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Downscaling of Satellite Rainfall Data Using Remotely Sensed NDVI and Topographic Datasets †

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Abstract: Rainfall is a key factor in hydrological, meteorological, and water management applications in restricted regions or basins, but its measurement remains difficult in mountainous or otherwise remote places due to a lack of readily available rain gauges. While satellite rainfall data offer a better temporal resolution than other sources, the majority of this data are only available at a coarse geographic resolution, which distorts the true picture of precipitation. Thus, researchers at the University of Agriculture in Faisalabad used the normalized difference vegetation index (NDVI) monthly data and 1 km topography data for the whole Indus Basin from 2002 to 2011 to reduce the TRMM's spatial resolution from 25 km to 1 km. An approach to downscaling based on a regression model with residual correction was established in this study. First, we resampled the NDVI and TRMM datasets to a 25 km resolution and established a regression model connecting the two datasets. Precipitation was forecasted at a distance of 25 km. The TRMM 3B43 product was then adjusted downward by the projected precipitation to achieve the residual value. The IDW method was used to reduce the resolution of the residual image from 25 km to 1 km. Rainfall was predicted using a regression model applied to NDVI at a 1 km spatial resolution. The final downscaled precipitation was created by combining the modeled precipitation at 1 km resolution with the residual image. The result was double-checked by the post-processing steps of validation and calibration.

Keywords: downscaling; rainfall; NDVI; TRMM; spatial resolution; meteorological observation

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1. Introduction

Rainfall is an important factor for hydrological, meteorological, and water management applications in specific regions as well as in basins. Rainfall has a significant impact on agriculture production because all plants require water to survive. A healthy crop needs a consistent pattern of rainfall; an excess or a deficiency of rain can be damaging or even stressful to the crop. Additionally, rainfall is required for other production activities, including irrigation and disaster mitigation [1]. Point rain gauge stations are the standard method for collecting rainfall data. However, accurate basin-level rainfall estimation remains an enormous challenge [2]. More precise rainfall measurements are required for basin-scale water management planning, water accounting, and hydrological research [3–5]. An insufficient number of rain gauges in the Indus Basin makes it difficult to conduct research and provide timely flood warnings, as point measurements do not provide an accurate representation of real average rainfall values; moreover, rain gauges are prone to a variety of random and systematic errors [6]. To address this problem, researchers have created a new downscaling technique that makes use of the correlation between high-resolution TRMM and normalized difference vegetation index (NDVI). This downscaling technique makes use of TRMM precipitation, which estimates the coarse scale, and NDVI patterns on the fine scale. Significant improvements in bias, correlation, and root-mean-square error were found after shrinking the full-period mean annual precipitation for both wet and dry seasons. A downscaling method was used because the 0.25 km resolution is too low for use at the basin scale and a higher resolution is preferred for hydrological studies. For this reason, using 1 km downscaling is advantageous in hydrological applications [7]. The majority of the random errors in rain gauge readings come from two sources: observational errors and instrumental errors, and together they can account for a discrepancy of up to 30% [8].

It is for this reason that satellite-based sensors are needed to provide more precise spatially distributed rainfall estimates [9]. Due to the errors and limitations of rain gauges, remote sensing data is often seen as the best option. Since the development of remote sensing technology, using satellites to estimate rainfall has become a realistic option until proper ground trothing occurs [5]. Space-based sensors cover a wide area and operate for extended periods of time, making it possible for new technologies to significantly improve the accuracy and timeliness with which we estimate rainfall [7]. When satellite rainfall estimates are calibrated and validated correctly, we can gain a deeper understanding of spatially distributed precipitation in both subtropical and tropical regions, while downscaled precipitation estimates can be later validated with a separate precipitation dataset [7].

In this study, we used NDVI monthly data and topography data at a scale of 1 km from 2002 to 2011 for the entire study area to reduce the Tropical Rainfall Measuring Mission's (TRMM) spatial resolution from the value of 25 km.

2. Materials and Methods

The Indus Basin is the study area, and the elevations examined span from zero to 8,616 m above sea level. Pakistan experiences two distinct seasonal patterns across its four distinct climate seasons (summer, winter, spring, and fall). Pakistan spans the coordinates 23°45′–36°75′ North and 61°30′–75°50′ East. Plains, hills, desert, forests, and plateaus can be found in the southern part of the study area, while the Karakoram Mountains can be found in the northern part.

2.1. Data

2.1.1. Tropical Rainfall Measuring Mission

TRMM is a combined collaboration between the National Aeronautics and Space Administration (NASA) and Japan Aerospace Exploration Agency [10]. The NASA Goddard Earth sciences data from 2002 to 2011 was used to obtain the RMM 3B43 data (http://mirador.gsfc.nasa.gov/ (accessed on 1 January 2015)).

2.1.2. Rain Gauge Stations

The Pakistan Metrology Department provided information from their network of rain gauges. Data on rainfall over a specific time was used for this analysis.

2.1.3. NDVI

NDVI is an essential parameter for estimating rainfall and an important index that describes the degree of greenness of land surfaces. Given MODIS' superior spatial resolution and global coverage, we decided to use its NDVI data. The NDVI-containing MODIS data from 2002 to 2011 were obtained from the EOS Gateway (https://lpdaac.usgs.gov/ (accessed on 20 January 2015)).

2.1.4. Digital Elevation Model

The digital elevation model (DEM) 2002–2011 was downloaded from the NASA shuttle radar topography mission website (http://www.glcf.umd.edu/data/srtm (accessed on 30 January 2015)) projected onto the study area by using ERDAS software.

2.2. Methodology

The stepwise procedure to downscale precipitation is explained below.

2.2.1. Factor Analysis

The following relationships were determined:
The relationship between NDVI and TRMM annual precipitation.
The relationship between altitude and TRMM annual precipitation.

2.2.2. Establishment of Model

The model was established for regression analysis at a low resolution between NDVI and TRMM, and the precipitation was estimated at 25 km. Mathematically, this can be expressed as shown in (1):

$$\mathrm{f(NDVI,\ DEM) = PTLR} \tag{1}$$

Then, using Equation (1), the relationship with precipitation was estimated at high resolution (1 km). Mathematically, it is expressed as shown in (2):

$$\mathrm{f(NDVI,\ DEM) = PTHR} \tag{2}$$

2.2.3. Residual Conversion

The difference between precipitation and TRMM 3B43 values are residual values (ΔT) at 25 km. By using Inverse Distant Weighting (IDW) interpolation techniques, 25 km residual values were converted to 1 km values by using (3):

$$\mathrm{TRMM - PTLR = \Delta T} \tag{3}$$

2.2.4. Accurate Rainfall

The converted (ΔT) was added to the model, where the NDVI and TRMM data sets were used, and accurate precipitation was calculated by using (4):

$$\mathrm{PTcorr. = PTHR + \Delta THR} \tag{4}$$

2.2.5. Monthly Precipitation from Yearly Precipitation

Monthly precipitation was extracted from annual precipitation by determining the monthly fraction and multiplying it by annual downscale precipitation by using (5) and (6):

$$\mathrm{fraction\ i} = \frac{\mathrm{org.TRMM\ i}}{\sum_{\mathrm{i}=1}^{12}\mathrm{TRMM\ i}} \tag{5}$$

$$\mathrm{PTi = fraction\ i\ \times PTHR} \tag{6}$$

where i in (5) represents monthly precipitation as estimated from the original TRMM 3B43 product.

2.2.6. Validation and Calibration

The downscaled precipitation was validated by using rain gauge data. The slope (b) of the regression analyses and coefficient of determination (R^2), the linear coefficient through the origin (a = 0), and the relative root mean square error (RRMSE) were calculated by using (7), and the root mean square error (RMSE) by using (8):

$$\mathrm{RRMSE} = \sqrt{\frac{\sum_{i=1}^{n}(\mathrm{Oi}-\mathrm{pi})^2}{n}}.100/\mathrm{Oi} \tag{7}$$

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(\mathrm{Oi}-\mathrm{pi})^2}{n}} \tag{8}$$

where P is the yearly precipitation downscaled from TRMM 3B43, O is the observed precipitation from rain gauge stations, Oi is the mean value of the annual/monthly observed values, I is the station number index, and n is the total number of rain gauge stations. The downscaled results were compared to the rain gauge data first, and then the coefficient of determination (R^2) was determined. If the station data and precipitation product have no correlation, the value will be 0, and vice versa if the correlation is perfect. Second, precision was quantified via b. This shows by how much the actual value is higher or lower than what was observed. Third, the root-mean-squared error (RRMSE) gives a percentage value for the dissimilarity between the estimated and observed values. If the RRMSE is less than 10%, the validation is considered excellent; if it is between 10% and 20%, the validation is good; if it is between 20% and 30%, the validation is acceptable; and if it is more than 30%, the validation is poor [11]. By focusing on highly biased results, the RRMSE test gives a measure of the prediction model error rate. Lastly, when it comes to root-mean-square error (RMSE), smaller values are preferable.

3. Results and Discussion

3.1. NDVI and TRMM Regression

Images from the Tropical Rainfall Survey show that rainfall in the northern and northwestern parts along the Indus Basin is actually much higher, around 1200 mm y^{-1}, than in the central and southeastern regions, around 400 mm y^{-1}. The normalized differential vegetation index essentially exhibited the same example as TRMM precipitation, and an unmistakable spatial resolution connection exists between TRMM and NDVI as shown in Figure 1. The resolution dependence of the normalized distinct vegetation index and the tropical precipitation measurement duty relationship were tested at different resolutions.

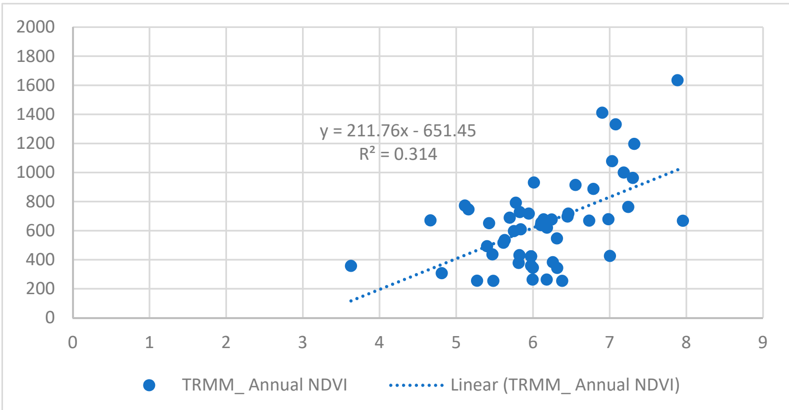

Figure 1. Relationship between NDVI and TRMM.

A consistent exponential relationship at 1 km resolution was demonstrated at these resolutions, showing that an unmistakable relationship between blueness and precipitation exists. The curve shows that the linkages acquired inordinately high NDVI values when the association with dispersed precipitation and water no longer restricted growth. The strongest associations were found in the normalized difference in vegetation index, which varied somewhere between 0.2–0.7, and in precipitation, which varied from 200 to

800 mmy^{-1}. Different functions were tried at a nominal resolution of 25 km, but resulted in a lower R2 value. For the linear function, it was 0.55; for exponential, it was 0.52; and the quadratic polynomial, c was 0.53. The value of the correlation varied with the resolution. The difference vegetation index was normalized in all cases affected by variables, e.g., topography, soil, vegetation type, temperature, irrigation system, and human impact. Using this ideal fit to a smaller degree of determination, we evaluated the neighborhood's precipitation pending a comparative response at the ideal scale. In other words, the degree of greenness, as reflected by the normalized difference vegetation index, is a factor of many different variables, including precipitation.

3.2. Residual Correction

However, after subtracting the modelled TRMM at 25 km from the 3B43 precipitation, several regions had considerable residuals:

$$\mathrm{TRMM} - \mathrm{PTLR} = \Delta\mathrm{T} \tag{9}$$

The other map shows a portion of the precipitation that was not elucidated using only the normalized differential vegetation index. Residues with negative values showed greener areas than expected, specifying rainfall. These negative ranges can have additional water sources (i green has a deep root system). Residual areas with positive values (green) indicate less green than the indicated observed normal precipitation. The abrupt, vegetative low slopes of the sections or ranges of hills with heavy rainfall located in the oversaturation zone of the TRMM-adjusted and normalized Difference Vegetation Index may clarify this residual value. The number of residuals were reduced using the introduction through the internal functions of TRMM (ΔTRMMLR). High-resolution residues were obtained from TRMM using the IDW technique.

3.3. Accurate Precipitation

Final downscaled rainfall was obtained by adding model rainfall at 1 km and residual image at 1 km resolution. The resultant image is shown in Figure 2.

$$\mathrm{PTcorr.} = \mathrm{PTHR} + \Delta\mathrm{THR} \tag{10}$$

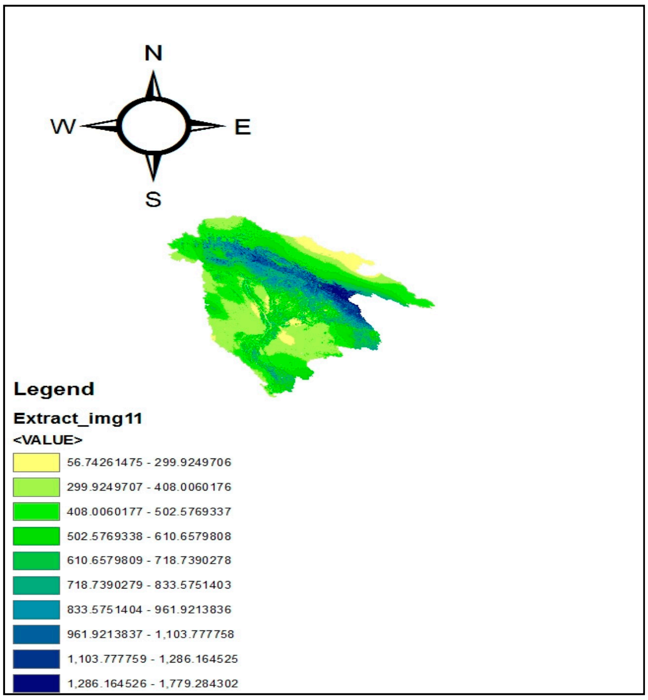

Figure 2. TRMM rainfall at 1 km resolution.

3.4. Validation

Using information from rain gauges, the validity of the proposed method to improve rainfall mapping was accepted. A total of 115 stations across the Indus Basin have complete precipitation records between 2002 and 2011. These stations' data were used in the validation process. Validation indicators were determined after data from the first low-resolution TRMM and the downscaled precipitation value were extracted from the station locations. As shown in Table 1 and Figure 3, the results of the validation showed that the R^2, the bias, and relative root mean square error were significantly improved after applying the downscaling methodology. This downscaling methodology is very promising, and the resulting high-resolution rainfall map was more accurate than the initial TRMM assessment.

Table 1. Original TRMM and final TRMM.

Original TRMM 3B43					TRMM Final			
Year	**Original R^2**	**B**	**RRMSE%**	**RMSE mm**	**Final R^2**	**b**	**RRMSE%**	**RMSE, mm**
2002	0.77	0.95	27.84	71.84	0.81	1.17	19.42	50.11
2003	0.77	0.93	28.83	72.69	0.85	1	16.72	42.16
2004	0.78	0.97	23.19	66.98	0.81	1.07	17.63	50.92
2005	0.82	0.99	23.72	81.46	0.87	1.04	14.45	49.62
2006	0.79	0.87	28.31	79.63	0.82	1.12	8.73	24.56
2007	0.78	0.91	33.44	98.57	0.84	1.09	19.15	56.54
2008	0.75	0.94	32.36	86.01	0.77	1.09	21.7	57.68
2009	0.79	1	25.48	75.4	0.84	1.07	16.07	47.58
2010	0.83	0.97	22.78	67.67	0.87	1.09	23.33	69.3
2011	0.77	0.93	30.66	83.99	0.78	1.17	25.81	70.7
Average	0.78	0.94	27.66	78.42	0.82	1.09	18.3	51.91

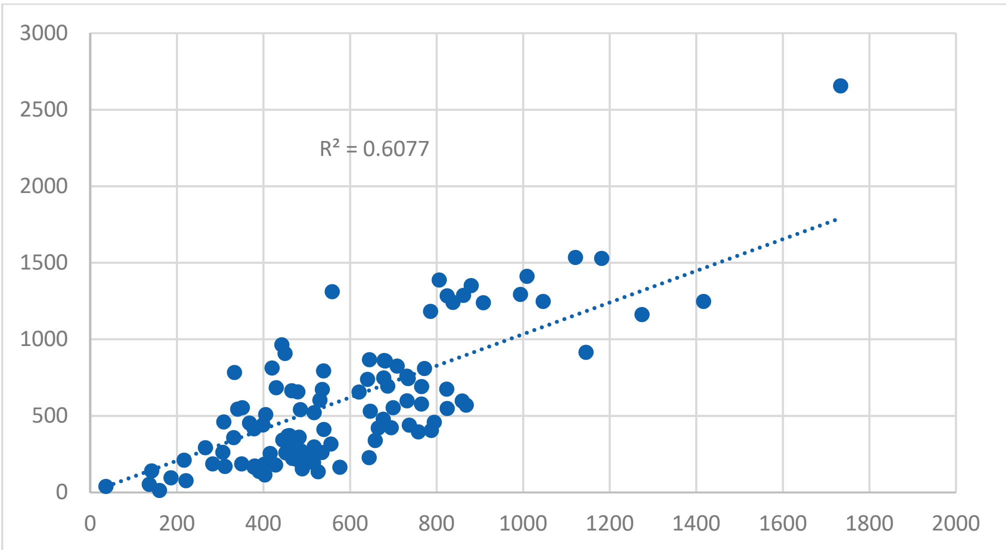

Figure 3. Correlation between downscaled TRMM base on NDVI and rain gauges.

4. Conclusions

Downscaling of the TRMM rain gauge in the Indus River basin was investigated using TRMM 3B43 monthly precipitation products and the NDVI imaging time series from 2002 to 2011. The results of the downscaling method based on a direct scale-dependent relationship between precipitation and NDVI was validated on the precipitation data set. Several conclusions can be drawn from this study:

- This study showed that adopting the degree of vegetation as a substitute for rainfall on an annual basis could boost the geographical resolution and precision of rainfall evaluations.

- The downscaling approach resulted in extremely significant improvements in the accuracy and spatial resolution of the average rainfall from 2003–2011.
- Expanding this method at a higher temporal resolution should be the focus of future research (e.g., regular or month to month).

The primary finding of this study is that the NDVI can be used to improve the spatial resolution of rainfall data from the Tropical Rainfall Measuring Mission (TRMM) in the Indus Basin, and that the approach shown here is universally applicable to other semiarid and dry parts of the world.

5. Recommendation

Further downscaling methods that consider both NDVI and DEM at different spatial (local, national, and global) and higher temporal (weekly and daily) resolutions should be developed in the future. Therefore, it is important to describe the relationship between NDVI and TRMM at various scales (i.e., 75-100 km) and determine the optimal resolution for establishing this relationship. The presented methodology is general in nature and applicable to other semi-arid regions of the world, and in the Indus Basin NDVI can also be used to accurately downscale TRMM precipitation.

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