipitation measured at each rainfall station and the simulated monthly precipitation are shown in figure 3. From figure 3, it can be seen that: (1) The correlation coefficient between the downscaling simulated values and the measured values of Lushan, Mingshan, Ya’an and Tianquan stations is more than 0.90, and the discrete points are highly concentrated and evenly distributed near the regression line. The correlation between the downscaling simulated values and the measured values is significant and the data consistency is high. (2) At Baoxing and Xingjing stations, the R value of the downscaling simulated values and the measured values is more than 0.85, and the distribution of discrete points is relatively concentrated near the trend line, and the data consistency is relatively high. (3) At Hanyuan station and Shimian station, the R value between the downscaling simulated values and the measured values is more than 0.80 and the data consistency is low, but Bias and RMSE are low, which indicates the data accuracy is high. Among them, Shimian station has the lowest data consistency among the eight stations. The main reason is that Shimian station is located in the valley area, with an elevation of 891 m, surrounded by the middle mountain area (elevation 1000-3500 m), and the elevation difference is large, which is mainly manifested by complex and diverse mountain geomorphological characteristics. So that great differences can be seen between data of rainfall stations and TRMM satellite precipitation, leading to low consistency of data. (4) Among all rainfall stations, Lushan station has the most significant correlation between the two types of data, R= 0.941, Bias= -0.07, RMSE= 33.83. The data deviation is the lowest, and it is the most reliable station with the highest consistency and accuracy among the eight rainfall stations. The accuracy of downscaling simulated data and the consistency between the measured data and the downscaling simulated data of each station are obviously different in space, which is mainly related to the accuracy of TRMM 3B43 detection data itself, the complex topography of each station and the accuracy of multiple linear regression model.

![Figure 2. The scatter plots of the measured monthly precipitation and TRMM 3B43 monthly precipitation (a) and downscaling monthly precipitation (b) in ya’an.](image-url)
\[ y = 1.124x + 10.11 \]
\[ R = 0.888 \]
\[ \text{Bias} = 0.25 \]
\[ \text{RMSE} = 52.02 \]

(a) Baoxing Station

\[ y = 0.974x - 4.491 \]
\[ R = 0.941 \]
\[ \text{Bias} = -0.07 \]
\[ \text{RMSE} = 33.83 \]

(b) Lushan Station

\[ y = 0.834x - 0.005 \]
\[ R = 0.926 \]
\[ \text{Bias} = -0.17 \]
\[ \text{RMSE} = 44.58 \]

(c) Mingshan Station

\[ y = 0.499x + 19.27 \]
\[ R = 0.924 \]
\[ \text{Bias} = -0.35 \]
\[ \text{RMSE} = 91.83 \]

(d) Ya'an Station

\[ y = 0.690x + 20.37 \]
\[ R = 0.869 \]
\[ \text{Bias} = -0.09 \]
\[ \text{RMSE} = 50.07 \]

(e) Yingjing Station

\[ y = 0.719x - 6.586 \]
\[ R = 0.910 \]
\[ \text{Bias} = -0.33 \]
\[ \text{RMSE} = 63.82 \]

(f) Tianquan Station
Figure 3. Linear relation and error statistics between monthly precipitation at downscales and monthly precipitation at various rainfall stations.

4.3 Spatial and temporal distribution characteristics of monthly precipitation in the study area

The monthly downscaling simulated precipitation of each station from 2000 to 2008 was analyzed by eigenvalue statistics. The statistical results are shown in Table 1. From Table 1, it can be seen that the minimum monthly precipitation of 8 stations in the whole region is 0 mm, which occurs in January and December. The standard deviations of precipitation data series are 3.98 mm and 4.19 mm, respectively. The maximum monthly precipitation is 578.55 mm, which occurs in August, and the corresponding standard deviation is 132.25 mm. The average value shows that the annual precipitation is mainly concentrated from May to September, and the precipitation is over 100 mm, the total precipitation from May to September accounts for about 77% of the annual precipitation.

Table 1. Statistics of annual monthly precipitation characteristic value in Ya’an.

| month | minimum value | maximum value | average value | standard deviation (mm) |
|-------|---------------|---------------|---------------|-------------------------|
| 1     | 0.00          | 17.47         | 9.93          | 3.98                    |
| 2     | 1.70          | 44.78         | 16.29         | 9.59                    |
| 3     | 4.67          | 75.56         | 37.69         | 19.25                   |
| 4     | 35.73         | 169.74        | 76.68         | 21.44                   |
| 5     | 54.06         | 165.02        | 104.07        | 26.26                   |
| 6     | 76.56         | 218.26        | 144.45        | 29.80                   |
| 7     | 78.64         | 345.44        | 177.97        | 58.87                   |
| 8     | 55.93         | 578.55        | 239.72        | 132.25                  |
| 9     | 50.68         | 199.80        | 117.76        | 34.43                   |
| 10    | 19.69         | 116.07        | 64.41         | 21.99                   |
| 11    | 2.08          | 77.89         | 25.07         | 16.87                   |
| 12    | 0.00          | 20.42         | 7.49          | 4.19                    |

The distribution of monthly average precipitation in 2000-2008 at 1 km spatial resolution in the study area is shown in figure 4, and the variation trend of monthly precipitation in the main flood season is shown in figure 5. From figure 4, it can be seen that the central Ya’an has concentrated precipitation in January, November and December. The northern precipitation in February, March, April, July and August is more than the southern precipitation. The southern precipitation in May, June, September and October is more than the northern precipitation. The precipitation in August is the most abundant, and the maximum monthly average precipitation is 319.13 mm, which appears at
Baoxing Station in the north. Secondly, in July, the maximum precipitation is 215.81 mm, which appears at Lushan Station in the north. Compared with the monthly average precipitation of nine years in the whole region, the maximum monthly precipitation of Baoxing Station in August and Lushan Station in July are higher than the average of the whole region in corresponding period. The minimum precipitation in January is 5.12 mm, which appears in Hanyuan station in the south. From January onwards, the monthly average precipitation in ya’an increases gradually. The monthly average precipitation from May to September exceeds 100 mm. In July and August, ya’an enters the main flood season. The monthly average precipitation is higher than 200 mm. After September, the monthly average precipitation gradually decreases, which is consistent with the trend of the monthly average precipitation in Table 1 for nine years.
Figure 4. Distribution of annual monthly average precipitation in ya’an.

Figure 5. Change trend of monthly precipitation in the main flood season of ya’an from 2000 to 2008.

The main flood season in ya’an is July to August. As can be seen from figure 5, the precipitation in ya’an has been decreasing gradually within the nine years, with a minimum of 115.51 mm in 2006. The precipitation in August fluctuates greatly, with a minimum of 105.60 mm and a maximum of 436.33 mm in 2002 and 2003, respectively.

5. Conclusion and Prospect

Based on the TRMM 3B43 monthly precipitation data in ya’an from 2000 to 2008, the monthly precipitation data at 1 km resolution in the study area were obtained by constructing the multiple linear regression equation between longitude, latitude, elevation, vegetation normalization index, aspect and satellite monthly precipitation data, and employing the method of “regression model + residual” to reduce the scale. The reliability of the downscaling model was verified by the measured data of 8 rainfall stations, and then the spatial and temporal distribution characteristics of monthly precipitation data in the study area were analyzed. The conclusions are as follows:

(1) The overall accuracy test shows that the R values of TRMM 3B43 data before and after downscaling are 0.863 and 0.854, and Bias values of them are -0.08 and -0.12, respectively. The correlation and accuracy between the original data and the downscaling results are basically the same. Accuracy test of single station shows that the measured data from about 75% rainfall stations are highly correlated with downscaling simulated precipitation, and the data deviation of each station is small, with the absolute value is no more than 0.35. And the root mean square error of 75% rainfall stations is relatively small. Among them, the correlation coefficient between predictive values and measured values in Lushan station is as high as 0.941, Bias is -0.07 and RMSE is 33.83. The test results show that the 1 km downscaling model in this paper has certain credibility on the regional scale, and is suitable for the precipitation study in ya’an.

(2) Monthly downscaling simulation results show that the precipitation in ya’an is concentrated in
the middle region in January, November and December, but the amount of precipitation is relatively small, the low-value area is located in the southern Hanyuan; the north is more than the south from February to April the same in July and August. The high-value area is located in the northern Baoxing and Lushan; the south is more than the north in May, June, September and October. The precipitation in ya’an increases significantly from May to October, and enters the main flood season in July and August. The precipitation in August reaches the maximum in the year.

After downscaling, the spatial resolution of TRMM precipitation data is improved and its continuous spatial distribution is stronger, which reduces the limitation of analyzing the spatial and temporal variation characteristics of precipitation in ya’an. However, there are still some errors between the downsampling data and the measured data, which are mainly related to the factors affecting the accuracy of TRMM data and the accuracy of the constructed multivariate linear regression model. Therefore, in the future research, we can consider using the measured precipitation to revise the processing, in order to improve the reliability of the data, or using GPM satellite precipitation, which has higher spatial and temporal accuracy[20], to make it more suitable for the analysis of spatial and temporal variation characteristics of precipitation in the study area.

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