Long-Term Precipitation Estimates Generated by a Downscaling-Calibration Procedure Over the Tibetan Plateau From 1983 to 2015

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Abstract The World Meteorological Organization stipulates a minimum of 30 years of historical data is needed to obtain meaningful results in climatological research. However, large numbers of studies have explored downscaling approaches based on the TRMM Multi-Satellite Precipitation Analysis (TMPA) data, which span only from 1998 to the present, to obtain the precipitation estimates (~1-km resolution). The main aim of the present study was to develop a new method for obtaining long-term (>30 years) precipitation estimates at ~1-km resolution and to apply that method to a region with complex topography, the Tibetan Plateau. First, PERSIANN-CDR (Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks—Climate Data Record) data were used for downscaling. Considering the characteristics of the PERSIANN-CDR data, a new downscaling-calibration procedure utilizing a combination of a spatial data mining downscaling algorithm (Cubist) and a geographical ratio analysis calibration method was proposed. We found that (1) both the original PERSIANN-CDR data (Bias ~40.79%) and the downscaled results before calibration (Bias ~26.78%) overestimated the precipitation compared with ground observations; (2) the final downscaled results based on the PERSIANN-CDR data after calibration were close to the ground observations (Bias ~5%); (3) compared to the results interpolated based on the PERSIANN-CDR data (E <−1.0), both the downscaling procedure and calibration procedure contributed significantly to the accuracy of the final downscaled results (E ~0.83). These findings suggest that the proposed downscaling-calibration procedure has great potential as an approach for retrieving long-term precipitation estimates (~1-km resolution) over the Tibetan Plateau.

1. Introduction

Precipitation is a vital variable in both meteorological and climatological research, because of its central role in water cycles and energy exchanges (Wentz et al., 2007). Although measuring precipitation is a challenge due to its significant spatial and temporal variability at meteorological scales (Huffman et al., 2007), long-term precipitation estimates with higher quality and finer spatial resolution are essential for many scientific studies and practical applications (e.g., soil science, ecology, water resource research, and climate studies), especially over regions with complex topography (Liu et al., 2016). In soil science, for example, Sanchez et al. (2009) highlighted the need to generate climate variables at finer resolution (e.g., 30/90/1-km scales) to quantitatively predict and map soil properties in relation to carbon cycling and climate change. Long-term precipitation estimates at finer spatial resolutions are also critical to investigating the water balance over the Tibetan Plateau (TP). The TP, which is considered the “water tower of Asia,” is the source of freshwater for five large rivers (the Indus, Ganges, Brahmaputra, Yangtze, and Yellow Rivers) that provide water to >1.4 billion people (Immerzeel et al., 2010). Thus, long-term precipitation data at finer spatial resolutions and with higher accuracy are essential in various fields (Higgins et al., 2007; Karl et al., 1995). Acquiring such data is a particular challenge for the TP, which has relatively few rain gauges because of its geographical location, natural environment, and complex topography (Ma, Xu et al., 2018; Ma, Zhou et al., 2018; Xie &
Xiong, 2011). Therefore, new approaches capable of generating long-term gridded precipitation estimates for this region at finer spatial resolution (~1 km) and with greater accuracy are needed.

Traditional interpolation methods for deriving precipitation estimates are unsuitable for the TP because of the limited number and uneven distribution of rain gauges in the region (McVicar et al., 2007). During the last three decades, various satellite-based projects measuring precipitation have been successfully conducted, including the Global Precipitation Climatology Project (GPCP; Huffman et al., 1997) and the Tropical Rainfall Measurement Mission (TRMM) (Huffman et al., 2007; Kummerow et al., 1998). In addition, a variety of satellite-based precipitation products have been generated, most of which are freely accessible, including GPCP and GPCP-1DD (Adler et al., 2003), CMAP (Xie & Arkin, 1997), TMPA v7 (Huffman et al., 2007), CMORPH (Joyce et al., 2004), PERSIANN (Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks) (Sorooshian et al., 2000), PERSIANN-CCS (Hong et al., 2004), PERSIANN-CDR (Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks—Climate Data Record) (Ashouri et al., 2015), and MSWEP (Multi-Source Weighted-Ensemble Precipitation) (Beck et al., 2017; Beck et al., 2018). Although these products provide much more reliable precipitation information over nongauged areas, their spatial resolution (e.g., 0.1°–2.5°) is too coarse to meet the needs of models and the scientific fields noted above.

Various studies have examined downscaling TMPA data to obtain precipitation estimates; however, those studies only obtained data from 1998 to the present, which is less than the period of 30 years that has been suggested as the minimum required for climatological research (Burroughs, 2003). Notwithstanding, the previous work on downscaling forms a good basis for exploring downscaling approaches capable of providing long-term precipitation estimates with finer spatial resolution and higher quality. Immerzeel et al. (2009) downscaled the TMPA data based on an exponential relationship between precipitation and the normalized difference vegetation index (NDVI) at the annual scale. In a study considering topographical effects, Jia et al. (2011) applied a multiple linear regression (MLR) model between TMPA data and a combination of both NDVI and the digital elevation model (DEM) to obtain the downscaled results. Duan and Bastiaanssen (2013) proposed two calibration methods based on the downscaling methods of Immerzeel et al. (2009) and Jia et al. (2011), and these yielded more accurate downscaled results. Matin and Bourque (2013) selected the “best set” predictor variables and regression parameters for enhancing TMPA data by using correlation and stepwise-regression analysis based on environmental variables (e.g., land surface temperature, DEM, and enhanced vegetation index) together with trigonometric functions of time. Regarding the nonstationary relationship between TMPA data and the NDVI and/or DEM, Xu et al. (2015), Chen et al. (2015), and Chen et al. (2018) used a geographically weighted regression (GWR) method to downscale the TMPA data. In other work in this area, Ma, Shi, et al. (2017) reported that various land surface characteristics (LSCs) were spatially correlated with precipitation to varying degrees, and used a spatial data mining algorithm (termed Cubist) to downscale the TMPA data at the annual scale; their method outperformed traditional downscaling algorithms (e.g., GWR and MLR) over the TP.

The main aim of the present study was to develop a new method for obtaining long-term (>30 years) precipitation estimates at a spatial resolution of ~1 km. The principal objectives of this study were (1) to introduce a new satellite-based precipitation product (PERSIANN-CDR) for downscaling; (2) to evaluate the PERSIANN-CDR data set, using TMPA data and ground observations, over the TP; (3) to provide a new downscaling-calibration procedure for generating long-term downscaled results with reasonable accuracy; and (4) to identify the feasibility of downscaling PERSIANN-CDR data over the TP.

2. Study Area and Materials

2.1. Study Area

The TP is situated in southwestern China and occupies an area of approximately 2.57 million km² (Figure 1). It is the highest and largest plateau (average elevation >4,000 m) outside of the Antarctic and Arctic. Because of its topography and location, the TP is characterized by various climatological conditions and land covers (An et al., 2001). There are three main atmospheric circulation patterns alternately regulating the TP: the Indian monsoon (primarily in summer); the westerlies (mainly in winter); and the East Asian monsoon, which influences the eastern border (Yao et al., 2012). Different atmospheric circulation systems carrying differing amounts of water vapor form the seasonal spatial precipitation patterns. For instance,
approximately 90% of the total annual precipitation occurs in the southeastern TP in the wet season (from March to August), while in the northwestern TP the main precipitation occurs in winter, influenced by the westerlies (Shen et al., 2011; Shi et al., 2015). Based on TMPA data from 1998 to 2013, precipitation over the TP has followed different trends having clear spatially heterogeneous characteristics. For example, along the southern Himalayas the annual precipitation has decreased by more than 20 mm/year, while from the west of India to eastern Pamir the rate of annual precipitation has increased by >20 mm/year (Ma, Xu, et al., 2018). Because of the significant increase in the occurrence of extreme precipitation events in the Yarlung Zangbo River Basin from 1958 to 2010 (~43.0%), Fan et al. (2018) noted the potential for an increase in flood disasters (runoff), particularly in the eastern part of the middle reaches and the southern part of the lower reaches. Wang et al. (2017) reported that in the eastern TP annual runoff from 2003 to 2014 increased markedly in the dry part but decreased in the wet part, mainly because of changes in precipitation. In terms of air temperature, from 1982 to 2000 the warmest and coldest months were July (up to ~15°C) and January (as low as ~−7°C), respectively (Zhong et al., 2011). Different climatic zones of the TP are characterized by particular land covers including forests, shrublands, and grasslands, with grasslands (e.g., meadows and steppes) occupying ~70% of the TP, mainly in the central and eastern parts (Piao et al., 2011; Shen et al., 2011).

2.2. Materials
2.2.1. Ground Observations
Point-based ground observations of precipitation were obtained from the Chinese Meteorological Data Sharing Service System (http://cdc.nmic.cn/home.do). Data for 107 meteorological stations were collected, although the numbers of working rain gauges varied over the period 1983 to 2015. For each year, only data from rain gauges that collected data continuously throughout the year were used. The rain gauges were sparsely and irregularly located because of the geographical location and natural environment of the TP (Figure 1).

2.2.2. PERSIANN-CDR
The PERSIANN-CDR was developed by the Center for Hydrometeorology and Remote Sensing. This provided a consistent daily precipitation data set comprising long-term precipitation estimates (0.25°; 60°S–60°N; 30+ years; 1 January 1983 to 31 December 2015) at a resolution of 0.25° (www.ncdc.noaa.gov/cdr/operationalcdrs.html) (Ashouri et al., 2015). PERSIANN-CDR data were generated based on an artificial
neural network (ANN) algorithm (Sorooshian et al., 2000) to meet the demand for a consistent and long-term precipitation data set for use in various fields. The main procedures for generating the PERSIANN-CDR were as follows: (1) the National Centers for Environmental Prediction stage IV hourly precipitation data were used to pretrain the parameters of the ANN model, which were then kept fixed while the model was run for the full historical record of the Infrared (IR) data (the archive of global IR data is available through the International Satellite Cloud Climatology Project); and (2) 2.5° monthly GPCP precipitation data were used to reduce the biases of the PERSIANN-estimated precipitation at high tempospatial resolutions, and the bias-corrected PERSIANN precipitation estimates were called the PERSIANN-CDR data (for Climate Data Record) (Ashouri et al., 2015).

2.2.3. TMPA Data
The TRMM was launched by the National Aeronautics and Space Administration and Japan Aerospace Exploration Agency in 1997 (Kummerow et al., 1998), and the TMPA data are considered to be the “best” precipitation products in the TRMM era (1998 to 2015), especially the TMPA v7 data (Ma, Shi, et al., 2017; Ma, Zhou, et al., 2017). Therefore, the TMPA 3V43 V7 data (0.25°/monthly; 50°N–50°S) were selected for comparison with PERSIANN-CDR data; the TMPA 3B43 V7 data are freely accessible from http://mirador.gsfc.nasa.gov (Huffman et al., 2007).

2.2.4. Vegetation Data
The NDVI has been widely used to monitor vegetation productivity and has been shown to be strongly correlated with the volume, frequency, and spatial distribution of precipitation (Iwasaki, 2009; Xiao & Moody, 2004). In this study we obtained NDVI data from a remote sensing data set (the Global Inventory Monitoring and Modeling System: GIMMS-NDVI3g; July 1981 to December 2015) derived from advanced very high resolution radiometer (AVHRR) sensors on board the National Oceanic and Atmospheric Administration (NOAA) satellites. Using comparisons with Landsat images, Beck et al. (2011) showed that the GIMMS-NDVI3g data were the most suitable AVHRR data set for assessing temporal changes and had reasonable accuracy in terms of absolute values. The newest version of GIMMS-NDVI3g data was released with a resolution of 1/12° (approximately 8 km)/15 days (https://ecocast.arc.nasa.gov/data/pub/gimms/).

2.2.5. Topographical Characteristics
The DEM from Shuttle Radar Topography Mission was used as the basic topographical data in this study (Rodriguez et al., 2006). The DEM data (~90 m) for the TP were obtained from http://www.gscloud.cn/. Other related topographical characteristics were based on the DEM data, including slope, aspect, curvature, radiation, slope-length and steepness (LS), topographic wetness index (TWI), multiresolution valley bottom flatness index (MrVBF), and the terrain ruggedness index (Ma, Shi, et al., 2017).

2.2.6. Land Surface Air Temperature Data
It is difficult to obtain long-term (1983 to present) land surface temperature data at reasonable resolution. Therefore, in this study we used the GHCN_CAMS Gridded 2m Temperature (Land; 0.5°/monthly) data, which provided global land surface air temperatures from 1948 to 2015 (https://www.esrl.noaa.gov/psd/data/gridded/data.ghcncams.html). This data set is unique in at least two aspects: (1) it uses as its source two large data sets from the Global Historical Climatology Network (GHCN) and Climate Anomaly Monitoring System (CAMS), and (2) it was generated by applying optimal interpolation algorithms, specifically the anomaly interpolation approach (Fan & Dool, 2008).

3. Methods
3.1. The Downscaling-Calibration Procedure to Obtain Downscaled Results Based on PERSIANN-CDR Data for the TP
Cubist uses a divide-and-conquer strategy to recursively divide the vector of independent variables into unique subgroups and develops rule-based linear models in each subgroup, with each group defined as a distinct path using a classification tree (Quinlan, 1992). Ma, Shi, et al. (2017) first used it as a spatial data mining algorithm to downscale TMPA 3B43 data over the TP. There are three main features of Cubist: (1) it allows the entire region to be divided into a number of distinct subregions, on the basis of the geographical similarities of the LSCs in each subregion; (2) for each subregion, a MLR model is built based on a stepwise regression strategy, which is very useful for determining the optimal combination of independent variables representing the spatially varying relationships; and (3) to explain the dependent variable (in this study the satellite-based precipitation estimates), the selected independent variables (e.g., NDVI and DEM) in
the corresponding MLR model are ranked by decreasing importance in the linear models, which reveals the importance of each selected independent variable in the corresponding subregion. Ma, Shi, et al. (2017) provide detailed instructions on the use of Cubist to downscale TMPA data.

Geographical differential analysis and geographical ratio analysis (GRA) are the two most common calibration approaches (Cheema & Bastiaanssen, 2012; Duan & Bastiaanssen, 2013). Ma, Zhou, et al. (2018) used the GRA method to calibrate TMPA 3B43 data following removal of anomalies and demonstrated that acceptable accuracy was achieved. In contrast, the geographical differential analysis can result in some pixels having negative values in the calibrated downscaled results. Hence, the GRA algorithm was used in this study to calibrate the downscaled annual precipitation estimates.

### 3.2. Main Downscaling Procedures

First, Cubist was used to downscale PERSIANN-CDR data for 1983 to 2015 over the TP, in combination with the selected environmental variables. This was followed by GRA calibration to obtain precipitation estimates at a resolution of ~1 km with reasonable accuracy. The seven main sequential procedures used to obtain the final downscaled results based on the downscaling-calibration procedure were as follows:

1. The basic assumption in downscaling the PERSIANN-CDR data was that the LSCs were correlated with precipitation at various scales, while some land cover types were not (e.g., snow and water bodies). Hence, the pixels representing snow and water bodies were removed from the original LSC data sets. For example, the pixels having NDVI (8 km) values <0 were first removed. Because of errors in the satellite-based product (e.g., GIMMS), some regions covered by lakes had NDVI values >0. In these cases, information from other LSCs was used to eliminate the NDVI pixels showing no response to precipitation (e.g., the value of Aspect over water bodies is always −1.0). Consequently, the reserved NDVI pixels (~8 km) were resampled to those at the resolution of ~1 km using the nearest-neighbor sampling strategy. Figure 2 shows the spatial pattern of the average NDVI values over the TP from 1983 to 2015 at ~1 km. Additionally, a NDVI data set at 0.25° resolution was generated by aggregating the original GIMMS NDVI3g data at 1/12° resolution.

2. As the NOAA GHCN_CAMS Land Surface Air Temperature (LSAT) data are too coarse to use nearest-neighbor sampling to obtain LSAT data at ~1 km resolution, we used inverse distance weighting (IDW) to interpolate the LSAT data to ~1-km resolution from 0.5°. The nearest-neighbor sampling method was also used to generate the LSAT data at 0.25° resolution based on the original LSAT data at 0.5°.

3. The other land topography data sets with the original resolution of ~90 m were aggregated to the corresponding data sets at ~1- and ~25-km resolution. The PERSIANN-CDR data (the dependent variable) and the LSCs (the independent variables) for corresponding pixels were then used to generate the Cubist models at a resolution of 0.25°.

4. The Cubist models representing the relationships between the PERSIANN-CDR data and related LSCs at 0.25° were then applied to the corresponding LSCs at ~1-km resolution to obtain the primary downscaled estimates of precipitation. The Cubist models consisted of a set of rules (e.g., MLR models) and the corresponding samples based on which each MLR model was generated. In this case the samples with spatial information from all rules could be labeled separately as the various subregions, which is potentially useful for investigating the nonstationary characteristics.

5. The downscaled results from Step 4 were interpolated into precipitation estimates for the entire region at ~1-km resolution, enabling the pixels eliminated in Step 1 to be filled. At this point, the downscaled results before calibration had been acquired.

6. Because of the influence of the PERSIANN-CDR data, the downscaled results at this stage overestimated the precipitation relative to ground observations. Therefore, a combination of calibration procedures was performed. To improve the downscaled results, we separated the rain gauges into two groups (calibration and validation gauges, in a ratio of ~2:1), taking into account both their locations and the rainfall volumes at those locations (Figure 1).

7. To calibrate the downscaled results using GRA, we first computed the ratio \( \frac{P_{\text{point ratio}}}{P_{\text{uncal}}^{\text{DSCDR}}} \) between the rain gauges (RGS) and the corresponding pixels for the uncalibrated downscaled results \( P_{\text{uncal}}^{\text{DSCDR}} \) obtained in Step 4, using equation (1):
We then produced the 1-km pixel ratio map \( \left( P_{\text{ratio}}^\text{1km} \right) \) using the IDW based on point values \( \left( P_{\text{point}}^\text{ratio} \right) \) (Duan & Bastiaanssen, 2013). Finally, the downscaled results after calibration using the GRA method \( \left( P_{\text{cal-GRA}}^\text{1km} \right) \) were obtained by multiplying the \( P_{\text{uncal-1km}}^\text{DS-CDR} \) value by the interpolated results of the ratio \( P_{\text{ratio}}^\text{1km} \) (equation (2)):

\[
P_{\text{cal-GRA}}^\text{1km} = P_{\text{uncal-1km}}^\text{DS-CDR} \times P_{\text{ratio}}^\text{1km}
\]

The overall process for downscaling the PERSIANN-CDR data is shown as a flowchart in Figure 3.

3.3. Validations

Ground observations made at independent rain gauges were used to validate the gridded precipitation data sets. Five diagnostic indices were used: mean absolute error (MAE), root mean square error (RSME), coefficient of determination \( (R^2) \), Bias, and the Nash-Sutcliffe coefficient \( (E) \) (Adebesin et al., 2018).

4. Results

4.1. Comparison of PERSIANN-CDR and TMPA Data at the Annual Scale

TMPA data provide the “best” precipitation estimates in the TRMM era. Comparisons of the PERSIANN-CDR (from 1983 to 2015) and TMPA 3B43 (from 1998 to 2015) data with ground observations over the TP are shown in Figure 4. Although the PERSIANN-CDR data provided consistent satellite-based precipitation estimates, their accuracy was less than that of the TMPA data in terms of the \( R^2 \), MAE, RSME, and Bias indices. The \( R^2 \) for the PERSIANN-CDR data (~0.45) was much lower than that for the TMPA data (~0.67), and both the MAE and RMSE for the PERSIANN-CDR data (~250.61 and ~325.28 mm/year, respectively) were larger than those for the TMPA data (~135.27 and ~201.42 mm/year, respectively). The TMPA data overestimated precipitation by approximately 22.61%, but overestimation based on the PERSIANN-CDR data was significantly higher (Bias ~40.79%). One interesting finding was that the accuracy of the PERSIANN-CDR data was relatively close to that for the TMPA data for the years prior to 1998 (1996 and

\[
P_{\text{point}}^\text{ratio} = \frac{\text{RGS}}{P_{\text{uncal-1km}}^\text{DS-CDR}} \quad (1)
\]
especially in terms of Bias (Figure 4d). The PERSIANN-CDR data generally overestimated precipitation to a much greater extent than did the TMPA data, relative to ground observations over the TP. As the PERSIANN-CDR and TMPA data are both satellite-based precipitation products with the same spatial resolution (0.25°), they were compared spatially at the annual scale from 1998 to 2015. The general spatial patterns of precipitation over the TP captured by both data sets were similar, and there was no obvious anomaly in the PERSIANN-CDR data.

To further investigate the results, the PERSIANN-CDR and TMPA data were compared based on the average values for 1998–2015 in the TRMM era (Figure 5). For the TP, the PERSIANN-CDR and TMPA data were similar in terms of Bias (~8.08%). However, there was a significant difference centered around precipitation of approximately 1,000 mm/year. For regions where TMPA showed precipitation <1,000 mm/year, the PERSIANN-CDR data overestimated the precipitation relative to the TMPA data (Bias ~20%), but where the TMPA data showed precipitation >1,000 mm/year, the PERSIANN-CDR data significantly underestimated the precipitation relative to the TMPA data (Bias ~−30%). The PERSIANN-CDR data generally correlated reasonably well with the TMPA data ($R^2 \sim 0.60$), especially in regions where the TMPA values were <1,000 mm/year ($R^2 \sim 0.83$). However, these two data sets showed significant noncorrelation in regions where the TMPA data were >1,000 mm/year ($R^2 \sim 0.17$).

4.2. Downscaled Results Based on the PERSIANN-CDR Data 1983–2015

The PERSIANN-CDR data were generally captured well at the annual scale from 1983 to 2015 using Cubist models and various LSCs, with the four indices for this period having values of $R^2 \sim 0.94$, MAE ~60.84

Figure 3. Flowchart of the process for downscaling the PERSIANN-CDR data from 1983 to 2015, over the TP.
mm/year, RMSE ~89.55 mm/year, and Bias ~0.20%. In this study we used the downscaling procedure for the year 1987 as an example. Table 1 shows the fitting functions and the corresponding $R^2$ values for the various subregions. As a data mining algorithm, Cubist generated a set of linear models having differing combinations of land surface variables and was based on the assumption of a nonstationary relationship.

**Figure 4.** Validation of the PERSIANN-CDR and TMPA 3B43 v7 data using (a) $R^2$, (b) MAE, (c) RMSE, and (d) Bias against ground observations over the TP from 1983 to 2015.
between precipitation and LSCs. A number of linear models (12) were selected for the year 1987, based on model accuracy and robustness. In each subregion, the number and kinds of LSCs were determined according to the stepwise regression strategy. The NDVI was most important in rule 4, LSAT in rules 7

Table 1

| Region | Linear models |
|---|---|
| 1 | $-259.52 + 1.85 \times \text{Rugg} + 619.0 \times \text{NDVI} + 8.5 \times \text{LSAT} + 30.0 \times \text{MrVBF} + 0.03 \times \text{DEM} + 0.00024 \times \text{Radi} (R^2 = 0.85)$ |
| 2 | $1227.83 - 185.0 \times \text{MrVBF} + 0.16 \times \text{DEM} + 13.1 \times \text{LSAT} - 4.8 \times \text{Aspect} - 0.65 \times \text{Rugg} + 6.5 \times \text{Slope} + 285.0 \times \text{NDVI} - 3.0 \times \text{TWI} (R^2 = 0.81)$ |
| 3 | $3018.31 - 331.0 \times \text{TWI} + 239.0 \times \text{MrVBF} + 0.37 \times \text{DEM} + 39.9 \times \text{LSAT} + 641.0 \times \text{NDVI} - 0.00219 \times \text{Radi} (R^2 = 0.86)$ |
| 4 | $731.45 + 969.0 \times \text{NDVI} - 0.00113 \times \text{Radi} + 0.051 \times \text{DEM} - 26.0 \times \text{TWI} + 24.0 \times \text{MrVBF} + 0.39 \times \text{Rugg} + 2.6 \times \text{LSAT} - 0.6 \times \text{Slope} (R^2 = 0.91)$ |
| 5 | $2715.46 + 506.0 \times \text{MrVBF} - 386.0 \times \text{TWI} - 2.01 \times \text{Rugg} + 0.0034 \times \text{Radi} - 0.14 \times \text{DEM} + 511.0 \times \text{NDVI} + 28.0 \times \text{LSAT} (R^2 = 0.99)$ |
| 6 | $739.88 - 96.0 \times \text{TWI} + 0.17 \times \text{DEM} + 631.0 \times \text{NDVI} + 67.0 \times \text{MrVBF} + 11.5 \times \text{LSAT} - 0.00087 \times \text{Radi} + 1.7 \times \text{Slope} + 0.1 \times \text{Rugg} (R^2 = 0.82)$ |
| 7 | $-272.44 + 36.2 \times \text{LSAT} - 0.28 \times \text{DEM} + 795.0 \times \text{NDVI} + 1.29 \times \text{Rugg} + 28.0 \times \text{MrVBF} - 0.00093 \times \text{Radi} - 25.0 \times \text{TWI} + 4.0 \times \text{Slope} - 5.0 \times \text{LS} + 0.5 \times \text{Aspect} (R^2 = 0.89)$ |
| 8 | $-1498.33 + 0.46 \times \text{DEM} + 223.0 \times \text{MrVBF} + 2.24 \times \text{Rugg} - 0.0026 \times \text{Radi} + 7.1 \times \text{Aspect} + 15.1 \times \text{LSAT} + 408.0 \times \text{NDVI} + 6.0 \times \text{LS} (R^2 = 0.91)$ |
| 9 | $1682.24 + 15.9 \times \text{LSAT} - 0.0036 \times \text{Radi} + 823.0 \times \text{NDVI} + 43.0 \times \text{LS} + 0.15 \times \text{DEM} + 23.0 \times \text{MrVBF} + 0.18 \times \text{Rugg} + 0.5 \times \text{Slope} (R^2 = 0.75)$ |
| 10 | $2365.52 - 0.0029 \times \text{Radi} + 14.9 \times \text{Slope} + 1.3 \times \text{Rugg} + 25.0 \times \text{LS} - 0.08 \times \text{DEM} - 8.0 \times \text{TWI} + 3.0 \times \text{MrVBF} (R^2 = 0.79)$ |
| 11 | $1514.55 - 0.48 \times \text{DEM} + 34.9 \times \text{LSAT} + 38.0 \times \text{LS} + 87.0 \times \text{NDVI} + 1.0 \times \text{Aspect} + 9.0 \times \text{MrVBF} - 9.0 \times \text{TWI} (R^2 = 0.82)$ |
| 12 | $6550.65 - 0.0089 \times \text{Radi} - 253.0 \times \text{TWI} + 234.0 \times \text{MrVBF} + 0.27 \times \text{DEM} + 1.6 \times \text{Slope} + 1.8 \times \text{LSAT} (R^2 = 0.93)$ |

Note. GIMMS-NDVI3g, GHCN_CAMS Gridded 2m Temperature, digital elevation model, aspect, slope, topographic wetness index, multiresolution valley bottom flatness index, slope-length and steepness, radiation, and terrain ruggedness index were termed as NDVI, LSAT, DEM, Aspect, Slope, TWI, MrVBF, LS, Radi, and Rugg, respectively.
and 9, and the topographical variables were important in the other linear models. The values of $R^2$ also varied among linear models representing different subregions (from ~0.75 to ~0.96).

The data sets with spatial coordinates were also separated into subgroups, based on which linear models were generated. The $R^2$ values for each of these linear models were determined (Figure 6) using the IDW interpolating algorithm, from 0.25° to ~1 km resolution. Figure 6 shows the spatial patterns of the $R^2$ values between the PERSIANN-CDR data and their corresponding predicted values for the various subregions over the TP for the year 1987. The $R^2$ values also varied spatially, with larger values in the southeastern and northeastern TP but relatively smaller values in the northwest and southwest.

Although the PERSIANN-CDR data could be significantly captured by the Cubist models and the LSCs, the PERSIANN-CDR data demonstrated limited accuracy when compared to ground observations. Therefore, we applied a calibration procedure on the downscaled results. To clearly demonstrate the different contributions of the downscaling procedure and calibration procedure, the PERSIANN-CDR data were also directly interpolated into the precipitation estimates (~1 km), which were then calibrated by the same calibration procedure as was applied to the downscaled results. Figure 7 shows the spatial patterns of the original PERSIANN-CDR data, the downscaled results based on PERSIANN-CDR data before calibration, the downscaled results based on PERSIANN-CDR data after calibration, the results interpolated based on the PERSIANN-CDR data before calibration, and the results interpolated based on the PERSIANN-CDR data after calibration, in the year 1987. The results show that the original PERSIANN-CDR data and the downscaled results shared similar spatial patterns, but the downscaled results provided much more detailed information than did the original PERSIANN-CDR data, and the calibrated downscaled results showed differences at the regional/local scales. The spatial patterns of the results interpolated based on the PERSIANN-CDR data before calibration were very similar with those of the original PERSIANN-CDR, while the results interpolated based on the PERSIANN-CDR data after calibration demonstrated obvious features resulting from the calibration of the data using ground observations.

The average precipitation over the TP in 1987 based on the PERSIANN-CDR data was 483.54 mm/year (standard deviation ~402.86 mm/year), which was similar to the downscaled result before calibration (average...
value $\sim 498.62$ mm/year; standard deviation $\sim 388.45$ mm/year). However, after calibration based on ground observations, the average value decreased to 383.42 mm/year (standard deviation $\sim 345.39$ mm/year). The average value of the results interpolated based on the PERSIANN-CDR data before calibration was around 483.36 mm/year (standard deviation $\sim 400.25$ mm/year), very close to that of the original PERSIANN-CDR, whereas the corresponding average value after calibration was around 379.35 mm/year (368.41 mm/year).

Although both the original PERSIANN-CDR data and the downscaled results shared similar spatial patterns and general trends, with the precipitation volume decreasing from the southeastern to northwestern TP, the

Figure 7. The spatial distributions of (a) the original PERSIANN-CDR data; (b) the downscaled results based on PERSIANN-CDR data before calibration; (c) the downscaled results based on PERSIANN-CDR data after calibration, (d) the results interpolated based on PERSIANN-CDR before calibration, and (e) the results interpolated based on PERSIANN-CDR after calibration, in the year 1987 over the TP.
average values and the standard deviations were significantly different. The average values (standard deviations) for the PERSIANN-CDR data and the downscaled results before calibration were almost the same but were significantly greater than the average values for the downscaled results after calibration based on ground observations. The spatial patterns of the original PERSIANN-CDR data and the downscaled results based on PERSIANN-CDR data were very similar to those of TMPA data and the downscaled results based on TMPA data, respectively (Ma, Shi, et al., 2017). This indicates that it was reasonable to downscale the PERSIANN-CDR data from 1983 to 2015.

Figure 8 shows the ability of the downscaling-calibration procedure to capture wet and dry years, the variation in average values of the PERSIANN-CDR data, the downscaled results both before and after calibration, and the ground observations. First, the trends in the average values of the PERSIANN-CDR data were highly correlated with those of the ground observations, which indicates that the PERSIANN-CDR data reflected the characteristics in dry and wet years. Second, the average values of the downscaled results before calibration were similar to but less than those of the original PERSIANN-CDR data. Third, in a result attributable to the use of calibration against ground observations, the average values of the downscaled results after calibration were significantly lower than those of the original PERSIANN-CDR data, the downscaled results before calibration, and ground observations. As noted above, the downscaled results both before and after calibration, as well as the original PERSIANN-CDR data, were consistent with the ground observations, in terms of the long-term variations of average values.

4.3. Validation of the PERSIANN-CDR Data and the Downscaled Results Based on Ground Observations

The PERSIANN-CDR data, the downscaled results both before and after calibration, and the results interpolated based on PERSIANN-CDR data before and after calibration were independently assessed against rain gauge observations (Figure 9). The Nash-Sutcliffe coefficient \(E\), which ranges from \(-\infty\) to 1, was used to assess these precipitation estimates, with \(E = 1\) implying perfect alignment between the predicted and observed data. The \(E\) values of the original PERSIANN-CDR data and the results interpolated directly from the PERSIANN-CDR data were very similar and both less than \(-1.0\), while the downscaled results before calibration show an improved \(E\) value of \(-0.08\). This indicates that direct interpolation based on the original PERSIANN-CDR data did not improve the quality of itself, whereas the downscaling procedure did enhance the quality. Among all of the data examined, the downscaled results after calibration showed the largest \(E\) value (~0.83), indicating that the calibration procedure did not mainly guarantee the accuracy of the final results. The original PERSIANN-CDR data significantly overestimated the precipitation by approximately 50% (Bias ~44.65%), and the errors were relatively large (MAE ~246.66 mm/year; RMSE ~322.59 mm/year). Similar results were obtained for the data obtained by interpolation based the PERSIANN-CDR data before calibration (Bias ~44.34%, MAE ~244.67 mm/year; RMSE ~320.46 mm/year). Although the downscaled results before the calibration procedure (generated by a combination of Cubist and LSCs) were improved (e.g., the \(R^2\) value increased from 0.50 to 0.60), they still overestimated the precipitation (Bias ~27.33%) and were associated with relatively large errors (MAE ~183.25 mm/year; RMSE ~235.11 mm/year),
This may have been caused by the strong simulated capabilities of the combination of the Cubist model and the selected LSCs on the PERISANN-CDR data for the TP at the annual scale from 1983 to 2015. However, the performance of the downscaled results after calibration was greatly improved (Figure 9c). The downscaled results after calibration showed strong correlation ($R^2 \sim 0.84$), were associated with reduced errors (MAE $\sim 81.05$ mm/year; RMSE $\sim 99.97$ mm/year), and were very similar to the ground observations (Bias $\sim 4.19\%$), which outperformed the results interpolated based on the PERISANN-CDR data after calibration (Bias $\sim 15.78\%$, MAE $\sim 129.74$ mm/year; RMSE $\sim 170.75$ mm/year). As reported by Duan and Bastiaanssen (2013), the gridded precipitation estimates with finer spatial resolution were comparable.

Figure 9. Scatterplot of validations based on ground observations against (a) the original PERSIANN-CDR data; (b) the downscaled results based on the PERSIANN-CDR data before calibration; (c) the downscaled results based on the PERSIANN-CDR data after calibration; (d) the results interpolated based on PERSIANN-CDR before calibration; and (e) the results interpolated based on PERSIANN-CDR after calibration, over the TP from 1983 to 2015.
with point-based ground observations (e.g., rain gauge data). Thus, the calibration procedure was conducted on the downscaled results at a finer spatial resolution (~1 km), not directly on the original PERSIANN-CDR data. Additionally, the downscaled results based on PERSIANN-CDR data after calibration showed spatial distributions similar to those based on TMPA data from 2000 to 2013 (Ma, Shi, et al., 2017).

The results of the validation of the five data sets against ground observations over the TP at the annual scale are shown in Figure 10. The validated data sets include (i) the original PERSIANN-CDR data; (ii) the downscaled results based on the PERSIANN-CDR data both before and after calibration (1983 to 2015), the TMPA data from 1998 to 2015, and the downscaled results based on TMPA data for 2000 to 2013 (Ma, Shi, et al., 2017). (a) $R^2$, (b) MAE, (c) RMSE, and (d) Bias.

**Figure 10.** Correlation statistics of ground observations over the TP at the annual scale with the original PERSIANN-CDR data, the downscaled results based on the PERSIANN-CDR data both before and after calibration (1983 to 2015), the TMPA data from 1998 to 2015, and the downscaled results based on TMPA data for 2000 to 2013 (Ma, Shi, et al., 2017). (a) $R^2$, (b) MAE, (c) RMSE, and (d) Bias.
showed improved correlation (average $R^2$ ~0.60; range ~0.43 to ~0.72), and this was similar to the correlation of the TMPA data (average $R^2$ approximately 0.67; range ~0.45 to ~0.78). The $R^2$ values of the PERSIANN-CDR data, the TMPA data, and the downscaled results based on the PERSIANN-CDR data before calibration based on ground observations were less than those of the downscaled results based on the TMPA data (average $R^2$ ~0.74; range ~0.63 to ~0.80). In addition, the downscaled results based on the PERSIANN-CDR data after calibration showed the highest correlation with the ground observations (average $R^2$ ~0.84; range ~0.72 to ~0.91).

The trends in the $R^2$ values were similar to those of the error measures (MAE and RMSE). The PERSIANN-CDR data had the largest errors (average MAE ~250 mm/year and a range of 161.65–322.68 mm/year; average RMSE ~325.28 mm/year and a range of 229.88–409.68 mm/year). Additionally, the MAE and RMSE of the downscaled results based on PERSIANN-CDR before calibration decreased to ~184.21 mm/year (range 122.13–236.22 mm/year) and ~234.51 mm/year (range 145.67–295.79 mm/year), respectively. The errors for the TMPA data were smaller than those for the downscaled results based on the PERSIANN-CDR data before calibration (average MAE ~135.27 mm/year and range 107.72–196.28 mm/year; average RMSE ~201.91 mm/year and range 160.49–271.91 mm/year). Similarly, the downscaled results based on the TMPA data for the TP from 2000 to 2013 were an improvement on the original TMPA data and had finer spatial resolution and greater accuracy (e.g., average MAE ~113.19 mm/year and range 92.66–134.71 mm/year; average RMSE ~151.64 mm/year and range 115.14–179.05 mm/year). The errors for the downscaled results based on the PERSIANN-CDR data after calibration were the smallest among the five gridded precipitation data sets (average MAE ~79.82 mm/year and range 66.43–97.02 mm/year; average RMSE ~97.66 mm/year and range 82.99–112.94 mm/year).

The Bias values for the five data sets were also significantly different. The original PERSIANN-CDR data showed the greatest overestimation (average Bias ~40.79%; range 22.69–55.51%). The average Bias for the downscaled results based on the PERSIANN-CDR data before calibration decreased to approximately 26.77% (range 8.39–40.04%) but was still greater than that for the TMPA data (average Bias ~22.61%; range 16.57–29.27%) and the downscaled results based on the TMPA data (average Bias ~12.59%; range 6.69–18.16%). However, after calibration of the downscaled results based on the PERSIANN-CDR data, the average Bias was ~4.57% (range 3.55% to 14.43%).

5. Discussion

5.1. Advantages and Limitations of the Downscaling Algorithm

Various algorithms have been proposed for downscaling TMPA data from 0.25° to ~1-km resolution. These can be classified into two families: linear models and nonlinear models. Nonlinear models include simple exponential and polynomial relationships, GWRs (Duan and Bastiaanssen, 2013; Immerzeel et al., 2009; Xu et al., 2015), and data mining and artificial intelligence (AI)-based algorithms (e.g., ANN, Support Vector Machine (SVM), and random forest [RF]) (Shi & Long, 2015; Zhang et al., 2018). The AI-based algorithms (e.g., RF) generally outperform the linear and exponential models (Shi & Long, 2015), while for mountainous regions the GWR outperforms the AI-based ANN model (Zhang et al., 2018).

Compared with other AI-based algorithms (ANN, SVM, and RF), the Cubist approach to downscaling coarse satellite-based precipitation data provides various advantages including the following: (1) the models generated by Cubist are interpretable and (2) its use effectively avoids overfitting the dependent variable, which provides the option for users to define the number of linear models. Therefore, in this study we used the state-of-the-art Cubist algorithm to downscale the PERSIANN-CDR data for the TP.

However, use of this downscaling algorithm has limitations. First, the number of linear models is decided by the researcher when the Cubist models are built. Although in the present work the MAE index was used to determine the optimal number of linear models based on a 10-fold cross-validation strategy (Ma, Shi, et al., 2017), this approach may not be the only method for finding the “optimal” number; hence, the method used to determine the number of subregions remains an open topic that should be further investigated. Second, the downscaling algorithm was suitable for downscaling the PERSIANN-CDR data at the annual scale but not at the monthly scale because of the existence of spatially varying monthly lags of the NDVI in response...
to monthly precipitation. In addition, the PERSIANN-CDR data could not be downscaled for regions where the precipitation had no relationship with the LSCs (e.g., water bodies, snow covered areas, roads, and roofs).

5.2. Rationale for Using the Combination of Downscaling and Calibration of the PERSIANN-CDR Data With Ground Observations to Acquire the Final Downscaled Results

Although the PERSIANN-CDR data were well captured by the Cubist models and the LSCs, the downscaled results based on the PERSIANN-CDR data before calibration still overestimated the precipitation relative to ground observations, because of the significant overestimation in the PERSIANN-CDR data itself. Xu et al. (2015) noted that the accuracy of downscaled precipitation estimates has a strong positive relationship with that of the original TMPA data. After evaluating the PERSIANN-CDR data (from 1983 to 2015) against the TMPA data (from 1998 to 2015) and ground observations (from 1983 to 2015), we found that the PERSIANN-CDR data overestimated the precipitation more significantly than did the TMPA data. Therefore, the relationships between the quality of downscaled results based on the PERSIANN-CDR before calibration and that of the original PERSIANN-CDR data were also explored in this study. Figure 11 shows that the quality of the downscaled results based on the PERSIANN-CDR before calibration relied greatly on the quality of the original PERSIANN-CDR data. As PERSIANN-CDR data significantly overestimated precipitation estimates, the downscaled results based on the original PERSIANN-CDR data required the calibration procedure be used to provide precipitation estimates with both finer spatial resolution and higher accuracy.

Figure 11. The relationships between the quality of downscaled results based on the PERSIANN-CDR data before calibration and that of the PERSIANN-CDR data against ground observations from 1983 to 2015. (a) $R^2$, (b) MAE, (c) RMSE, and (d) Bias.
Calibrating the satellite-based precipitation measurements using ground observations could greatly improve the accuracy of these products (Cheema & Bastiaanssen, 2012). Because of the significant discrepancies in spatial scales between the PERSIANN-CDR data and data from point-based rain gauges, the combination of a calibration procedure using ground observations after downscaling the PERSIANN-CDR data was an optimum approach to obtaining precipitation estimates at finer spatial resolution (~1 km) and with reasonable accuracy for the period 1983 to 2015.

5.3. Usability of GIMMS-NDVI3g and LSAT for Downscaling the PERSIANN-CDR Data Over 30 Years

Although NDVI data are accessible from Moderate Resolution Imaging Spectroradiometer (MODIS) at 1-km resolution, a disadvantage of these data in the present study was their limited temporal span (from 2000 to present), which did not extend to the period from 1983 to 2000. Therefore, the GIMMS-NDVI3g data at 8-km resolution were used to downscale the PERSIANN-CDR data. The spatial patterns of (a) the average reserved NDVI from 2000 to 2015 at 1-km resolution from MODIS and (b) the average reserved NDVI from 1983 to 2015 at 1-km resolution from GIMMS-NDVI3g data using the nearest-neighbor sampling method for the TP (shown in Figure 12) indicated that these two data sets were highly correlated in both spatial pattern and magnitude. In terms of the magnitude, the average annual NDVI value from MODIS was approximately 0.21 (range 0.02–0.82; standard deviation ~0.16), and the average annual NDVI value from GIMMS was approximately 0.23 (range 0.01–0.88; standard deviation ~0.23). Therefore, it was reasonable to use GIMMS-NDVI3g to replace the MODIS NDVI data to downscale the PERSIANN-CDR data for the TP from 1983 to 2015.

As land surface temperature information was not readily accessible for the period from 1983 to 2015, the NOAA GHCN_CAMS LSAT data at 0.5° resolution were used as one of the LSCs in downscaling the PERSIANN-CDR data. To determine its suitability, the LSAT data at 0.01° resolution interpolated from the LSAT at 0.5° were compared with the corresponding values from DEM data. We found that the interpolated 1-km LSAT data set was reasonable; for example, as the elevation increased by 100 m, the LSAT data decreased proportionally, by 0.5°C (the expected value was 0.6°C) (Figure 13).

5.4. Future Directions for Obtaining Long-Term Downscaled Results With Better Quality

Future projects including the land surface temperature climate change initiative (http://cci.esa.int/lst) aim to build on existing CDRs of land surface temperature (Ghent et al., 2017; Good et al., 2017), extending these back to the 1980s and improving accuracy at finer spatiotemporal resolutions; this would provide more suitable ancillary data for downscaling the PERSIANN-CDR data. Additionally, in the present study the PERSIANN-CDR data were downscaled only at the annual scale from 1983 to 2015. Future research could provide solutions for obtaining precipitation estimates (~1-km resolution) at more frequent temporal
scales (monthly, weekly, and daily). Although this study focused on the development of downscaling approaches applicable to other suitable data sets, in future research other long-term gridded precipitation products, such as the MSWEP, should be explored for their potential for downscaling.

6. Conclusion

The World Meteorological Organization stipulates a minimum of 30 years of historical data is needed to obtain meaningful results in climatological research. However, large numbers of studies have explored downscaling approaches based on the TMPA data, which span only from 1998 to the present, to obtain the precipitation estimates (~1 km resolution). In the present study, we sought to retrieve long-term (>30 years) precipitation estimates over the TP. Considering the characteristics of the PERSIANN-CDR data, a new downscaling-calibration procedure, involving the combination of a spatial data mining downscaling algorithm (Cubist) and a GRA calibration method, was proposed to downscale the PERSIANN-CDR data. We found that (1) because of the high level of overestimation in the PERSIANN-CDR data (Bias ~ 40.79%) and the nature of error propagation in the downscaling field, the downscaled results before calibration overestimated the precipitation compared with ground observations from rain gauges (Bias ~ 26.78%); (2) the final downscaled results based on the PERSIANN-CDR data after calibration were close to the ground observations (Bias ~ 5%); (3) compared to the results interpolated based on the PERSIANN-CDR data ($E < -1.0$), both the downscaling procedure and calibration procedure contributed significantly to the accuracy of the final downscaled results ($E \approx 0.83$); and (4) the GIMMS-NDVI3g and LSAT data sets also demonstrated great potential as auxiliary variables for downscaling the PERSIANN-CDR data in the long term. These findings suggest that the proposed downscaling-calibration procedure has great potential as an approach for retrieving long-term precipitation estimates (~1 km resolution) over the TP from 1983 to 2015, based on the PERSIANN-CDR data and ground observations.

Competing financial interests

The authors declare no competing financial interests.

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