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ORIGINAL PAPER

The spatial downscaling of TRMM precipitation data for the middle part of the Chinese Tianshan Mountains

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Abstract
Remote sensing data makes great contribution to complements the inadequacy of the instruments in the region, especially at the high elevation and with complex underlying surfaces. In the paper, downscaling models based on the relationships among the precipitation, elevation, and vegetation are used. The multiple linear regression models are established with Tropical Rainfall Measuring Mission (TRMM) 3B43 dataset, the Digital Elevation Model (DEM) from the Shuttle Radar Topography Mission (SRTM), and Normalized Difference Vegetation Index (NDVI) at a high various spatial scales. The spatial resolution of TRMM 3B43 precipitation fields were downscaled from 0.25° to 1 km during 2014–2016 in the middle part of Chinese Tianshan Mountains. The results of downscaling show better agreements with the ground measurements. The downscaling results reduce the underestimation for TRMM precipitation at Bayanbulak and Balun, and it also reduces the overestimation for TRMM at Korla. However, at Yining, the differences value between the measured data and downscaling results are increased in 2014 and 2015, whereas precision of downscaling is increasing in 2016. In general, spatial downscaling can improve the precision of TRMM precipitation data. Therefore, spatial downscaling method is a feasible approach for studying the precipitation of Chinese Tianshan Mountains; it will provide more precise precipitation data sources.

Keywords Chinese Tianshan middle part · Precipitation · TRMM satellite · Downscaling

Introduction

Precipitation is a key factor when studying hydrological and meteorological and plays an important role in water cycling and energy exchange processes (Xie and Arkin 1997; Liu et al. 2008). In addition, precipitation is related to the conditions of the underlying surface (Defriesr 1994; Ding et al. 2007; Jia et al. 2011), including the Digital Elevation Model (DEM) topography, slope, aspect, and Normalized Difference Vegetation Index (NDVI), et al. Thus, obtaining high-resolution precipitation data can substantially affect the temporal and spatial precision of precipitation distributions (Bindlish and Barros 2000; Feidas 2010; Hirpa et al. 2010). To get more high-resolution (spatial and temporal) precipitation data for the Mountains region, different downscaling techniques (dynamical and empirical statistical) were used to "downscale" precipitation data with reanalysis data, climate models data, and remote sensing data from global to regional and local scales (Lloyd 2005; Benestad 2010; Wagner et al. 2012).

Traditional studies on the temporal and spatial characteristics of precipitation are reliant on actual station data, although obvious differences value will occur if only ground observation data are used due to the large elevational fluctuations in mountain areas and the sparse distribution of meteorological stations (Wilheit 1986). Recently, remote sensing satellite data have been used in precipitation studies to improve the precision and accuracy of the results, and remote sensing data include the Global Precipitation Climatology Project (GPCP, Huffman et al. 1997, 2001, 2009), Global Satellite Mapping of Precipitation (GSMaP, Kubota et al. 2000), and Tropical Rainfall Measuring Mission (TRMM, Kummerow and Barnes 1997, Kummerow et al. 2000; Huffman et al. 2007;

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Almazroui 2011; Liu et al. 2015a). However, remote sensing satellite data with low spatial resolution cannot precisely reflect the temporal and spatial distribution of regional precipitation. Therefore, spatial downscaling is required for remote sensing satellite precipitation products to achieve a higher precision.

Previous studies on downscaling remote sensing satellite precipitation products have considered the effects of topography and vegetation (Turk and Miller 2005; Jia et al. 2011). For example, Guan et al. (2009) performed a downscaling analysis on Next Generation Radar (NEXRAD) data based on the topographical factors. Immerzeel et al. (2009) established a non-linear regression model between TRMM 3B43 precipitation data and a Moderate Resolution Imaging Spectroradiometer (MODIS) vegetation index based on the correlation between the vegetation index and precipitation to increase the TRMM resolution by up to 1 km. Jia et al. (2011) performed a downscaling analysis on TRMM 3B43 data according to NDVI and DEM data. Xu et al. (2015) used a new algorithm by introducing a regional regression model termed as geographically weighted regression (GWR) to downscale the TRMM 3B43 data. Although previous downscaling analyses of remote sensing satellite data have involved vegetation index and topography, the study areas were mainly concentrated in plains or basins instead of areas at high elevation and with complex underlying surfaces (Immerzeel et al. 2009; Jia et al. 2011). Therefore, these downscaling processes need to be verified in mountain areas. Tianshan Mountains is the birthplace of many inland rivers in the arid area of Northwest China (Yuan et al. 2003; Li et al. 2006). The precipitation in Chinese Tianshan Mountains not only determines the total amount of regional water resources but also directly affects the distribution of water resources, the formation of river runoff, the distribution and development of Alpine glacier and snow, then directly related to the ecological environment and socio-economic development in the middle and lower reaches (Wang et al. 2015). Due to the limitation of the observation stations, it is difficult to obtain high-resolution (spatial and temporal) precipitation data in Chinese Tianshan Mountains. Therefore, how to utilize the limited observational data of stations, integrate the ground observations, spatial interpolation, and satellite remote sensing to quickly assimilate and fuse these data of precipitation is the hotspot issues (Bindlish and Barros 2000; Feidas 2010).

The aims of this study are to (1) analyze precision of TRMM 3B43 during 2014–2016 in the middle part of Chinese Tianshan Mountains; (2) employ the DEM with 3″ (approximately 90 m) in spatial resolution, NDVI with 1 km in spatial resolution and the TRMM precipitation data with 0.25° in spatial resolution to downscale the TRMM 3b43 to 1-km spatial resolution. The precision of the results of downscaling was verified by comparison with the measurements of stations.

Material and methods

Study area

The Chinese Tianshan Mountains is one of the largest mountain ranges located in Central Asia and transverse part of China, Kazakhstan, Kyrgyzstan, and Uzbekistan. Approximately 2/3 of the Tianshan Mountains is in the Xinjiang Uygur autonomous, China. The Chinese Tianshan Mountains are the dividing line between north and south Xinjiang and located between latitudes 39.6° N and 45.5° N and longitudes 73.5° E and 96.1° E (Wang et al. 2011). The principal of Chinese Tianshan Mountain runs east to west at elevations ranging from − 188 to 8806 m (Fig. 1).

The precipitation of Chinese Tianshan Mountains is dominated by the westerly circulation (Liu et al. 2015b). Therefore, the Tianshan Mountains has relatively abundant precipitation comparing with the average precipitation of arid central Asia (Schiemann et al. 2008). The annual precipitation of Chinese Tianshan Mountains shows spatial variation with large precipitation in the northwestern region and small precipitation in the southeastern (Yuan et al. 2001; Zhong et al. 2017). Based on the integrity and continuity of the precipitation data, this paper performed a downscaling analysis of TRMM precipitation data in the middle part of the Chinese Tianshan Mountains (41° 30′ ~ 44° 36′ N, 80° 64′ ~ 87° 24′ E).

Meteorological station data

Precipitation data from meteorological observation stations are provided by the China meteorological data sharing service (http://www.cma.gov.cn/2011qxfw/2011qsjgx/). There are 16 metrological stations throughout the Chinese Tianshan area (Wenquan, Yining, Zhaosu, Urumqi, Baluntai, Dabancheng, Kumishi, Bayanbulak, Bycheng, Korla, Torugart, Wuqia, Kashgar, Akqi, Barkol, and Yiwu). To verify the model results, ground measurements of middle part of study region were selected from the Yining, Kumishi, Bayanbulak, and Baluntai.

Tropical Rainfall Measuring Mission

The TRMM satellite was developed by the National Aeronautics and Space Administration (NASA) and Japan Aerospace Exploration Agency (JAXA) and launched in November 1997. The track of satellite was set at an altitude of around 400 km, an inclination of 35° and the cycle of 92.5 min (Fleming et al. 2011). The aim of the TRMM is to provide the data for more scientific understanding of global energy and water cycling based on precipitation and latent heat (Kummerow and Barnes 1997; Kummerow et al. 2000). Since the year 1997, the products have updated several

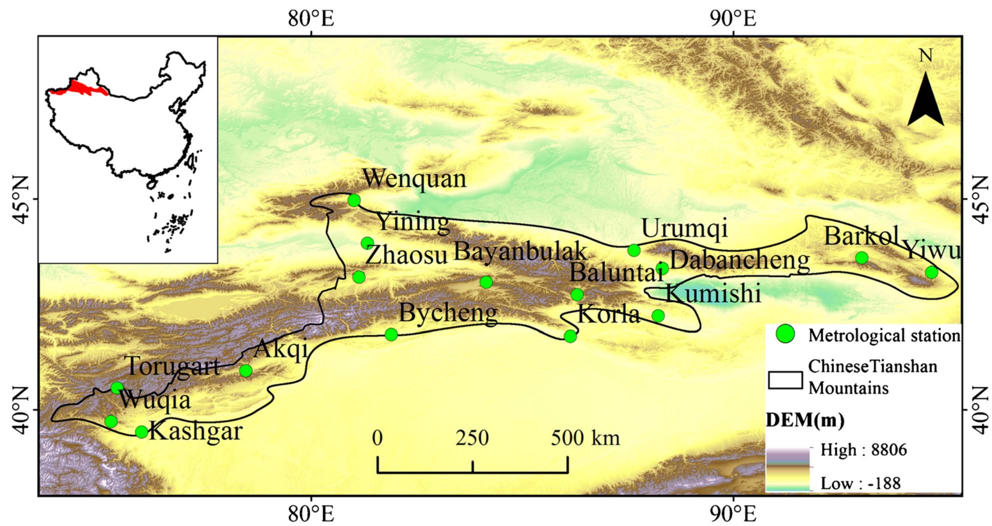


Fig. 1 The location of the Chinese Tianshan Mountains and the location of the 16 metrological stations

algorithms and techniques (Haddad et al. 1997; Iguchi et al. 2000; Yang et al. 2015, 2017, 2018).

SRTM DEM

The Shuttle Radar Topography Mission (SRTM) was established by National Aeronautics and Space Administration (NASA) and National Intelligence Mapping Agency (NIMA) and launched in February 2000. It provided free surface elevation information for meeting all kind needs of public. The dataset coverage extends from 56° S to 60° N by latitude (Reuter et al. 2007).

Normalized Difference Vegetation Index (NDVI)

Aim at detecting and monitoring the variety of vegetation and extraction of canopy biophysical parameters, Normalized Difference Vegetation Index (NDVI, Running et al. 1994; Justice et al. 1998; Huete et al. 2002) contains consistent, spatial, and temporal information on coverage and growth of vegetation.

Methods

Downscaling method

The specific steps of downscaling are as follows (Fig. 2):

1. This article used the remote sensing data of TRMM 3B43 annual precipitation, DEM, and average annual NDVI with three different scales, the resolution of TRMM 3B43 is 0.25° × 0.25°, which equals to 27.5 km, the resolutions of DEM and NDVI are 90 m and 1 km.
2. Correlation coefficient was calculated to verify the accuracy of the TRMM 3B43 precipitation data (Fig. 3).
3. Under the resolution of 0.25°, multiple linear regression models were established based on the annual cumulative precipitation data of TRMM 3B43, latitude and longitude, elevation, and slope of the year of 2014, 2015 and 2016, respectively (Fig. 4).

The model is defined as follows:

$$Y = a + bX_1 + cX_2 + dX_3 + eX_4 + fX_5 \quad (1)$$

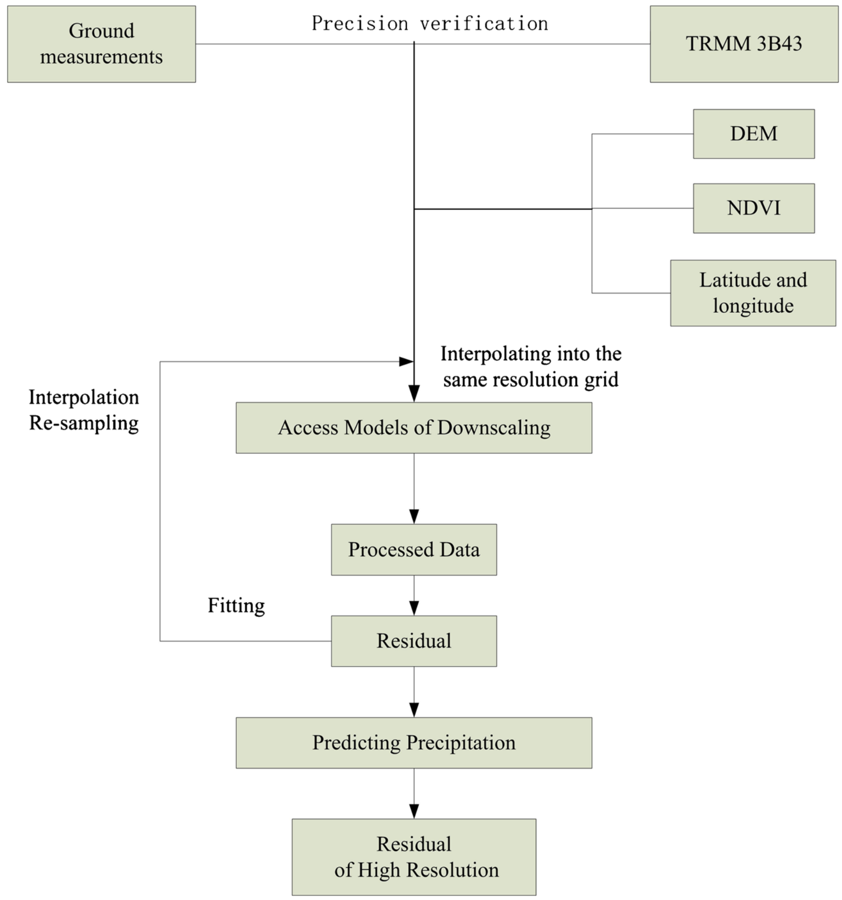
where Y is the accumulated annual precipitation of a certain year, X_1 is the longitude, X_2 is the latitude, X_3 is the elevation, X_4 is the annual max value of NDVI, and X_5 is the slope. In addition, a, b, c, d, e, and f are the fitting coefficients of the multiple linear regression models.

4. After performing projection transformation on the TRMM precipitation data, the longitude, latitude, DEM, annual max value of NDVI, and slope in the study area are re-collected at a resolution similar to that of the TRMM precipitation data, which is 0.25° (Fig. 5). Model 1 is simulated with 0.25° spatial resolution. According to the established downscaling regression model, the regression coefficient between the estimated precipitation and TRMM original data is fluctuating around 0.90, implying a high model correlation.
5. The differences value

$$\triangle = Y_t - Y \quad (2)$$

where, Y is the accumulated annual precipitation of a certain year, and Y_t is the annual precipitation data of TRMM over the certain year.

Fig. 2 Technical routine of downscaling method



6. Resampling the images with 0.25° spatial resolution to the 1° spatial resolution. Then, the regression coefficient is substituted into the DEM, NDVI, and slope images with a 1 km resolution to obtain high-resolution precipitation estimates (Table 1).
7. The differences value △ with 0.25e resolution is interpolated by using the spline function method and re-collected based on the differences value at 1-km resolution. The estimated precipitation at 1-km resolution is then superimposed with the differences value at 1-km resolution via a raster calculator to obtain high-resolution precipitation data.

Validation

Due to the lack of measurements, we choose the instrument data (Bayanbulak, Yining, Baluntai, Korla) to test. The validation results are based on the comparison between the 3-year observation data from these four stations (there is a total of 12 pairs of data used for validation) by three indexes. The coefficient of determination (R^2), the bias (B) and the root mean square error (RMSE) were calculated, which are expressed as

$$R^2 = \left[\frac{\sum\left(Y-\overline{Y}\right)\left(Y_t-\overline{Y_t}\right)}{\sqrt{\sum\left(Y-\overline{Y}\right)^2}\sqrt{\sum\left(Y_t-\overline{Y_t}\right)^2}} \right. \quad B = \sum\frac{Y_2-Y}{Y} \tag{3}$$

$$\mathrm{RMSE} = \sqrt{\frac{\sum(Y_t-Y)^2}{n}} \tag{4}$$

where, Y is the measured annual precipitation of a certain year, Y_t is the annual precipitation data of TRMM over the certain year, and n is the number of data.

Results

Assessment of TRMM 3B43 precipitation data in Tianshan Mountains

Considering the research period and the continuity of the meteorological station data, 16 meteorological stations (including Yining, Zhaosu, Urumqi) were selected to analyze the

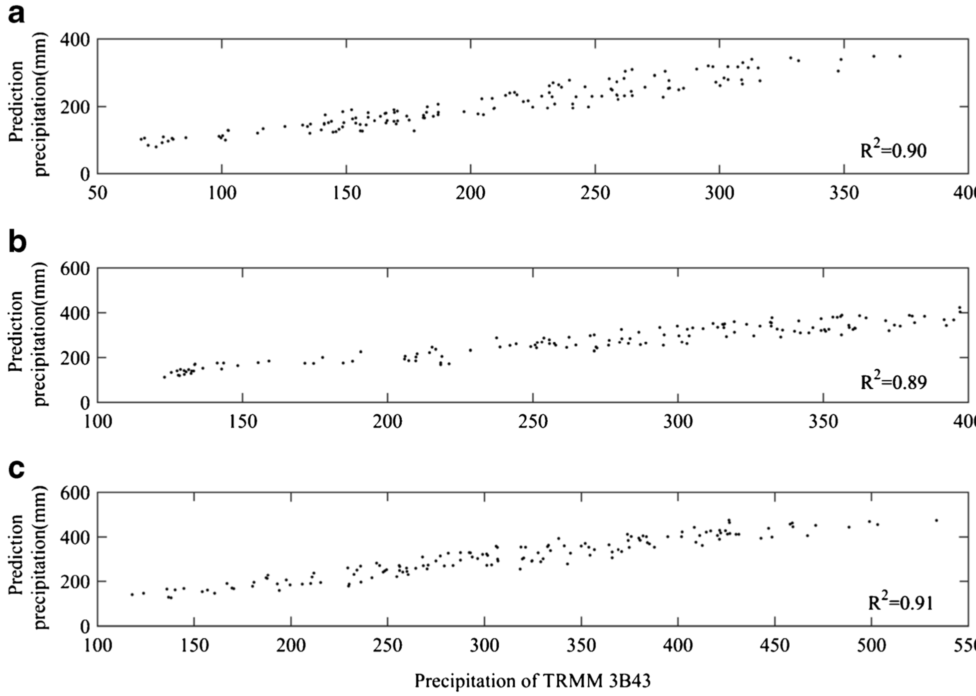


Fig. 3 Scatter density plot between TRMM precipitation and precipitation simulation based on the downscaling models for **a** 2014, **b** 2015, and **c** 2016

applicability of TRMM 3B43 precipitation in Chinese Tianshan Mountains. Figure 6(a) shows the regression between the annual average precipitation from the observation stations and TRMM 3B43 values during the period 2014–2016. Figure 6(b) shows the regression between the monthly average data from the observation stations and TRMM values in 2016. The correlation coefficients are 0.72 and 0.69, respectively, demonstrated that high annual and monthly correlations between TRMM precipitation and observation stations data and a high applicability of TRMM 3B43 precipitation data

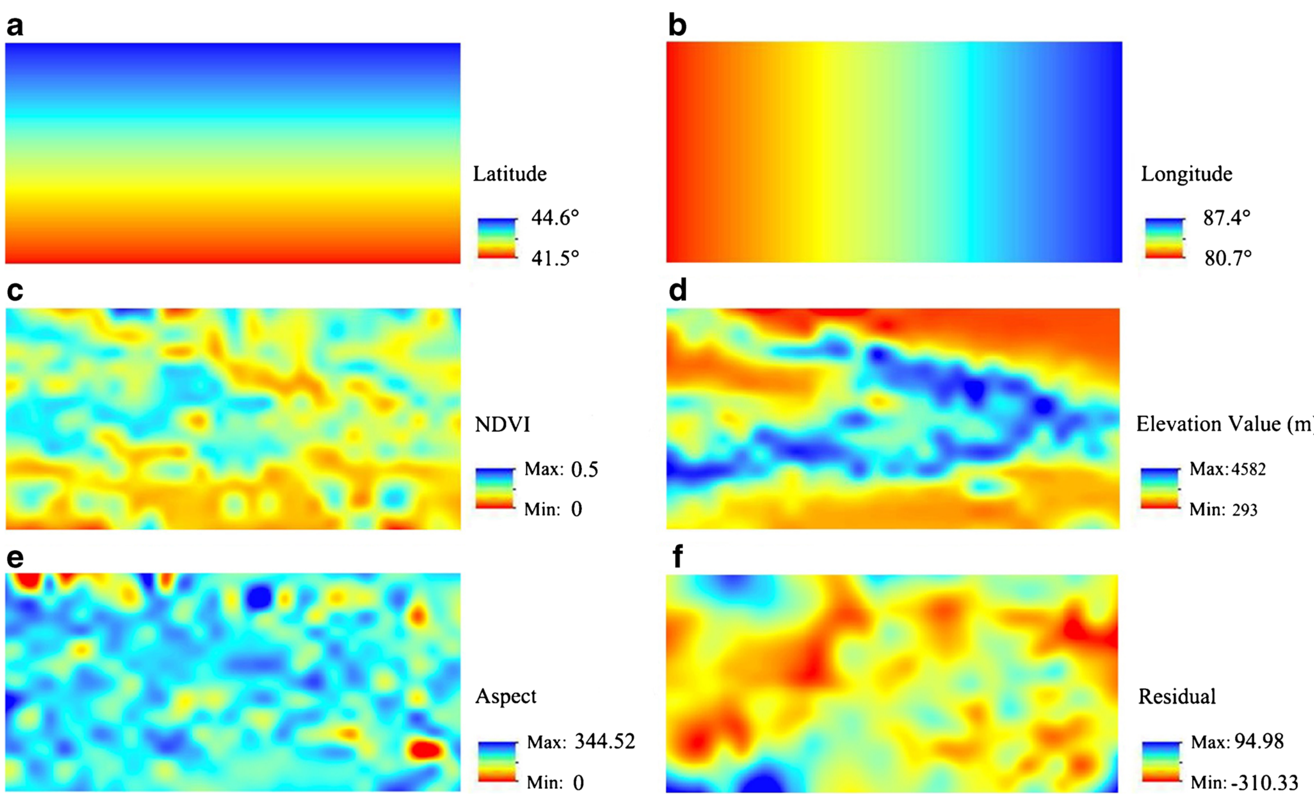


Fig. 4 Images of 1-km resolution after re-sampling and interpolation for **a** latitude, **b** longitude, **c** NDVI, **d** DEM, **e** aspect, and **f** residual

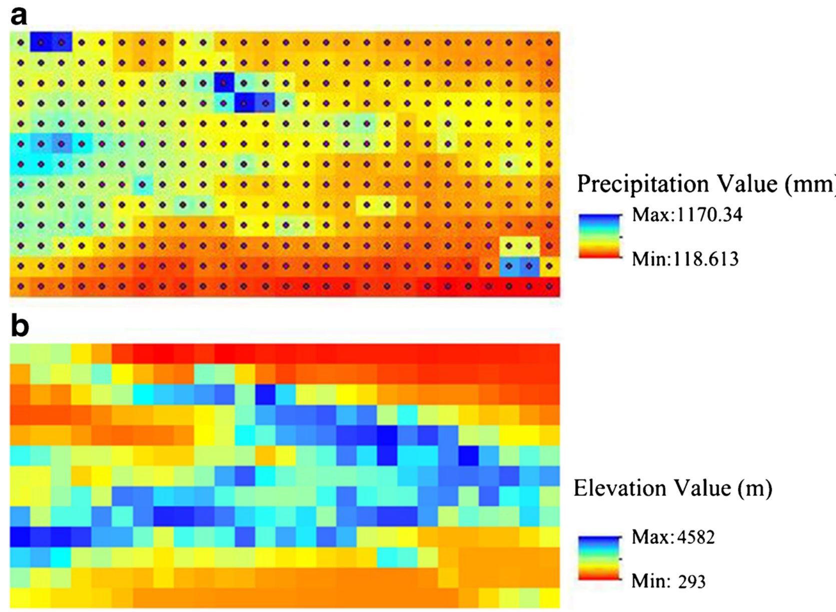


Fig. 5 **a** Image of TRMM 3B43 under the 0.25° resolution and **b** image of DEM under the 0.25° resolution

in the Chinese Tianshan Mountains. However, the accuracy of the TRMM 3B43 monthly precipitation data among the different stations remains heterogeneous (Table 2), with large differences value observed in Wenquan, Urumqi, and Kashgar. Accordingly, the uncertainties are observed because of the effects of topography, climate, ocean and continent location, etc. Therefore, a downscaling method is used to improve the accuracy of the TRMM precipitation data.

Downscaling results and validation

With the downscaling model, the high-resolution precipitation data of 1 km from 2014 to 2016 were obtained (Fig. 7). In order to further verify the results of downscaling results, 4 observation stations in the study area were selected, and the measured data, the TRMM 3B43 data and downscaling results, were compared and analyzed (Table 3 and Fig. 8). In general, it can be seen that the differences value between the downscaling results and the measured data is smaller than the raw TRMM3B43 and the measured data; accordingly; the accuracy of the TRMM 3B43 precipitation data is improved.

The results of validation are demonstrated in Fig. 8 and Table 4, the coefficient of determination (R^2) between measurements and TRMM 3B43 increased after downscaling, while the root mean square error (RMSE), and the bias (B) between measurements and TRMM 3B43 are larger than the results of downscaling. The coefficient of determination is increased by 0.03; the bias and the root mean square error reduced by 0.004 and 16.12, respectively. A detailed analysis of the results indicated that TRMM 3B43 precipitation data are underestimated at Bayanbulak station, and the annual precipitation values are generally lower than the observed values. Downscaling results can reduce the level of underestimation and significantly reduce the differences value in TRMM 3B43 precipitation data. The TRMM precipitation data ranges in differences value from 19 to 33.44 mm. After downscaling, the differences value relative to the observed data are substantially reduced and range from 2.02 to approximately 21.41 mm. TRMM 3B43 precipitation data are also underestimated at Balun station, and the differences value range from 21.91 to approximately 53.8 mm. After downscaling, the differences value between the downscaling results and observation data are significantly reduced to 18.3 mm. For the Korla station, TRMM 3B43 precipitation data are overestimated, and the differences value relative to the observation station range from 12.62 to approximately 39.3 mm. After implementing the downscaling method, the differences value is reduced to 11.16~32.07 mm; thus, the models remain to be improved.

Table 1 Brief introduction of experimental data

Dataset	Resolution and precision	Covers	Format	Source of data
TRMM 3B43	0.25° × 0.25°(27.5 km)	50° N–50° S	HDF	http://trmm.gsfc.nasa.gov/DATA_DIR/ProductStatus.html
SRTM DEM v4.1	90 m (3″)	60° N–56° S	Geo tiff	http://www2.jpl.nasa.gov/srtm/ and http://srtm.csi.cgiar.org
NDVI	1000 m	Global	HDF	https://ladsweb.modaps.eosdis.nasa.gov

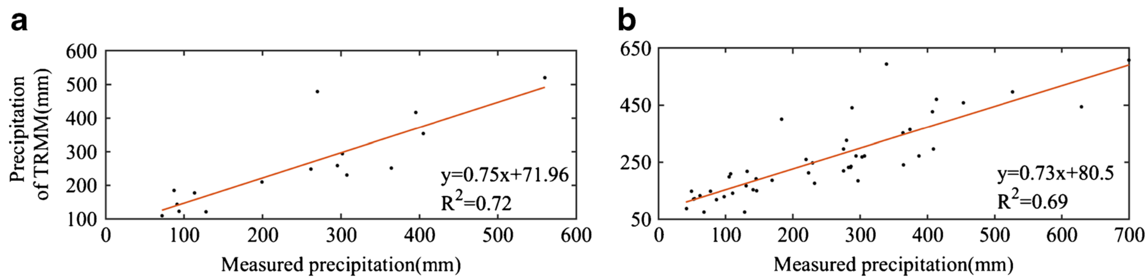


Fig. 6 Comparison between TRMM and measurements of **a** average precipitation during 2014–2016, **b** monthly average precipitation of 2016

For the Yining station, TRMM 3B43 precipitation data show a tendency towards overestimation compared with the observation data. However, after downscaling, the results for certain years are greater than that of the original TRMM 3B43 data. After downscaling, the differences value in 2014 and 2015 are greater than that of the original TRMM 3B43 precipitation data; whereas in 2016, the differences value are significantly smaller than that of the original TRMM 3B43 data and show a reduction from 57.11 to 3.44 mm. A possible reason for these results is that the differences value of TRMM precipitation is relatively small relative to the observation data; thus, the effect of downscaling is not apparent. Conversely, the differences value of TRMM data may be too great. Moreover, the annual precipitation at Yining is higher than that of the other stations, which may have contributed to the poor precision in this area compared with areas that have less precipitation. In addition, during the establishment of the model, the residual differences value was interpolated by using the spline function, and different interpolation methods will have different effects among the stations. Overall, the downscaling model reduced the differences value of the TRMM 3B43 and observation data and improved the accuracy of TRMM 3B43 precipitation data. The precipitation differences value for the recent 3 years shows an improvement of up to 2.02 mm with our downscaling model.

Spatial characteristics of precipitation in the Chinese Tianshan Mountains

According to the downscaling results, the precipitation in the west of middle part of the Chinese Tianshan Mountains is greater than that in the east and the precipitation in the north is greater than that in the south. The total precipitation reduces from the west to the east and increases from the north to the south, which has an obvious vertical distribution characteristics. Precipitation increases with increasing elevation, and the areas with the greatest precipitation are mainly located in high-elevation regions with snow coverage, whereas areas with less precipitation are mainly located along the rim of the north and south slope of Chinese Tianshan Mountains. In addition, precipitation is higher in the west than the east.

Table 2 The models of downscaling

Year	0.25° × 0.25° model of downscaling	R^2
2014	$Y = 54.11X_1 - 28.12X_2 + 0.05X_3 + 50.50X_4 - 0.37X_5$	0.90
2015	$Y = 53.19X_1 - 15.27X_2 + 0.05X_3 + 52.96X_4 - 0.32X_5$	0.89
2016	$Y = 29.17X_1 - 19.16X_2 + 0.05X_3 + 40.40X_4 - 0.35X_5$	0.91

Discussion

The downscaling results can reflect annual variations of precipitation. However, this algorithm still has differences value, and possible sources of differences value are discussed as follows.

1. Model. The establishment of the linear regression model and the interpolation of residuals in this study can describe the relationship between precipitation, NDVI, and topography as a linear relationship, certainly, the model can affect the downscaling results and corresponding introduce uncertainty into the downscaling results. In addition, residual differences value is interpolated by using the spline function, and different methods can lead to different results for the stations with different precipitations levels. Moreover, the model does not consider the complex influence of the topography mechanism. The precipitation will increased with the elevation due to the topographical lifting effect on airflow (Jia et al. 2011; Fang et al. 2013), it was also affected by the barrier effect on the air flow and topographical roughness. In addition, the model does not consider the lag period of the relationship between the precipitation and vegetation.
2. Data. The results of Yining show poorer precision, and the annual precipitation of Yining is higher than other stations. Thus, it may indicate that this model has poorer precision in areas with greater precipitation compared with areas with less precipitation. The accuracy of the result of the downscaling is influenced by the algorithm and discontinuity of the TRMM 3B43 data.
3. The downscaling results are related to the elevation. The predicted results reduce the bias in the Baluntai,

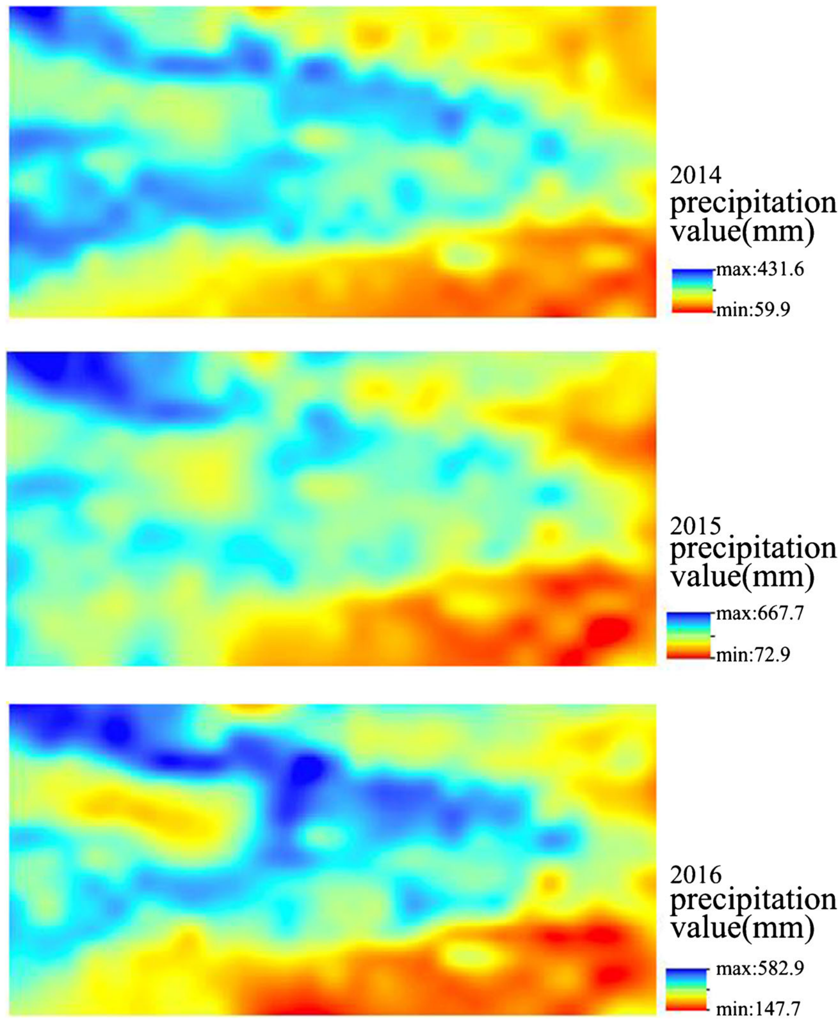


Fig. 7 The high-resolution precipitation data of 1 km from 2014 to 2016

Bayanbulak, and Korla, which elevation are 2458 m, 1739 m, and 932 m, respectively. The downscaling results shows even greater bias in Yining station, which probably because the evaluation of Yining is only 663 m. But the improvement of precession does not show liner relationship with the evaluation of the station.

4. Although monthly downscaling study was not performed here, it would have provided data and theoretical support to generate more precise precipitation among seasons and months. The limited number of stations in the middle part of the Chinese Tianshan Mountains also hinders our ability to verify the station data and perform an efficient evaluation of the TRMM 3B43 data.

Conclusions

Based on TRMM 3B43 precipitation data, meteorological stations data, DEM, and NDVI of the Chinese Tianshan Mountains during 2014–2016, a multiple linear regression model of downscaling TRMM precipitation data as well as with indexes of longitude, latitude, slope, aspect, DEM, and NDVI, and slope data is established. A spatial downscaling process is performed on the precipitation data to obtain spatial distribution in the Chinese Tianshan Mountains with a 1-km spatial resolution. The results are verified using observation data from the meteorological stations. The conclusions are as follows:

1. TRMM data are underestimated at Bayanbulak station and Balun station, and the annual precipitation is generally lower than the observed precipitation. The downscaling model can reduce the underestimation, and it also can reduce the differences value in the TRMM data. TRMM data at Yining station and Korla station display overestimation trend compared with the observation data. After downscaling, the differences value at Korla station is reduced significantly. However, at Yining station, the downscaling process improves the precision for the 2016 data but increases the differences value in 2014 and 2015 compared with the corresponding TRMM data.

Table 3 Comparison between annual average precipitation of TRMM and measurements

Station	Longitude/E	Latitude/N	Elevation/m	Annual average precipitation of station/mm	Annual average precipitation of TRMM 3B43 (mm)
Wenquan	81.07	44.97	1358	270.20	479.18
Yining	81.33	43.95	663	394.97	416.74
Zhaosu	81.13	43.15	1851	560.03	521.09
Urumqi	87.65	43.78	935	364.33	250.98
Baluntai	86.30	42.73	1739	295.27	258.69
Dabancheng	88.32	43.35	1104	87.50	185.38
Kumishi	88.22	42.23	922	71.87	108.97
Bayanbulak	84.15	43.03	2458	301.87	293.76
Bycheng	81.90	41.78	1229	113.23	177.98
Korla	86.13	41.75	932	93.50	123.39
Torugart	75.40	40.51	3504	404.93	353.27
Wuqia	75.25	39.72	2176	199.17	209.37
Kashgar	75.98	39.47	1289	91.50	143.10
Akqi	78.45	40.93	1985	261.57	248.18

2. The model fit well the area of high elevation and moderate precipitation. And the downscaling model improves the resolution of the original precipitation data of TRMM 3B43, making the downscaling results more clearly and specifically depict the spatial distribution characteristics of precipitation in the middle part of Chinese Tianshan Mountains. Its main feature is that the western part is more than the eastern part, and the north is more than that on the south.
3. TRMM data can be used for the study of precipitation and water resources allocation in the Chinese Tianshan Mountains. In the mountainous areas, topography has a great impact on precipitation, so the impact of slope, aspect, altitude, and vegetation should be considered when downscaling precipitation data. The difference value between the downscaling results and the meteorological station data is significantly reduced. The accuracy is significantly improved compared with the original TRMM 3B43 precipitation data. Therefore, the downscaling model constructed in this paper can be used for the precipitation downscaling study in the Chinese Tianshan Mountains and can provide reference for mountain precipitation downscaling in other regions. There is still large differences value in the downscaling results of some stations in some years, and there are many possible reasons, which are related

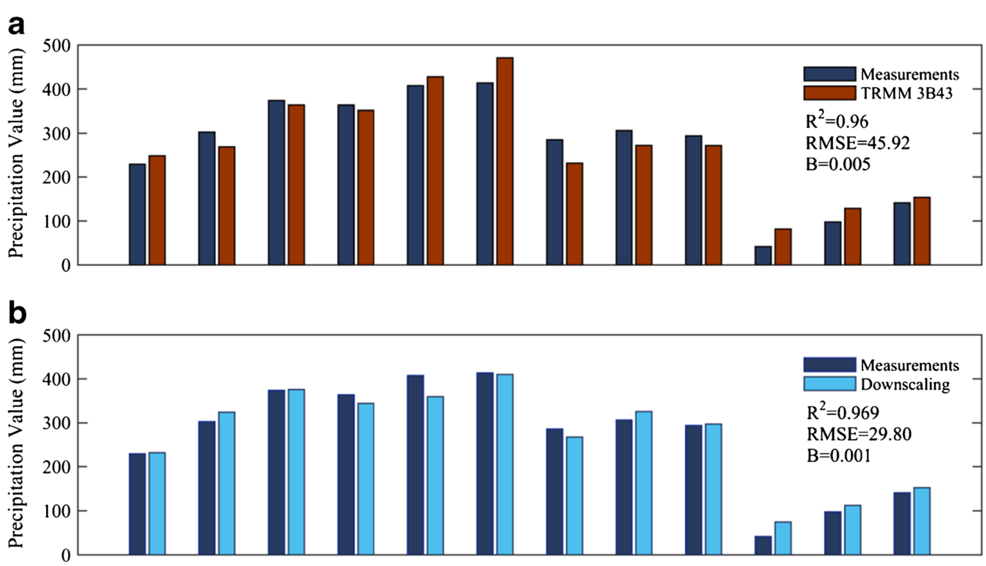


Fig. 8 **a** The comparison of TRMM 3B43 and measurements; **b** the downscaling results and measurements

Table 4 Comparison between annual precipitation derived from TRMM 3B43, results of downscaling models and measurement (mm)

Station	Type of precipitation	2014	2015	2016
Bayanbulak	Measurement	229.00	302.70	373.90
	TRMM 3B43	248.20	269.26	363.80
	Downscaling	231.52	324.12	375.92
Yining	Measurement	363.70	407.60	413.60
	TRMM 3B43	351.77	427.74	470.71
	Downscaling	344.29	359.48	410.16
Baluntai	Measurement	285.30	306.40	294.10
	TRMM 3B43	231.50	272.44	272.14
	Downscaling	267.00	325.80	297.24
Korla	Measurement	41.70	97.70	141.10
	TRMM 3B43	81.74	128.71	153.72
	Downscaling	74.63	112.32	152.77

to the precision of raw TRMM 3B43 data; we were unable to exclude the mutation value due to the short duration of the study.

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References

Almazroui M (2011) Calibration of TRMM rainfall climatology over Saudi Arabia during 1998–2009. Atmos Res 99(3-4):400–414

Benestad RE (2010) Downscaling precipitation extremes: correction of analog models through PDF predictions. Theor Appl Climatol 100(1-2):1

Bindlish R, Barros AP (2000) Disaggregation of rainfall for one-way coupling of atmospheric and hydrological models in regions of complex terrain. Glob Planet Chang 25(1):111–132

Defriesr S (1994) NDVI-derived land cover classification at a global scale. Int J Remote Sens 15(17):3567–3586

Ding M, Zhang Y, Liu L, Zhang W, Wang Z, Bai W (2007) The relationship between NDVI and precipitation on the Tibetan Plateau. J Geogr Sci 17(3):259–268

Fang J, Du J, Xu W, Shi P, Li M, Ming X (2013) Spatial downscaling of trmm precipitation data based on the orographical effect and meteorological conditions in a mountainous area. Adv Water Resour 61(11):42–50

Feidas H (2010) Validation of satellite rainfall products over Greece. Theor Appl Climatol 99(1-2):193–216

Fleming K, Awange JL, Kuhn M, Featherstone WE (2011) Evaluating the TRMM 3B43 monthly precipitation product using gridded rain-gauge data over Australia. Aust Meteorol Oceanogr J 61(3):171–184

Guan HD, Wilson JL, Xie HJ (2009) A cluster-optimizing regression-based approach for precipitation spatial downscaling in mountainous terrain. J Hydrol 375(3):578–588

Haddad ZS, Smith EA, Kummerow CD, Iguchi T, Farrar MR, Durden SL, Alves M, Olson WS (1997) The TRMM 'day-1' radar/radiometer combined rain-profiling algorithm. J Meteorol Soc Jpn 75(4):799–809

Hirpa FA, Gebremichael M, Hopson T (2010) Evaluation of high-resolution satellite precipitation products over very complex terrain in ethiopia. J Appl Meteorol Climatol 49(5):1044–1051

Huete A, Didan K, Miura T, Rodriguez EP, Gao X, Ferreira LG (2002) Overview of the radiometric and biophysical performance of the MODIS vegetation indices. Remote Sens Environ 83(1):195–213

Huffman GJ, Adler RF, Arkin P, Chang A, Ferraro R, Gruber A, Janowiak J, McNab A, Rudolf B, Schneider U (1997) The Global Precipitation Climatology Project (GPCP) combined precipitation dataset. Bull Am Meteorol Soc 78(1):5–20

Huffman GJ, Adler RF, Morrissey MM, Curtis S, Joyce R, McGavock B, Susskin J (2001) Global precipitation at one-degree daily resolution from multisatellite observations. J Hydrometeorol 2(1):36–50

Huffman GJ, Adler RF, Bolvin DT, Gu G, Nelkin EJ, Bowman KP, Hong Y, Stocker EF, Wolff DB (2007) The TRMM Multisatellite Precipitation Analysis (TMPA): quasi-global, multiyear, combined-sensor precipitation estimates at fine scale. J Hydrometeorol 8:38–55

Huffman GJ, Adler RF, Bolvin DT, Gu GJ (2009) Improving the global precipitation record: GPCP Version 2.1. Geophys Res Lett 36(17):153–159

Iguchi T, Meneghini R, Awaka J, Kozu T, Okamoto K (2000) Rain profiling algorithm for TRMM precipitation radar data. Adv Space Res 25(5):973–976

Immerzeel WW, Rutten MM, Droogers P (2009) Spatial downscaling of TRMM precipitation using vegetative response on the Iberian Peninsula. Remote Sens Environ 113(2):362–370

Jia S, Zhu W, Lű A, Yan T (2011) A statistical spatial downscaling algorithm of TRMM precipitation based on NDVI and DEM in the Qaidam Basin of China. Remote Sens Environ 115(12):3069–3079

Justice CO, Vermote E, Townshend JRG, Defries R, Roy DP, Hall DK, Salomonson VV, Privette JL, Riggs G, Strahler A, Lucht W, Myneni RB, Knyazikhin Y, Running SW, Nemani RR, Wan Z, Huete AR, Leeuwen WV, Wolfe RE, Giglio L, Muller JP, Lewis P, Barnsley MJ (1998) The Moderate Resolution Imaging Spectroradiometer (MODIS): land remote sensing for global change research. IEEE Trans Geosci Remote Sens 36(4):1228–1249

Kubota T, Shige S, Hashizume H, Aonashi K, Takahashi N, Seto S, Hirose M, Takayabu YN, Ushio T, Nakagawa K, Iwanami K, Kachi M, Okamoto K (2000) Global precipitation map using satellite-borne microwave radiometers by the GSMaP Project: production and validation. IEEE Trans Geosci Remote Sens 45(7):2259–2275

Kummerow CD, Barnes W (1997) The Tropical Rainfall Measuring Mission (TRMM) sensor package. J Atmos Ocean Technol 15:809–817

Kummerow C, Simpson J, Thiele O, Barnes W, Chang ATC, Stocker E, Adler RF, Hou A, Kakar R, Wentz F, Ashcroft P, Kozu T, Hong Y, Okamoto K, Iguchi T, Kuroiwa H, Im E, Haddad Z, Huffman G, Ferrier B, Olson WS, Zipser E, Smith EA, Wilheit TT, North G, Krishnamurti T, Nakamura K (2000) The status of the Tropical Rainfall Measuring Mission (TRMM) after two years in orbit. J Appl Meteorol 39(12):1965–1982

Li B, Zhu A, Zhang Y, Pei T, Qin C, Zhou C (2006) Glacier change over the past four decades in the middle Chinese Tien Shan. J Glaciol 52(178):425–432

Liu Q, Yang Z, Cui B (2008) Spatial and temporal variability of annual precipitation during 1961-2006 in Yellow River Basin, China. J Hydrol 361(3-4):330–338

Liu M, Xu X, Sun A, Wang K, Yue Y, Tong X, Liu W (2015a) Evaluation of high-resolution satellite rainfall products using rain gauge data over complex terrain in southwest China. Theor Appl Climatol 119(1-2):203–219

Liu X, Rao Z, Zhang X, Huang W, Chen J, Chen F (2015b) Variations in the oxygen isotopic composition of precipitation in the Tianshan mountains region and their significance for the westerly circulation. J Geogr Sci 25(7):801–816

Lloyd CD (2005) Assessing the effect of integrating elevation data into the estimation of monthly precipitation in Great Britain. J Hydrol 308(1):128–150

Reuter HI, Nelson A, Jarvis A (2007) An evaluation of void-filling interpolation methods for SRTM data. Int J Geogr Inf Sci 21(9):983–1008

Running SW, Justice CO, Salomonson V, Hall D, Barker J, Kaufmann YJ, Strahler AH, Huete AR, Muller JP, Vanderbilt V, Wan Z, Teillet P, Carneggie D (1994) Terrestrial remote sensing science and algorithms planned for EOS/MODIS. Int J Remote Sens 15(17):3587–3620

Schiemann R, Lüthi D, Schär C (2008) Seasonality and interannual variability of the westerly jet in the Tibetan Plateau region. J Clim 22(11):2940–2957

Turk FJ, Miller SD (2005) Toward improved characterization of remotely sensed precipitation regimes with MODIS/AMSR-E blended data techniques. IEEE Geosci Remote Sens Lett 43(5):1059–1069

Wagner S, Berg P, Schädler G, Kunstmann H (2012) High resolution RCM simulations for Germany: part II—projected climate changes. Clim Dyn 40(1-2):415–427

Wang S, Zhang M, Li Z, Wang F, Li H, Li Y, Huang X (2011) Glacier area variation and climate change in the Chinese Tianshan Mountains since 1960. J Geogr Sci 21(2):263–273

Wang T, Ren G, Chen F, Yuan Y (2015) An analysis of precipitation variations in the west-central Tianshan Mountains over the last 300 years. Quat Int 358:48–57

Wilheit TT (1986) Some comments on passive microwave measurement of rain. Bull Am Meteorol Soc 67(10):1226–1232

Xie P, Arkin PA (1997) Global precipitation: A 17-year monthly analysis based on gauge observation, satellite estimates, and numerical model outputs. Bull Am Meteorol Soc 78:2539–2558

Xu S, Wu C, Wang L, Gonsamo A, Shen Y, Niu Z (2015) A new satellite-based monthly precipitation downscaling algorithm with non-stationary relationship between precipitation and land surface characteristics. Remote Sens Environ 162:119–140

Yang Y, Lu D, Fu Y (2015) Spectral characteristics of tropical anvils obtained by combining TRMM precipitation radar with visible and infrared scanner data. Pure Appl Geophys 172(6):1717–1733

Yang Y, Fu Y, Qin F, Zhu J (2017) Radiative forcing of the tropical thick anvils evaluated by combining TRMM with atmospheric radiative transfer mode. Atmos Sci Lett 18(5):222–229

Yang Y, Wang H, Chen F, Zheng X, Fu Y, Zhou S (2018) TRMM-based optical and microphysical features of precipitating clouds in summer over the Yangtze-Huaihe River Valley, China. Pure Appl Geophys 18:222–229

Yuan Y, Li J, Zhang J (2001) 348-year precipitation reconstruction from tree-rings for the north slope of the middle Tianshan mountains. J Meteorol Res 15(1):95–104

Yuan Y, Jin L, Shao X, He Q, Li Z, Li J (2003) Variations of the spring precipitation day numbers reconstructed from tree rings in the Urumqi River drainage, Tianshan Mts. over the last 370 years. Chin Sci Bull 48(14):1507–1510

Zhong Y, Wang B, Zou CB, Hu BX, Liu Y, Hao Y (2017) On the teleconnection patterns to precipitation in the eastern Tianshan Mountains, China. Clim Dyn 49:1–17