Spatial Downscaling of TRMM Precipitation Using DEM and NDVI in the Yarlung Zangbo River Basin

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1. Introduction

Precipitation is central to hydrology, ecology and meteorology (Goovaerts, 2000; Langella et al., 2010). However, it is difficult to provide spatially-distributed precipitation data from traditional rain gauges (Wilheit, 1986). Remote sensing can provide spatial precipitation patterns, but the resolution of remotely-sensed precipitation data is often too coarse for hydrological simulation (Shaofeng, et al., 2011). Tropical Rainfall Measurement Mission (TRMM) has been used a lot in scientific researches, but its resolution (highest 0.25° ×0.25°) is still too coarse. Therefore it is important to generate precipitation data with finer resolution.

Precipitation is closely related to other geographic factors like vegetation and local terrain (Badas et al., 2005). As the resolution of these factors is relatively higher, the spatial resolution of precipitation can be greatly improved by establishing a statistical relationship between precipitation and these factors (Immerzeel, et al., 2009). In this study, we established a multi-regression model between precipitation and geographic factors of terrain and vegetation, and generated 1km × 1km pixel summer precipitation. The final results were validated based on in-situ observations in Yarlung Zangbo river basin at Tibet Plateau, China.

2. Study Area

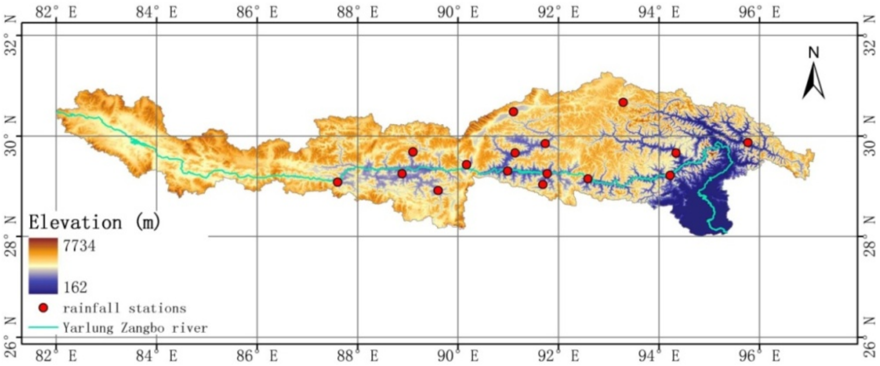

Figure 1. Topography and locations of rainfall stations in Yarlung Zangbo river basin.

The Yarlung Zangbo river basin locates in the south of Tibet Plateau and covers a total area of 240,480 km^2. The harsh natural environment makes it a poorly ungauged basin with only 16 rainfalls stations in the basin and the distribution is very uneven. Rainfall varies obviously in different elevation and the vegetation relies heavily on precipitation for water supply. Thus it is reasonable and feasible to conduct statistical spatial downscaling of precipitation data with topography and vegetation.

3. Dataset and Methodology

3.1 TRMM

TRMM was launched in November, 1997, and covers the area between 50° N and 50° S latitude. In this study, monthly TRMM 3B43 (0.25° ×0.25°) data from 2001 to 2010 were utilized.

A validation of monthly TRMM 3B43 data was conducted before the downscaling procedure, showing a satisfactory accuracy in the Yarlung Zangbo river basin.

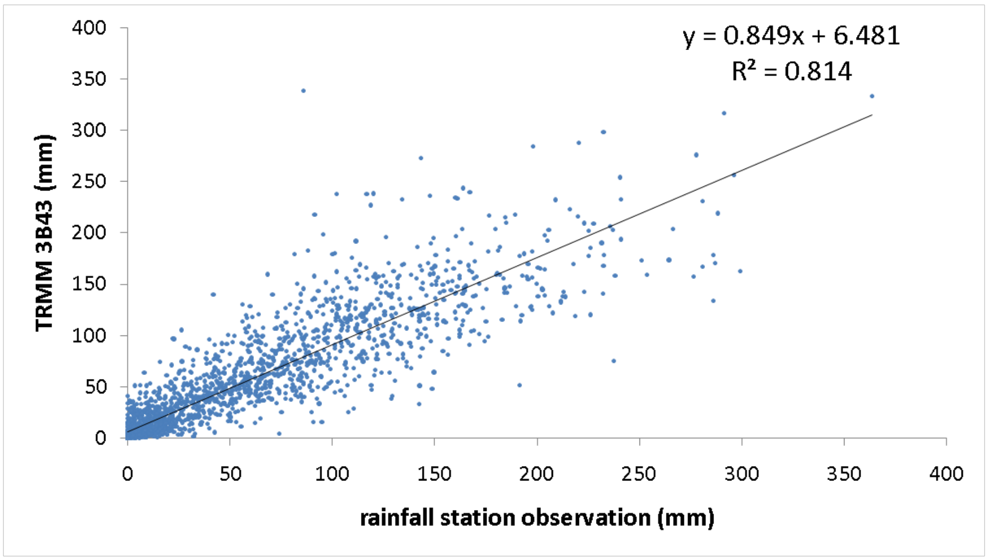

Figure 2. Scatter diagram between monthly TRMM 3B43 data and rainfall station observations

3.2 MODIS NDVI

Normalized Difference Vegetation Index (NDVI) is a measurement of vegetation activity and biomass (Tucker, 1979). Lots of researches have been conducted on the relationship between NDVI and precipitation (Iwasaki, 2009; Jean-Marie et al., 1997), revealing a positive correlation in general. In this study, MODIS monthly NDVI data with the same time span of TRMM data were used. The spatial resolution of MODIS NDVI is 1km.

3.3 SRTM DEM

The Shuttle Radar Topography Mission (SRTM) produced digital topography data for all land area between 60° north and 56° south latitude. The spatial resolution is 1 arc-second for United States and 3 arc-seconds for other areas. The DEM (Digital Elevation Model) data used in this study were resampled to 1km.

3.4 Methodology

The downscaling is based on the assumption that a firm correlation exists between TRMM precipitation data and predictive factors (DEM, NDVI) at different scales. The correlation built at coarse scale is then utilized at a finer scale to generate more detailed precipitation data. The main downscaling processes can be described as: (1) NDVI and DEM data were resampled to 0.25° , and a multi-linear regression model was established. (2) precipitation data at 0.25° scale was predicted using the regression model, representing the amount of precipitation that can be predicted. By subtracting the precipitation prediction from the original TRMM precipitation data, the prediction residual was obtained, which represents the part of precipitation that can not be predicted by the model. (3) The residual was resampled to 1km scale. (4) Apply the regression model to the original NDVI and DEM data of 1km resolution, precipitation prediction at 1km scale was obtained. By adding up the 1km precipitation prediction and the 1km residual, the final downscaled results were obtained.

3.5 Validation

First, the coefficient of determination (r^2), the bias, and the root mean square error (RMSE) between the predicted precipitation and the original TRMM 3B43 precipitation at 0.25° scale were calculated, in which

$$bias = \frac{\sum P_{predicted}}{\sum P_{original}} - 1$$

$$RMSE = \left(\sum_{i=1}^{n} \left(P_i - P_{original} \right)^2 / n \right)^{1/2}$$

Where $P_{predicted}$ is the precipitation prediction, $P_{original}$ is the original TRMM 3B43 precipitation, and n is the total number of pixels. Second, the final downscaled precipitation at 1km scale was validated using rainfall station observations.

4. Results and Discussion

4.1 TRMM and DEM correlation

Considering that the correlation between rainfall and DEM may vary with seasons, the correlation between TRMM precipitation and DEM is evaluated separately in four seasons. As is shown in Figure 3, a clear and negative relationship exists in four seasons, and the correlation coefficient *r* peaks in summer.

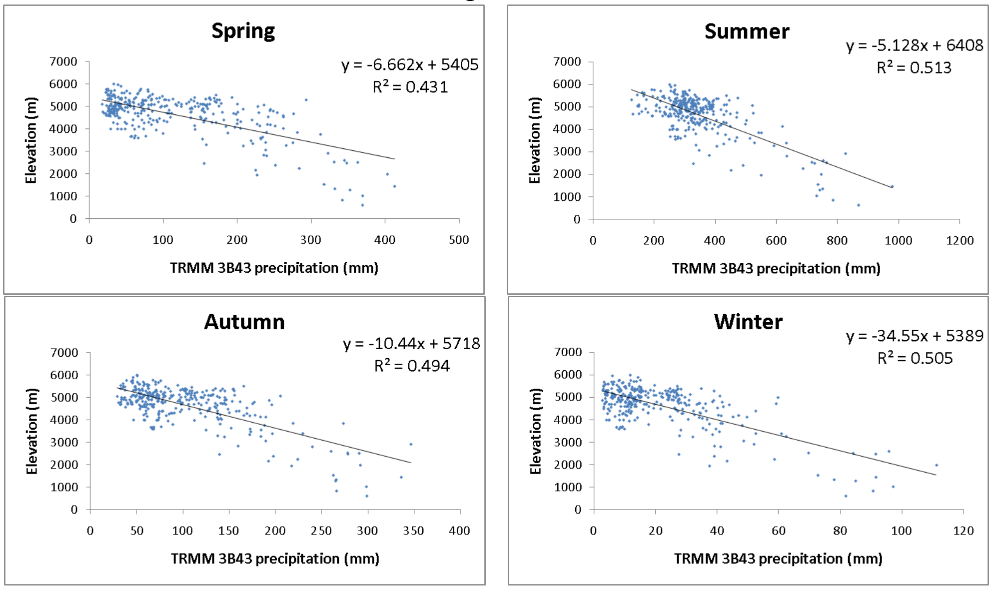

Figure 3. Scatter diagram between TRMM precipitation and DEM in four seasons.

4.2 TRMM and NDVI correlation

In general, there is a positive relationship between rainfall and NDVI. Unlike the evaluation result for rainfall and DEM, the correlation coefficient *r* is the highest in autumn, and is relatively lower in spring.

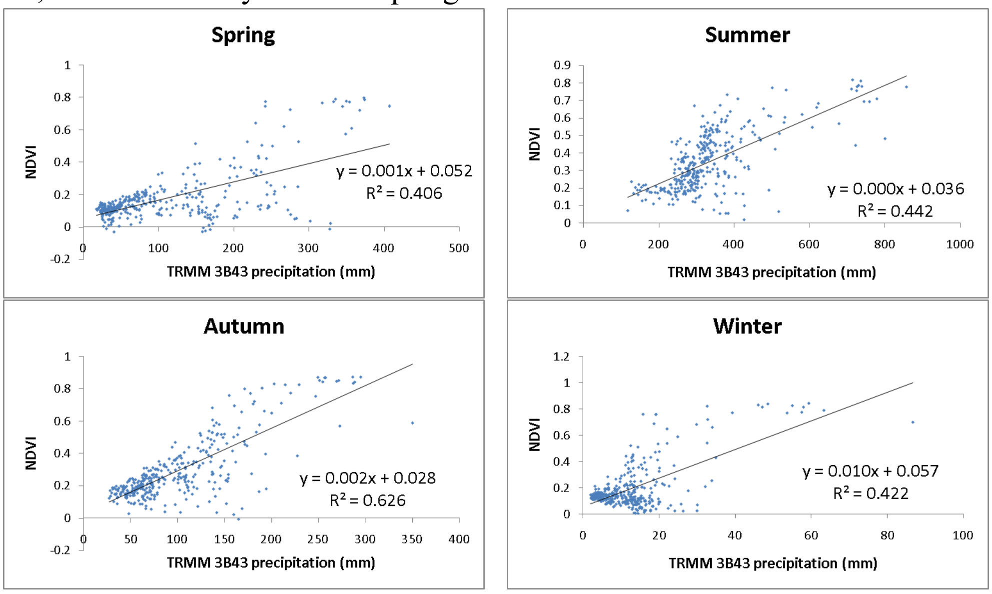

Figure 4. Scatter diagram between TRMM precipitation and DEM in four seasons.

4.3 Downscaling

Based on the analysis before, a stepwise multi-linear regression model was established. In general, the model-predicted precipitation proves to be in excellent agreement with the original TRMM 3B43 data in all seasons. It is noteworthy that the correlation between rainfall and vegetation may be lagging temporally. For example, the rainfall in spring was most related to NDVI of autumn, and NDVI in winter was the most relevant predictor to summer rain.

Season	r	r^2	bias	RMSE(mm)	Predictors
Spring	0.785	0.616	0.0009	54.18	NDVI of Autumn
Summer	0.788	0.622	-0.0003	71.42	NDVI of Winter, DEM
Autumn	0.792	0.627	0	34.53	NDVI of Autumn
Winter	0.687	0.471	0	7.54	NDVI of Summer, NDVI of Winter

Table 1. Validation for model output of the seasonal average precipitation from 2001 to 2010 at original 0.25° scale

4.4 Validation

Based on the statistical model established before, the 1km average summer precipitation was generated. The steps were: (1) the original NDVI and DEM data were resampled to 0.25° , and the predicted precipitation at 0.25° scale was generated (top left of Figure 5.). (2) By subtracting the prediction from the original TRMM 3B43 data, the residual at 0.25° was obtained (top right of Figure 5.). (3) The residual was then resampled to 1km scale (middle left of Figure 5.). (4) The precipitation prediction at 1km scale was obtained with the original NDVI and DEM data (middle right of Figure 5.). (5) Adding the 1km residual to the 1km prediction, the final downcaled precipitation at 1km scale was obtained (bottom of Figure 5.).

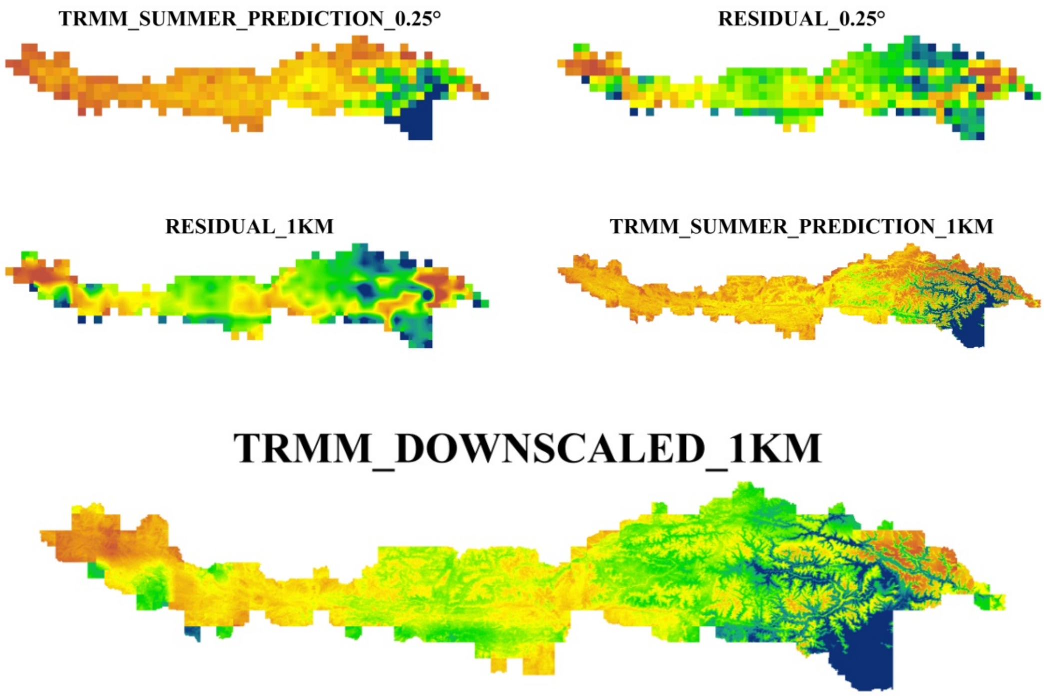

Figure 5. Overview of the downscaling results.

The efficacy of this downscaling method was validated using rainfall station observations. The 1km downscaled results are in good agreement with in-situ observations, the *bias* is a little higher, but the *RMSE* is even lower than that of the original TRMM 3B43 precipitation.

r	r^2	bias	RMSE(mm)
0.710	0.504	-0.068	38.13

Table 2. Validation for 1km downscaled results with rainfall station observations.

5. Conclusion

In this study, a multi-linear regression model was established between TRMM precipitation and DEM as well as NDVI, and the final downscaled results were validated using in-situ observations. A number of conclusions can be drawn from this study:

(1) NDVI and DEM are capable of representing the spatial patterns of precipitation in the Yarlung Zangbo river basin.

(2) NDVI is estimated to be a better predictor than DEM in the Yarlung Zangbo river basin.

(3) The correlation between rainfall and vegetation may be lagging temporally, leading to different predictors in different seasons.

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