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Performance of CMORPH, TMPA, and PERSIANN rainfall datasets over plain, mountainous, and glacial regions of Pakistan

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Abstract The present study aims at the assessment of six satellite rainfall estimates (SREs) in Pakistan. For each assessed products, both real-time (RT) and post adjusted (Adj) versions are considered to highlight their potential benefits in the rainfall estimation at annual, monthly, and daily temporal scales. Three geomorphological climatic zones, i.e., plain, mountainous, and glacial are taken under considerations for the determination of relative potentials of these SREs over Pakistan at global and regional scales. All SREs, in general, have well captured the annual north-south rainfall decreasing patterns and rainfall amounts over the typical arid regions of the country. Regarding the zonal approach, the performance of all SREs has remained good over mountainous region comparative to arid regions. This poor performance in accurate

rainfall estimation of all the six SREs over arid regions has made their use questionable in these regions. Over glacier region, all SREs have highly overestimated the rainfall. One possible cause of this overestimation may be due to the low surface temperature and radiation absorption over snow and ice cover, resulting in their misidentification with rainy clouds as daily false alarm ratio has increased from mountainous to glacial regions. Among RT products, CMORPH-RT is the most biased product. The Bias was almost removed on CMORPH-Adj thanks to the gauge adjustment. On a general way, all Adj versions outperformed their respective RT versions at all considered temporal scales and have confirmed the positive effects of gauge adjustment. CMORPH-Adj and TMPA-Adj have shown the best agreement with in situ data in terms of Bias, RMSE, and CC over the entire study area.

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1 Introduction

Precipitation is a crucial input of the earth's hydrological cycle and its accurate estimation is important to the fact that it is highly influential in many human-related activities like drinking and agricultural use (Gebere et al. 2015). It is also an impetuous factor in the occurrence of natural disasters like flooding and droughts (Guo et al. 2015). Pakistan's economy is highly dependent on agriculture (Hussain et al. 2016) where a hefty part of country's gross domestic product (GDP) is earned from agriculture and agriculture-related industry (Economic Survey 2009–2010). Along with agriculture, the natural calamities such as floods, droughts, and increased frequency of heat waves are also a function of rainfall. The frequency and intensity of occurrence of these calamities have been aggravated by the climate change since the last many decades (Khan et al. 2014). The consequents of these disasters are many folded on agriculture, livestock, food security, water

resources, public health, and economic status at large (Aslam et al. 2016). The extreme flooding episode of 2010, due to anomalous rainfall at northern parts, is a tragic reminder of the natural disasters which severely damaged the country's agriculture and infrastructure in the past (Webster et al. 2011). The frequency modeling of floods and droughts shows that both extremes are more frequent in upcoming decades aggravated by climate change (Khan et al. 2016). The effects of these calamities need to be solved through proper rainfall estimation and management. Indeed, accurate temporal and spatial variations of rainfall are the key factors to understand water cycle, and their trend analysis can be used to support decisions that are directly linked with coping calamities.

Traditional ground base methods of precipitation measurement such as radar and rain gauges imply a point-based approach which accurately measure rainfall but have remained representative of the fine spatial scale and generally suffer of no or less coverage over inaccessible tough terrains (Behrangi et al. 2014; Tong et al. 2014). With a near global coverage and a high spatio-temporal resolution, the satellite rainfall estimations (SREs) have become an important component of hydrometeorological research (Behrangi et al. 2014).

SRE is favored because of its free availability, particularly for developing countries like Pakistan. Previous studies have already checked the suitability of SREs by comparing it with actual rainfall data over Asia (Khan et al. 2014; Qin et al. 2014; Prakash et al. 2014), Shukla et al. 2014), Africa (Dinku et al. 2007; Pierre et al. 2011; Thiemig et al. 2012; Gosset et al. 2013), South America (Vila et al. 2009; Ochoa et al. 2014; Salio et al. 2014; Blacutt et al. 2015; Satgé et al. 2016), and Europe (Kidd et al. 2012). The performance of these SREs varies from region to region under different climatic conditions and from product to product. On a general way, Tropical Rainfall Measuring Mission (TRMM) Multisatellite Precipitation Analysis (TMPA) performs better for moderate rainfall events (Nair et al. 2009), Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks (PERSIANN) accuracy is usually high in dry and relatively flat regions (Gebere et al. 2015; Satgé et al. 2016), and Climate Prediction Center MORPHing (CMORPH) performs well over mountainous regions (Dinku et al. 2007; Dinku et al. 2010).

Very few studies address SRE potentiality over Pakistan. A study was conducted by Khan et al. (2014) to assess TMPA v7 Real Time (RT) and Adjusted (Adj) versions and CMORPH-RT during the monsoon on a daily time step. Best agreement with rain gauges measurements was found for TMPA-Adj v7. More recently, Anjum et al. (2016) assess the improvement brought by TMPA-v7 over the previously v6 on a more local scale over the Swat River watershed (14,039 km²). Results showed an improvement of rainfall estimation in TMPA-Adj v7 in comparison with TMPA-Adj v6. Both products are more accurate for monthly than daily precipitation estimate.

The present study is a way forward regarding SREs over the region as it compares for the first time PERSIANN, CMORPH, and TMPA performances over the whole Pakistan. It also consists of the first assessment of PERSIANN and the new CMORPH products over the region. RT and Adj versions of each product are considered to appreciate the potential gain induced by the adjustment. This consideration is necessary as an adjustment process may increase uncertainty in SRE estimation (Bitew and Gebremichael 2011; Gosset et al. 2013; Xue et al. 2013; Satgé et al. 2016). Different orogenic regions are considered, to understand SRE error topography dependencies previously found (Khan et al. 2014; Anjum et al. 2016). Moreover, each of the three defined classes corresponds to a specific geomorphologic climatic context: arid plain, dry to semi-humid mountain, and glacier region. This study will be highly supportive in assessing SREs of 11 rainfall stations located over Himalayas glacier region and will provide a first comprehensive feedback of SRE ability over Pakistan's glacier regions.

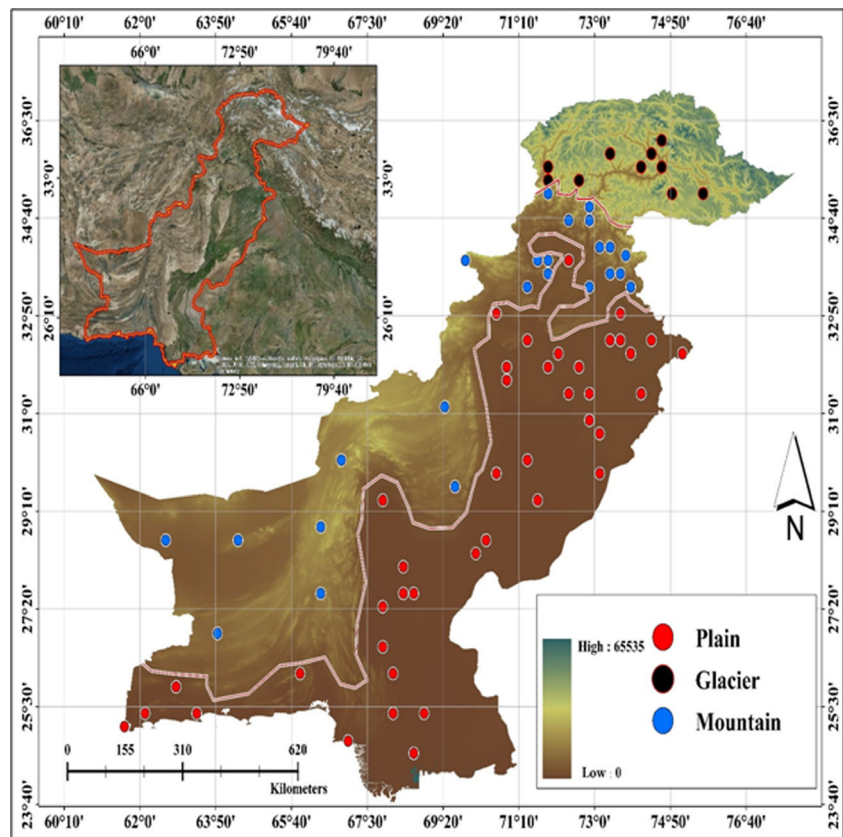
1.1 Study area

Pakistan is situated in the western zone of South Asia between 24 and 37 °N latitude and 62–75 °E longitude. Geographically, it is bounded at the north by China, east by India, while Afghanistan and Iran lie at the western side. The Arabian Sea marks the southern border (Fig. 1). The total area is 803,940 km² where elevation varies from a maximum of 8011 m maximum value at K2 (second elevated peak on earth) to about 0 m at the Arabian Sea.

The Indus River is the most important river of Pakistan. It crosses the country from its sources located in Mount Kailash in Tibet (China) to the Arabian Sea (Pakistan). The northern parts of Pakistan consist of very high mountains with permanent snow and glacier (Fig. 1). Dry mountains (*Koh-e-Suleman*) are located in western parts, there are many small *Nalas* (drainages formed after rainfall), which cause flooding in these areas during rainy seasons. Deserts are the important part of Pakistan's geography. Major deserts of Pakistan are *Thar* (southeastern), *Cholistan* (southeastern), *Thall* (central), and *Kharan* (southwestern).

Pakistan offers a great climatic variation influenced by orogenic divisions with various elevation zones and precipitation patterns (Hanif et al. 2013). Topography and temperature changes give rise to various rainfall patterns in the northern and southern mountains of Pakistan (Hanif et al. 2013). In the subtropical climatic region like sub-continent, the air circulations in the upper atmosphere influence the rainfall patterns greatly (Hanif et al. 2013). Pakistan receives 60% rainfall in July–September, the monsoon season in northern parts and about 30% in winter (December–March) rains (Sarfaraz et al. 2014) in the southern parts. Two dry plateaus Potwar and Baluchistan are dependent only on the rainfall for

Fig. 1 Study area with pixel location including at least on rain gauge and mean monthly rainfall for all the three considered regions with DEM values. *Upper left* is the regional location of Pakistan



agriculture, livestock, and human population. Potwar is located near Islamabad and Baluchistan is located in Baluchistan province (southwestern part). A little delay in the rain can cast immense damages to these regions which have very fertile lands and contribute about 13% to the country's total agriculture (Adnan et al. 2009). Accurate rainfall estimations can win the losing trusts of the local farmers so they can invest more and more in agriculture without fear of losses because of less rainfall occupancy (Adnan et al. 2009). Figure 2 has the details of rainfall patterns in three different topographic classes as glacier, mountain, and plain. Like rainfall patterns, the climatic vulnerabilities also differ in northern and southern mountains. The northern parts are affected by flooding and southern parts by the frequent occurrence of droughts. Both these north-south climatic vulnerabilities are also a function of rainfall.

2 Materials

2.1 In situ data

Pakistan Metrological Department (PMD) is in charge of the meteorological network. A total of 76 stations are available

from the 2008 to 2010 periods. The dataset was split into different zones to account with previously founding on SRE accuracy dependency. Indeed, SRE performance contrasts can be observed over a defined region due to emissivity/temperature contrast and/or warm rain cloud processes. For example, a rainfall deficit in the measurements of PERSIANN and TMPA was observed over the big Lake Titicaca, due to strong emissivity and temperature contrast observed above the lake (Satgé et al. 2016). Similar impacts should be observed over Pakistan's glacial region, induced by high emissivity related to snow and ice cover. In the same way, mountainous region is challenging because of warm rain cloud processes which could be misidentified as no rainy cloud by SREs (Dinku et al. 2010). Finally, arid region is challenging because of short rainfall event dominance which is not well captured by SREs (Tian et al. 2009; Gebregiorgis and Hossain 2013).

Three geomorphologic climatic zones are considered to account for SREs mentioned factors on SREs over Pakistan. They are plain, mountain, and glacial regions count with 10, 24 and 41 stations, respectively (Fig. 1). The class "Plain" includes stations located in low relief with no mountain influences in relation to warm rain cloud processes and emissivity/temperature contrast. The "Mountain" class includes stations located in the mountain part with no snow or glacial cover to

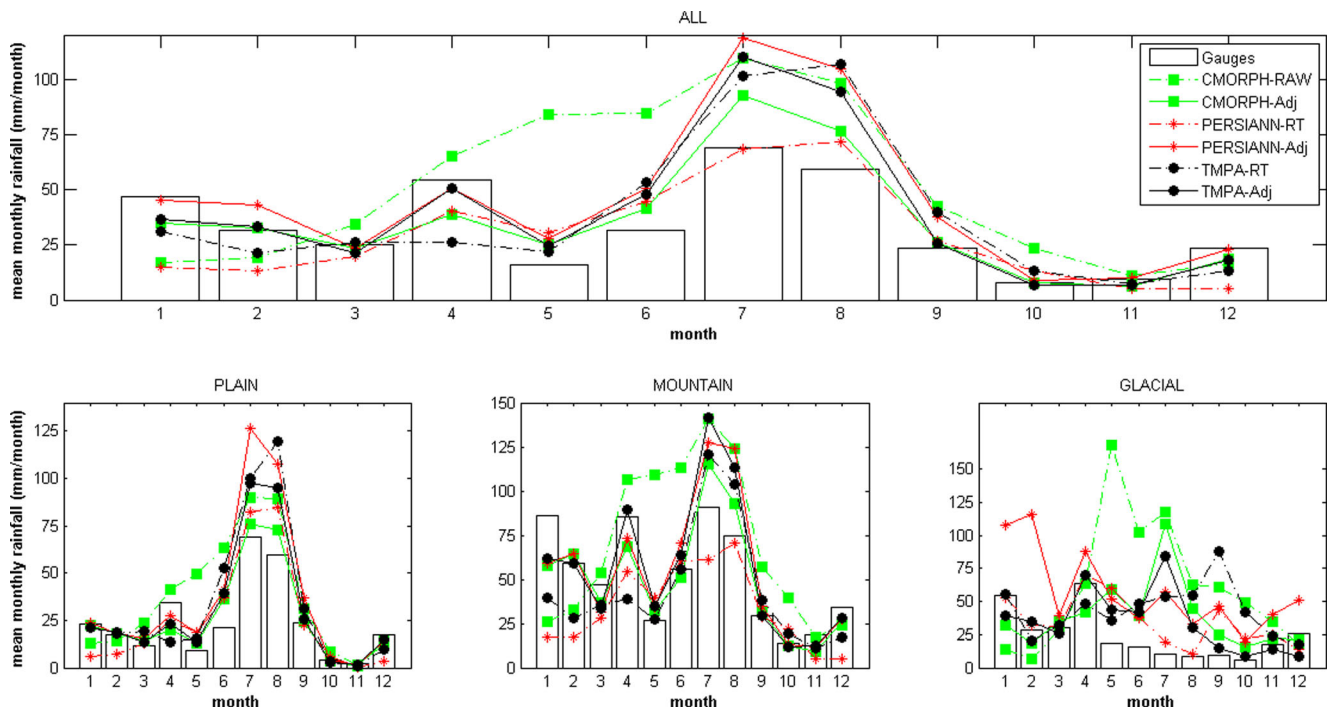


Fig. 2 Monthly rainfall for the 2008–2010 period for in situ and SREs

observe the potential effects of warm rain cloud process on SREs. Finally, with the predominance of glacial and snow cover, the “Glacial” class is considered to observe SRE potentialities over contrasted emissivity/temperature regions.

2.2 Satellite rainfall estimation products

Six SREs are considered in the foregoing analysis. All SREs used a combination of passive microwave (PMW) radiometers and IR data from Low Earth Orbital (LEO) and geosynchronous satellites, respectively, to estimate rain rates on a 0.25° spatial resolution.

TMPA is a product of the National Aeronautics and Space Administration (NASA) in collaboration with the Japan Aerospace Exploration Agency (JAXA). Six PMW radiometers named TRMM Microwave Imager (TMI), Special Sensor Microwave/Imager (SSM/I), Advanced Microwave Scanning Radiometer-EOS (AMSR-E), Advanced Microwave Sounding Unit-B (AMSU-B), Special Sensor Microwave Imager/Sounder (SSMIS), and Microwave Humidity Sounder (MHS) are used to estimate rainfall rates. IR data from the Climate Prediction Center (CPC) of the National Weather Service/NOAA (CPC-IR here-after), from the Meteorological Operational satellite program (MetOp) and from the 0.07° GridSat-B1 are used to fill the gaps between PMW measurements (Janowiak et al. 2001; Huffman et al. 2010; Huffman and Bolvin 2014). There exists a Real Time

version (TMPA-RT v7) only based on PMW and IR data and an adjusted version (TMPA-Adj v7). TMPA-Adj v7 is derived from TMPA-RT v7 according to an adjustment using gauge-based data from Global Precipitation Climatology Centre (GPCC) and Climate Assessment and Monitoring System (CAMS) (Janowiak et al. 2001; Huffman et al. 2010; Huffman and Bolvin 2014).

CMORPH is a product of the NOAA/Climate Prediction Center (NOAA/CPC). Rainfall estimates are derived from PMW radiometers (AMSU-B, SSM/I, TMI, and AMSR-E) and motion vectors derived from CPC-IR data are used to propagate PMW rainfall estimates in space and time (Joyce et al. 2004). The first version (CMORPH v0.x) used an evolving algorithm according to input data which has generated inhomogeneity, especially for the 2003–2016 period. Thus, it was recently replaced by the CMORPH v1 version using a fixed algorithm and homogeneous input data (NOAA 2012). Hereafter, we refer to CMORPH v1 using CMORPH and to the only satellite-based version using CMORPH-RT. A Bias correction method is applied on CMORPH-RT to produce an adjusted version called CMORPH-Adj. The procedure uses data from the CPC unified gauge analysis over land and the pentad Global Precipitation Climatology Project (GPCP) over the ocean (Xie et al. 2011).

PERSIANN is a product of the Center for Hydrometeorology and Remote Sensing (CHRS). A neural network technique (Hsu et al. (1997) and Sorooshian

et al. (2000)) is used to estimate rainfall rates from CPC-IR data. PMW data (TMI, AMSU-B, and SSM/I) is used to adjust neural network parameter to increase the rainfall estimate accuracy. There exists a real-time version (PERSIANN-RT) based only on satellite data and a derived adjusted version (PERSIANN-Adj). Monthly GPCP data are used to adjust PERSIANN-RT and provide PERSIANN-Adj. It is noteworthy that recently another PERSIANN rainfall product is available, the PERSIANN-CDR. PERSIANN-CDR use the same neural network as used previously but differs in terms of input IR dataset with the use of GridSat-B1 instead of CPC-IR, and PMWs data are not used (Ashouri et al. 2015). The aim of PERSIANN-CDR is to provide continuous daily rainfall data from 1983 to today and thus no RT version is available. As this study aims to assess the adjustment processes’ potentiality over rainfall estimate, we do not consider PERSIANN-CDR in our analysis.

TMPA-RT and Adj v7, CMORPH-RT and Adj, and PERSIANN-RT and Adj are assessed in this study. Data were acquired on a 0.25° and a 3-hourly spatial and temporal resolution, respectively, from the links reported in Table 1.

3 Method

3.1 Data processing

A total of 76 stations were available for the 2008–2010 period. These stations are distributed on 75 SRE resolution (0.25°) pixels (Fig. 1). For pixels with more than 1 rain gauge, the data were averaged to produce a single mean value per day and per pixel. Data were not interpolated because interpolation from a sparse and uneven rain gauge network could generate unrealistic estimations (Li and Heap 2008; Scheel et al. 2011; Satgé et al. 2016). The SRE daily accumulations are computed from 3:00 to 3:00 UTC to match the 8:00 to 8:00 local time of the gauge data in Pakistan. The native 0.25° spatial resolution is kept for all SRE products.

Table 1 Website links used for the SRE dataset download

Product	Link
TMPA-RT v7	http://mirador.gsfc.nasa.gov/
TMPA-Adj v7	http://mirador.gsfc.nasa.gov/
CMORPH-RT	ftp://ftp.cpc.ncep.noaa.gov/precip/CMORPH_V1.0/
CMORPH-Adj	ftp://ftp.cpc.ncep.noaa.gov/precip/CMORPH_V1.0/
PERSIANN-RT	http://chrs.web.uci.edu/persiann/data.html
PERSIANN-Adj	http://fire.eng.uci.edu/PERSIANN/

3.2 Comparison methods

Some values of daily rainfall estimation are missing in SRE time series. If a missing value is found, then that particular day is removed from all SREs and the rain gauge. Only months and years with 80% of the daily value were considered to compute the statistical scores (Clarke et al. 2011; Satgé et al. 2016). According to this selection, a total of 225 yearly and 2601 monthly rainfall amounts are available for the assessment. First, the root mean square error (RMSE), Bias, and correlation coefficient (CC) were computed considering all pixels. Then, to estimate the possible effects of topographic variations on the overall accuracy of SREs, a total of 75 pixels are divided as 41 plain pixels, 26 mountainous pixels, and 10 glacial pixels based on the elevation classes derived from DEM (Digital Elevation Model) (Fig. 1).

$$\text{bias} = \frac{\sum_{i=1}^n (P_{\text{SRE}_i} - P_{G_i})}{\sum_{i=1}^n P_{G_i}} \times 100 \tag{1}$$

$$\text{RMSE} = \frac{\sqrt{\frac{\sum_{i=1}^n (P_{\text{SRE}_i} - P_{G_i})^2}{N}}}{\frac{\sum_{i=1}^n P_{\text{SRE}_i}}{N}} \times 100 \tag{2}$$

where, N is the length of the series and it includes the rainfall total (monthly or yearly) from all available pixels; P_{G_i} is the gauge precipitation for the considered month or years i ; and P_{SRE_i} is the SRE precipitation for the considered month or year i .

The mean value of the RMSE, Bias, and CC total amounts was first computed to assess SREs at the regional scale and for each considered classes for both annual and monthly scale (Tables 1 and 2). We considered CC as significant if, its value was equal or greater than 0.7 (Condom et al. 2010; Satgé et al. 2016), RMSE is acceptable if, it was lesser than or equal to 50% (Adeyewa and Nakamura 2003; Condom et al. 2010; Satgé et al. 2016) and Bias as acceptable when $-10\% \leq \text{Bias} \leq 10\%$ (Brown 2006; Yang and Luo 2014; Satgé et al. 2016). The presentation of SRE rainfall estimation efficiency is projected in Fig. 5 in the form of calculation of monthly Cumulative Distribution Function (CDF). The spatial variations into SRE ability are observed by mapping pixel-based comparison considering RMSE, Bias, and CC to provide the spatial error distribution over Pakistan for the period 2008–2010 (Figs. 6, 7, and 8). Finally, a quick analysis is made on a

Table 2 Factors for Probability of Detection (POD) and the False Alarm Ratio (FAR)

		Gauges	
		Rain	No rain
SRE	Rain	a	b
	No rain	c	d

daily scale. Two categorical indexes focusing on the ability of SREs to correctly detect daily rainfall event occurrence are considered. They are the Probability of Detection (POD) and the False Alarm Ratio (FAR) as presented in Eqs. 3 and 4, respectively.

$$\text{POD} = \frac{a}{(a + c)} \quad (3)$$

$$\text{FAR} = \frac{b}{(a + b)} \quad (4)$$

POD is an indicator of how well a SRE detect rainfall event. Values vary from 0 to 1 with a perfect score of 1. FAR indicates how often a SRE detect rainfall events when actually no rainfall events were detected by the gauges.

The analysis limits to these two indices because the gauge network used is poorly representative of SRE in terms of spatial resolution at the daily scale. Actually, gauge measurement is a point measurement while SREs correspond to a mean rainfall estimates of an area of 625 km². Indeed, in the case of a perfect SRE, every rainfall event detected by the gauges should be detected by the SRE. However, lots of rainfall events detected by the SRE are missed by the gauges. In consequences, “a” and “c” factors should not be impacted by the different spatial resolution between gauges and SRE while a systematic overestimation and underestimation of “b” and “d” values should be observed (Table 2). Other indicators such as the CSI, ETS, and HSS are generally used to improve the analysis. However, these indexes rely on “b” and “d” values which are poorly represented from the gauge network. In this context, we only consider POD and FAR to limit the uncertainties in the results and provide a first insight on SRE ability at daily scale. POD and FAR are computed from all SREs at the global scale and for glacial, mountainous, and plain classes.

4 Results and discussion

4.1 Annual scale

All products exhibit the typical north-south gradient with rainfall amount decreasing from north to south. The slight west-east rainfall gradient is also captured by all SREs with a very arid region located in southwest dry mountains of Balochistan. It is particularly true for both PERSIANN-RT and Adj products. PERSIANN and TMPA products were already found to be well represented of regional rainfall gradient over the arid region as the Altiplano (Satgé et al. 2016) and Iran (Katirai-Boroujerdy et al. 2013).

For all SREs, higher rainfall amounts are found over the northward higher relief regions. CMORPH-RT product

considerably overestimates rainfall amounts in this region with mean annual rainfall superior to 2000 mm/year and high positive Bias of 35.4% (Fig. 3 and Table 1). On the contrary, PERSIANN-RT underestimates rainfall resulting in a negative Bias of -34.5%. All other products present Bias into or close to the acceptable threshold range fixed between -10 and 10%.

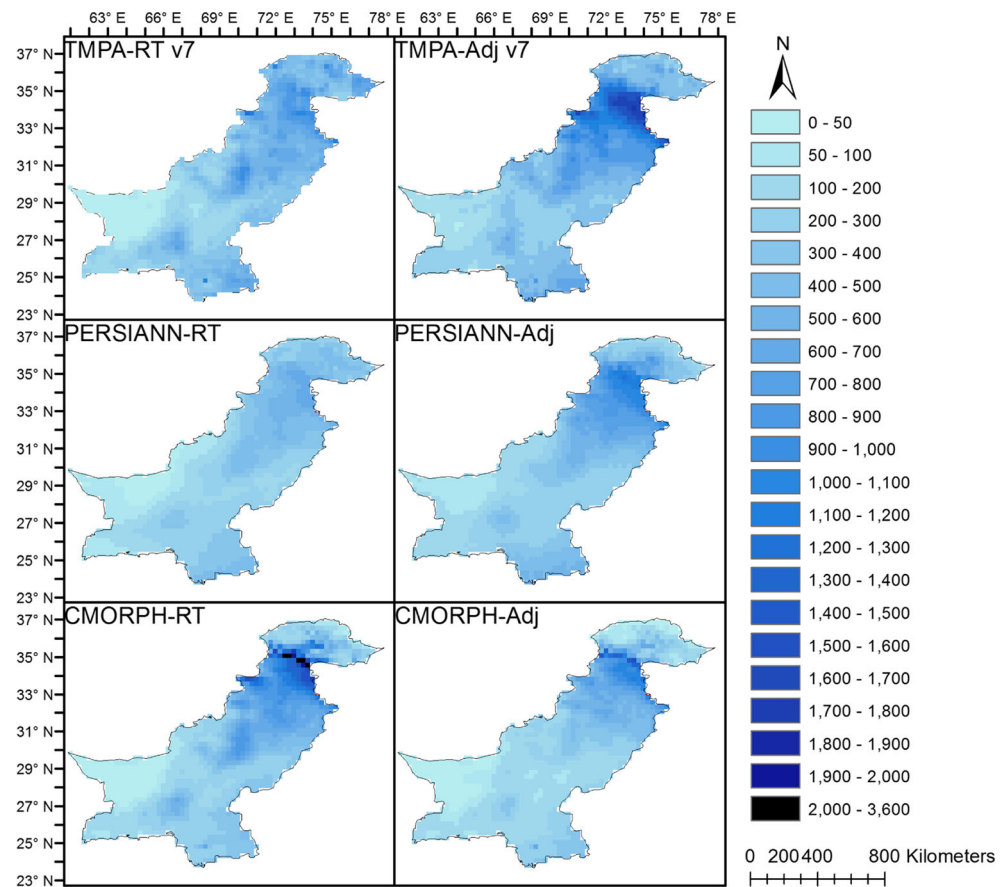
Over the glacial region, all products overestimate rainfall amounts (Table 3). The combined presence of cold cloud and ice cover may contribute to the overestimation. Here, cold clouds are associated with high relief. Researchers agree that rain/no rain classification based on cloud top IR temperature may fail in mountainous regions (Dinku et al. 2007; Dinku et al. 2010; Hirpa et al. 2010; Gebregiorgis and Hossain 2013). Below a temperature threshold, clouds are considered as rainy while the opposite case is considered when cloud top temperatures are above the temperature threshold. Hence, over Pakistan’s mountainous and glacial regions, cloud temperature threshold might be too high and lead to the misidentification of no-rainy clouds as rainy ones. In addition, over snow and ice, radiation absorption and surface temperature are much lower than the surrounding land. The strong land-snow ice contrast observed in those specific regions (in radiation absorption and temperature) is a potential source of error for PMW rainfall retrieval (Ferraro et al. 1998; Levizzani et al. 2002). Indeed, it can lead to a misidentification of snow and ice cover with the rainy cloud (Dinku et al. 2010) contributing to SREs overestimate rainfall over these regions. As a result, from mountainous to glacial areas, the Bias considerably increased for all the considered SREs (Table 1). It is particularly true for PERSIANN-RT and TMPA-RT passing from a negative to a positive Bias. This feature highlights the importance of caution measure into algorithms to enhance SREs in contrasted area (in radiation absorption and surface temperature) in the same way coastlines are (Adler et al. 1993). Thus, the glacial region of Pakistan is still challenging for SRE estimates.

SREs are more contrasted over the mountainous region. TMPA and PERSIANN-RT tend to underestimate rainfall amount by -14.5 and -34.5%, respectively, while CMORPH-RT tends to overestimate rainfall amount by 35.7%. Bias adjustment process decreases Bias value for all SREs to reach value ranging into the quality threshold (-10 to 10%) with a lower observed value for CMORPH-Adj (-3.7%).

Over the plain region, all SREs are less accurate than over mountainous and glacial regions. They tend to overestimate the rainfall amount with positive Bias value. Among all the considered products, CMORPH-Adj presents better statistic results overall with low Bias, RMSE and relative higher CC of 6.4, 77.6, and 0.59, respectively.

On a more general point of view, on the global scale, the Adj versions of CMORPH and TMPA present a significant enhancement in rainfall estimates in comparison with their RT versions with lower RMSE, Bias, and higher CC. The

Fig. 3 Regional mean annual rainfall pattern for the 2008–2010 period



adjustment effects are clear in Fig. 4, with Adj values fitting better with gauge measurement than RT values over the entire study period. The adjustment of PERSIANN-RT is more contrasted. Over mountainous region, the enhancement is obvious with an increase of CC and a decrease of both Bias and RMSE values. Over plain and glacial regions, RMSE and CC are better for PERSIANN-Adj than for PERSIANN-RT. However, PERSIANN-Adj is more biased than its RT version. Same observations are true at the regional scale. Thus, for PERSIANN products, the adjustment enhances the rainfall temporal variation description which is valuable for long-term precipitation variation studies.

According to the defined quality threshold value, with a CC superior to 0.7, an absolute Bias value inferior to 10% and a RMSE value very close to 50%, CMORPH-Adj is the best suited product to represent annual rainfall over Pakistan at the regional scale. TMPA-Adj is the second best product with RMSE and Bias values close to the 50% and 10% threshold value, respectively and a CC superior to 0.7.

According to the different regions considered, CMORPH-Adj presents better statistical results over plain region with RMSE and Bias of 58.1 and 13.6%, respectively. Same observations are true over mountainous region, where CMORPH-Adj outperformed all other

Table 3 Annual RMSE, Bias, and CC for all SREs at regional scale and for plain, mountain, and glacier region

	Bias				CC				RMSE			
	All	Plain	Mountain	Glacial	All	Plain	Mountain	Glacial	All	Plain	Mountain	Glacial
PERSIANN-RT	-11.80	2.6	-34.5	46.4	0.57	0.38	0.71	0.29	80.10	54.5	96.5	67.8
PERSIANN-Adj	35.50	46.2	8.3	134.8	0.66	0.49	0.75	0.4	56.80	66.9	45	61.9
TMPA-RT	14.70	36.4	-14.5	75.5	0.60	0.41	0.73	0.48	61.00	57.5	59.8	62.2
TMPA-Adj	18.20	23.6	9.3	42.3	0.74	0.52	0.76	0.67	52.90	49.8	44.3	61.5
CMORPH-RT	51.70	47.5	35.4	157.9	0.73	0.63	0.8	0.51	59.20	83.7	45.2	57.3
CMORPH-Adj	6.30	6.4	-3.7	60	0.74	0.59	0.81	0.53	56.90	77.6	44	60.7

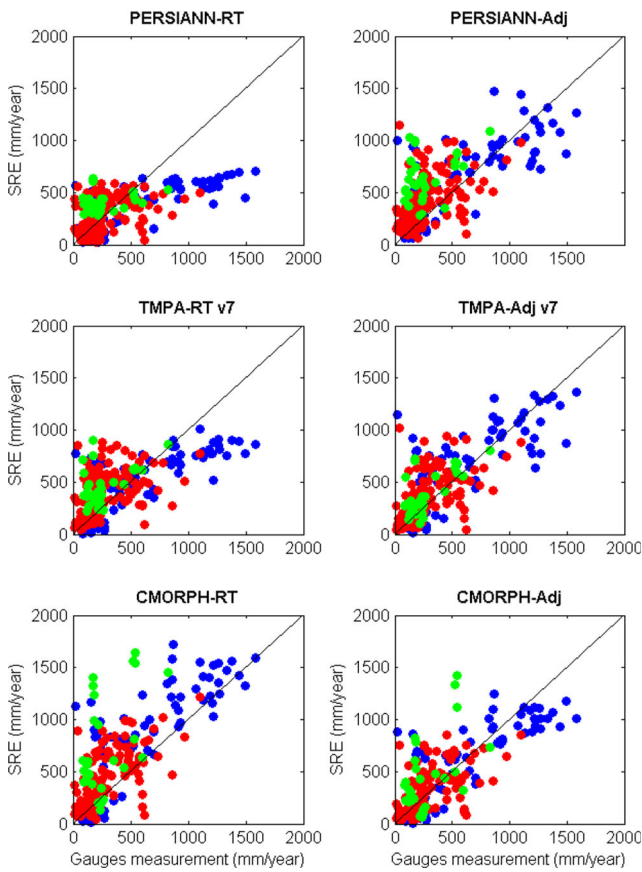


Fig. 4 Scatter plot of SREs versus gauge with plain, mountainous, and glacier region in red, blue, and green, respectively

SREs with the lowest Bias (−3.7%), higher CC (0.81), and lowest RMSE (44%). It is noteworthy that, over mountain, TMPA-Adj and PERSIANN-Adj also perform well with all statistic parameters into the quality threshold range. Over glacial region, SRE potentiality is very poor. In comparison to other SREs, TMPA-Adj rainfall estimates are closer to gauge estimates with the highest CC (0.67), lowest RMSE (44.3%), and close to lowest Bias value (42.3%).

4.2 Monthly scale

Figure 2 represents the monthly mean rainfall for the 2008–2010 period and for all SRE and gauge measurements. At a global scale, all SREs except CMORPH-RT have well captured the monthly variations in higher rainfall in July and August corresponding to the monsoon months. April rainfall peak is also well represented by SREs. PERSIANN-RT underestimates monthly amount and confirms annual tendency (Table 1). Same tendencies are observed over the plain region. SREs highly overestimate monsoon rainfall in July and August with CMORPH-Adj estimates closer to gauge estimates in comparison with over SREs. Over mountainous region, highest variations are observed between SREs. CMORPH, PERSIANN, and TMPA Adj are closer to gauges than their RT version highlighting the usefulness of such adjustment in this region. In the glacial region, from January to April, CMORPH and TMPA adjusted versions are close to gauge’s estimates. From May to October, all SREs highly overestimate monthly rainfall. This might be due to the temperature fluctuations from winter to summer and respective variable amounts of snowfall increase SRE uncertainties.

Table 4 presents RMSE, Bias, and CC for all SREs and all the considered regions (plain, mountainous, and glacial). On a global scale, none of the products fit the quality criteria defined with RMSE and Bias inferior to 50 and 10%, respectively, and with CC superior to 0.7. However, with Bias value of 6% into the defined quality threshold, a CC and RMSE close to the defined quality threshold, CMORPH-Adj monthly amounts are the most accurate over Pakistan at the global scale. All SREs present better statistical results over mountainous region probably due to the higher rainfall amounts observed in comparison with plain and glacial regions (Fig. 4). Over mountainous region, CMORPH-Adj is the most accurate product in terms of CC of 0.63 and Bias of −4.0%. It still suffers a quite high RMSE value. It is noteworthy that PERSIANN-Adj performed quite similar to CMORPH-Adj over mountainous region with very close RMSE, CC, and Bias values. Over glacial region, all SREs are poorly

Table 4 Monthly RMSE, Bias, and CC for all SREs and regional scale and for plain, mountain, and glacier regions

	Bias				CC				RMSE			
	All	Plain	Mountain	Glacial	All	Plain	Mountain	Glacial	All	Plain	Mountain	Glacial
PERSIANN-RT	4.0	−34.3	43.2	0.44	0.44	0.42	0.51	0.23	173.0	187.1	171.6	121.9
PERSIANN-Adj	48.5	7.9	129.9	0.54	0.54	0.50	0.62	0.36	128.8	157.2	105.1	108.6
TMPA-RT	37.6	−14.2	72.8	0.46	0.46	0.46	0.52	0.08	149.4	168.2	133.6	125.4
TMPA-Adj	25.1	9.3	40.2	0.58	0.58	0.54	0.61	0.29	132.5	156.7	107.3	135.9
CMORPH-RT	49.8	36.0	147.0	0.48	0.48	0.51	0.53	0.01	127.1	137.0	100.7	155.2
CMORPH-Adj	7.5	−4.0	55.0	0.57	0.57	0.56	0.64	0.15	137.2	160.9	104.6	164.2

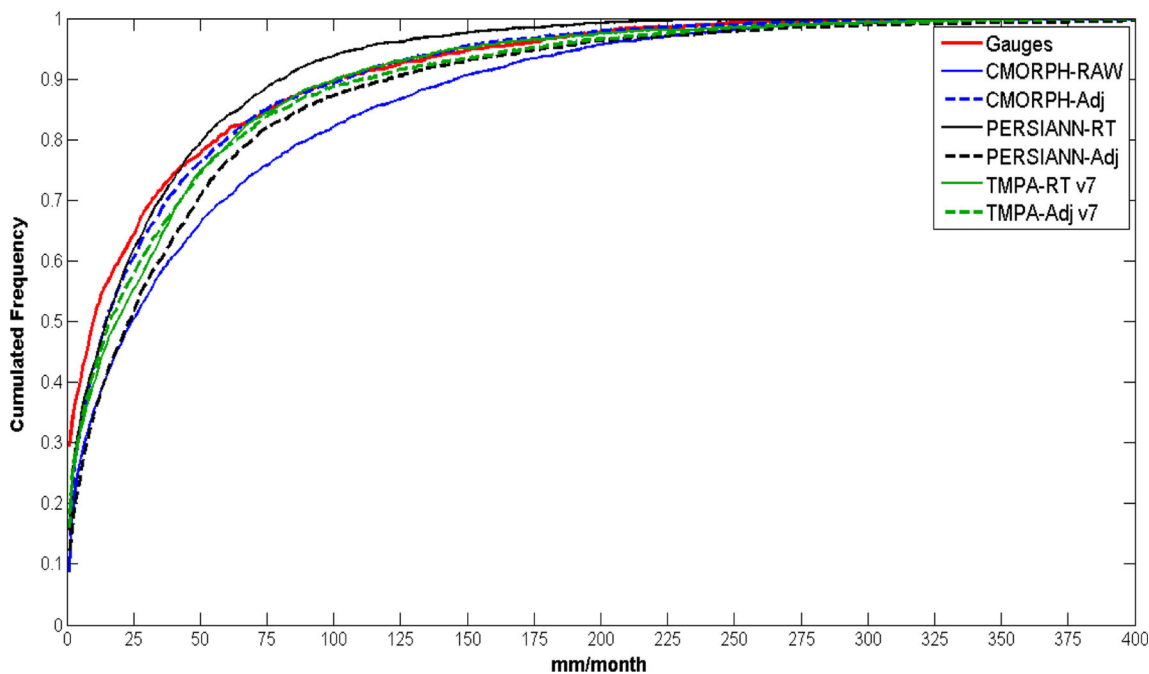
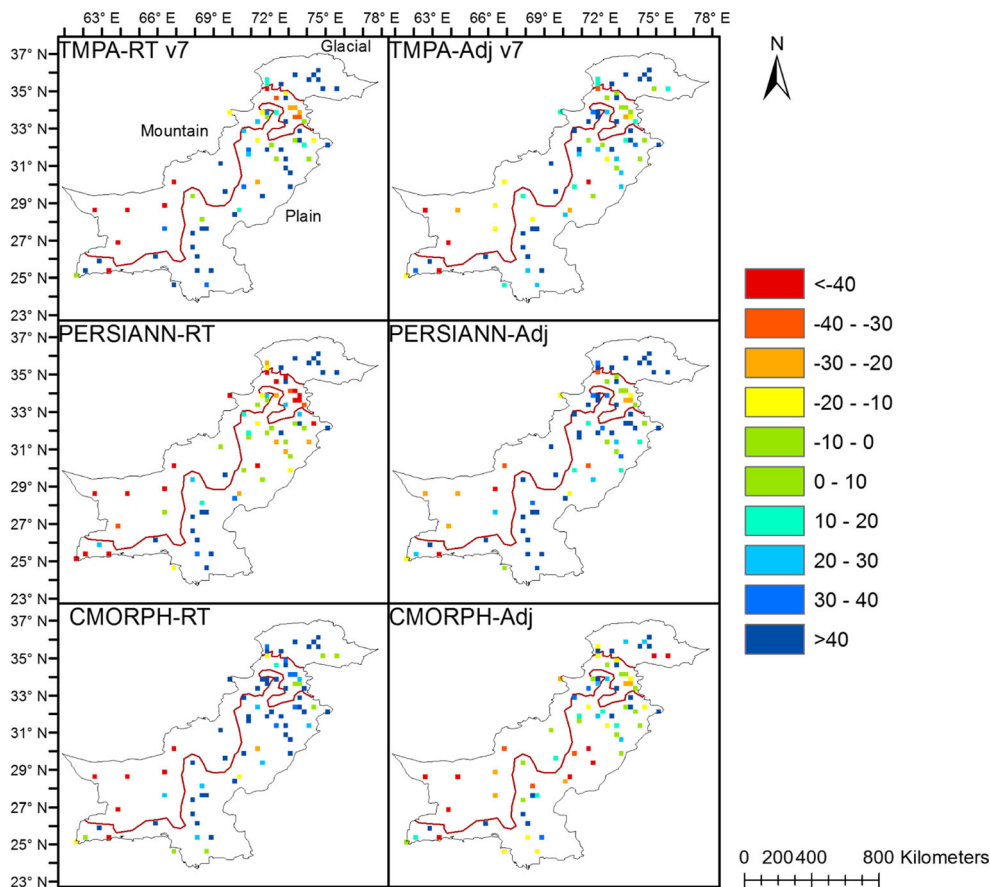


Fig. 5 Cumulative distribution function for SREs and gauges with a 1-mm month⁻¹ increment

correlated to gauge measurements and strongly overestimate rainfall estimates with Bias value superior to 100%.

Figure 5 represents the Cumulative Distribution Frequency (CDF) of monthly rainfall rates. The arid context of the region

Fig. 6 Spatial patterns of mean monthly Bias



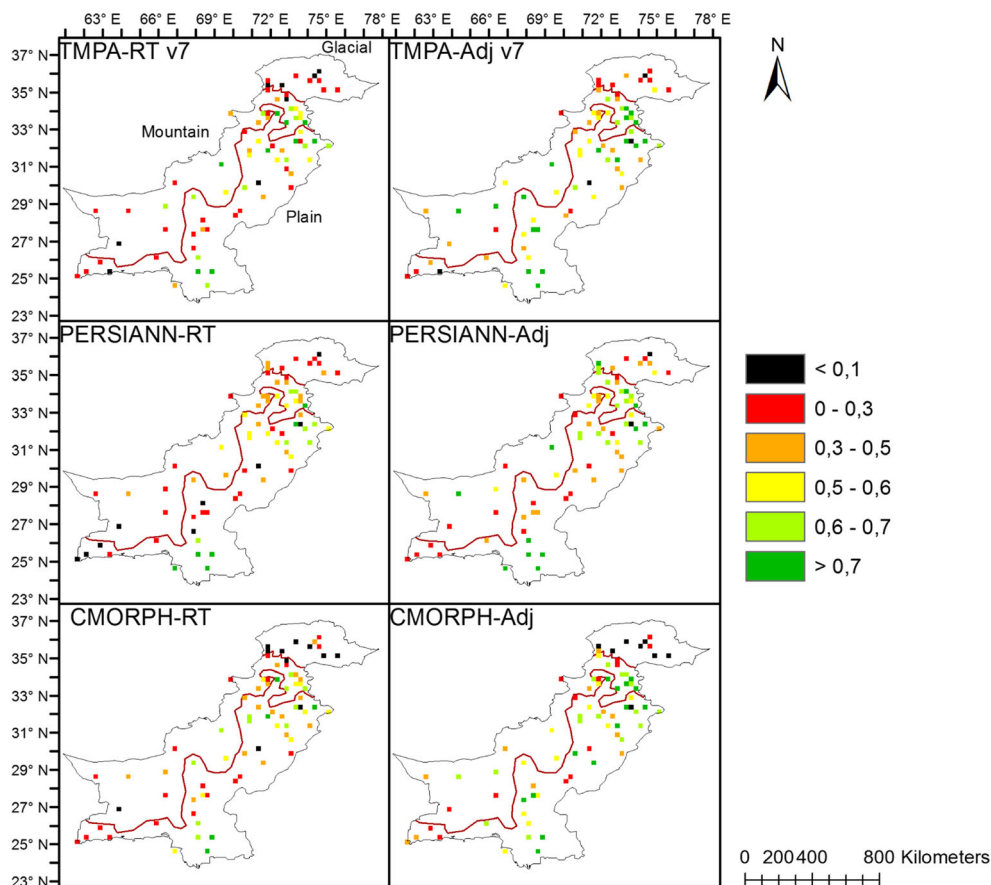
is clearly highlighted with close to 60 and 80% of rainfall amounts inferior to 25 mm and 50 mm month⁻¹, respectively. All SREs overestimate the relative proportion of low to moderate monthly rainfall. It confirms SRE deficiencies over low rainfall plain and glacial region with SREs highly overestimating rainfall amounts (Table 4, Fig. 5). PERSIANN-RT underestimates moderate to high rainfall amount occurrences while it is the closer SREs regarding low and moderate rainfall events. The adjustment enhances the representation of a moderate to high rainfall event but degrades the representation of low rainfall events (Fig. 5). As a result, PERSIANN-Adj is less biased than PERSIANN-RT over the mountainous regions where highest rainfall amounts are observed (Fig. 2 and Table 4) and confirm the adjustment benefit over this region. As low rainfall events count for 80% of rainfall occurrence, lowest Bias is observed on PERSIANN-RT (-11.8%) rather than on PERSIANN-Adj on the global scale (35.3%) (Table 4). TMPA-Adj fitted better the gauges CDF than TMPA-RT for low monthly rainfall amounts. As a consequence, TMPA-Adj has the lowest Bias than TMPA-RT over the plain and glacial regions where low rainfall amounts are observed (Fig. 2 and Table 4). CMORPH-RT overestimates the proportion of all rainfall amounts and confirms positive Bias observed on the global scale and for all the considered classes (Table 4). The adjustment leads to clear

enhancement with CMORPH-Adj curve fitting better the gauges one in comparison to all other SREs.

At the monthly scale, the adjustment effects are positive for CMORPH, TMPA, and PERSIANN products. CMORPH-RT adjustment decreases and increases the Bias and CC values at the global scale and for all the classes, while RMSE has remained close to superior. TMPA-RT adjustment has enhanced all the considered statistical parameters. Close to lowest Bias is observed at the global scale for TMPA-RT in relation to the negative Bias observed for mountainous classes that reduce the global Bias. PERSIANN-RT adjustment is strong over the mountain class where RMSE, CC, and Bias value are enhanced. It is more contrasted at a global scale and for the glacial and plain regions. Indeed, RMSE and CC values are better for the Adj than the RT version while Bias value increased. Therefore, at the global scale, even if PERSIANN-Adj is much biased than its RT version, the adjustment enhances monthly rainfall temporal variation description.

Figure 6 represents the Bias for the 75 pixels and for all SREs. It confirms the results observed in Figs. 2, 3, 4, 5 and Table 4. PERSIANN-RT underestimates high rainfall amount with a large proportion of pixels with high negative Bias especially, over the rainiest mountainous area. CMORPH-RT overestimates rainfall all over the domain except over the

Fig. 7 Spatial patterns of mean monthly CC



southwest arid region corresponding to the Balochistan plateau. In this region, all SREs tend to underestimate rainfall amounts with negative Bias. It might be a consequence of short rainfall events predominance which is not well captured by microwave sensor due to low receptivity. Almost all pixels located in the glacial upper part present an overestimation of rainfall and confirm SRE deficiency over snow and ice cover previously observed from Tables 3 and 4 and Figs. 2, 3, and 4. CMORPH-Adj and TMPA-Adj count with the highest proportion of pixel with Bias value into the threshold quality criteria domain. Adjustment decreases Bias value and confirms its positive effect. It is especially true for CMORPH products as CMORPH-RT and CMORPH-Adj are the most and less biased SREs. PERSIANN adjustment effect is more contrasted. It is only benefic over the rainiest mountainous region northern part (Fig. 6) with more pixels into the defined quality range for PERSIANN-Adj than PERSIANN-RT. This region counts with more rainfall amounts which are better represented by PERSIANN-Adj (Fig. 5). The opposite case is true over the plain arid region with a higher proportion of negatively biased pixels. This confirms PERSIANN-Adj Bias in low to moderate rainfall regions (Fig. 5 and Table 4).

Figure 7 displays the CC. As for Bias values, CC values are worst over the glacial region with very low value registered by all considered SREs. For all products, a general increase of

CC value is observed all over the domain and for adjusted versions. CMORPH-Adj and TMPA-Adj count the highest proportion of pixels superior or close to the threshold value all over the region and confirm the results observed in Table 4.

Figure 8 displays the RMSE pattern. RMSE is very high all over the domains and for all SREs. It is especially true over the arid southern part with RMSE value superior to 100%. A slight decrease of RMSE value is observable for TMPA-Adj and PERSIANN-Adj products thanks to the adjustment. On the contrary and as observable in Table 4, CMORPH-Adj RMSE is not enhanced by the adjustment and remained close to CMORPH-RT RMSE values.

Figures 6, 7, and 8 confirm the positive effect of gauge adjustment on TMPA, PERSIANN, and CMORPH products. The same observation was found in a similar semi-arid climate over the South American Andean region (Satgé et al. 2016) and central Asia (Guo et al. 2015). Regarding TMPA, TMPA-Adj rainfall estimates were also found to be the closest to the reference estimate than RT version over the continental United States and West Africa (Gosset et al. 2013; Chen et al. 2013). Over mountainous region and in a less extent over the plain, estimates of PERSIANN-Adj are more accurate than PERSIANN-RT. This has confirmed PERSIANN-Adj improvement over PERSIANN-RT as observed in Iran (Katiraie-Boroujerdy et al. 2013). CMORPH-Adj slightly

Fig. 8 Spatial pattern of mean monthly RMSE

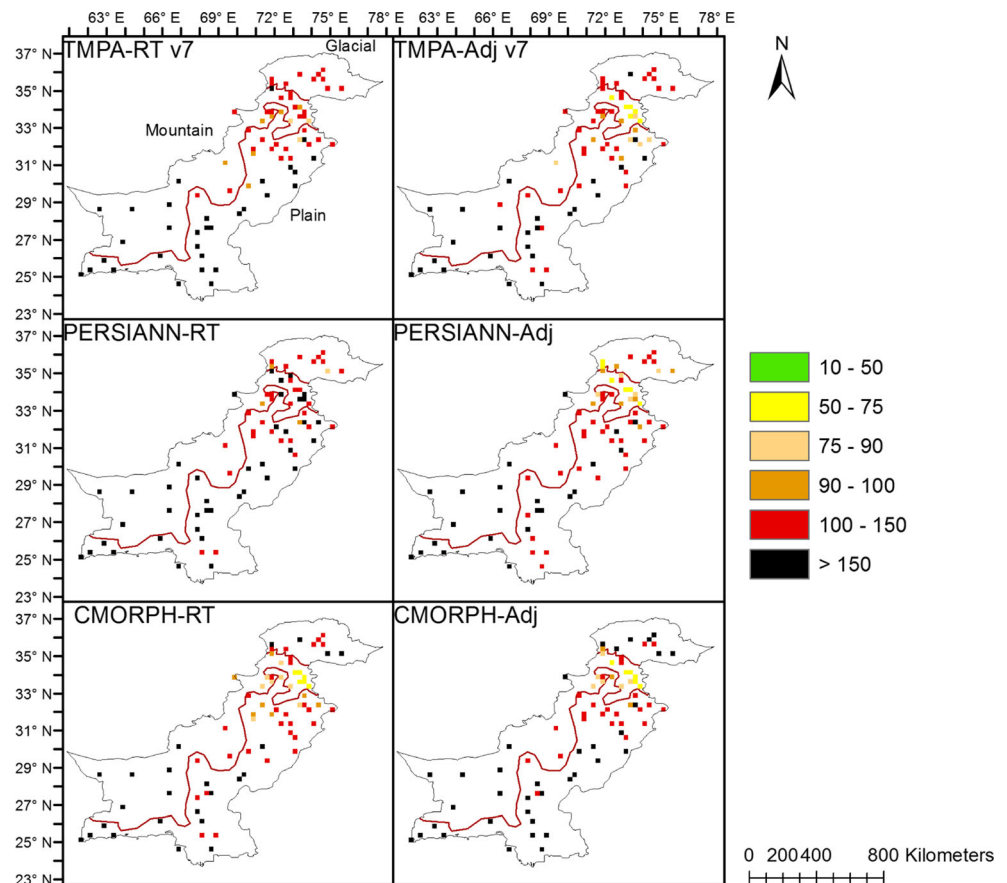


Table 5 POD and FAR values for all considered classes and global scale

	Classes	CMORPH-Adj	CMORPH-RT	PERSIANN-Adj	PERSIANN-RT	TMPA-Adj v7	TMPA-RT
POD	Glacial	0.62	0.63	0.52	0.46	0.49	0.31
	Mountain	0.63	0.61	0.46	0.36	0.44	0.37
	Plain	0.40	0.35	0.35	0.25	0.23	0.21
	All	0.54	0.51	0.43	0.34	0.37	0.30
FAR	Glacial	0.88	0.88	0.83	0.83	0.86	0.87
	Mountain	0.74	0.75	0.75	0.74	0.72	0.73
	Plain	0.84	0.86	0.87	0.86	0.84	0.84
	All	0.81	0.82	0.82	0.81	0.80	0.80

outperformed PERSIANN-Adj and TMPA-Adj over the mountainous region in terms of CC, Bias, and RMSE. This has confirmed CMORPH potentiality over such region as demonstrated for the CMORPH-RT first version (Dinku et al. 2007; Dinku et al. 2010). However, here, it is only true considering the CMORPH-Adj as CMORPH-RT estimates are highly inaccurate all over the domains. Finally, over glacial region, all SREs show consistent deficiency may be due to snow and ice cover. Thus, these regions are still challenging for the future SRE algorithms.

4.3 Daily scale

Table 5 represents values of POD and FAR at global scale and for plain, mountainous, and glacial regions.

As expected, FAR value is higher for all SREs at the global scale and for all classes. This should be attributed to the different spatial scale representability from gauge and SREs. The pixels are representative of an area of approximately 625 km² in which more rainfall events are expected to occur in comparison to the point gauge scale.

At the global scale, CMORPH product presents the better ability in detecting rainfall event occurrence with highest POD value among all the considered SREs. When considering the different classes, highest PODs are observed for all SREs over glacial and mountain regions than over plain. This trend highlights the relative higher ability of SREs in differencing rainy to no-rainy day over mountainous dominated region in Pakistan. Indeed, rain processes over plain and mountainous dominated regions differ in relation to the geomorphological context. The FAR slightly decreases from glacier to mountain classes and for all SREs. As previously discussed, glacial region dominated by ice and snow cover which could be misidentified as the rainy cloud by SRE algorithms and led to an increase of FAR. At the monthly and yearly scales, it is transposed by an overestimation of respective rainfall amount.

The relative high POD and low FAR over mountain class is in agreement with yearly and monthly analyses as both agree with a highest SRE potential over this region.

Generally, CMORPH products present higher POD than PERSIANN and TMPA products for all classes. FAR is high and close for all SREs and classes in relation to the poor representation of SREs by gauges induced at different spatial resolutions.

All adjusted versions enhance daily rainfall detection with higher POD and close FAR values at the regional scale and for all the considered classes.

The POD results presented here are representative of SRE ability because a rain event detected by gauges should be detected by SREs regardless the spatial resolution difference. However, FAR results should be considered with caution as they are highly dependent on the spatial resolution difference between gauges and SREs. For example, over the Andean plateau, lowest FAR values were found when more than one gauge by pixels was used (Satgé et al. 2016). More studies including denser rain gauge network are needed to clearly state on daily SRE potential over Pakistan.

5 Conclusions

Accurate rainfall estimation is very important for Pakistan's agricultural growth and safety from natural disasters like flooding and droughts. However, few rain gauges are observed over the region due to difficult access and limited financial support. In this context, a total of 75 rain gauges spread into 74 pixels were used to assess for the first time six SREs over Pakistan. The considered SREs are CMORPH (RT and Adj), TMPA (RT and Adj), and PERSIANN (RT and Adj). RT and Adj versions are both considered to have assessed adjustment effect over the region. SREs were assessed at regional scale and considering plain, mountainous, and glacial regions separately to assess their dependency on different morpho-climatologic contexts. The following conclusions are drawn from the analysis:

- All the products represent the typical north south rainfall patterns with higher rainfall region into the northern

mountainous part and the very arid desert in the south western part.

- SREs present strong deficiency over the Himalayan glacial region with a systematic overestimation of seasonal and monthly rainfall amounts. The snow and glacial cover might be misidentified as rainy cloud due to low temperature and high emissivity. This is highlighted by the daily analysis revealing higher FAR values for all SREs over the glacial regions.
- Future algorithms should carefully take into account those specifics cover to better consider the strong emissivity and temperature contrast towards the enhancement of rainfall estimate.
- CMORPH-RT strongly overestimates rainfall amount at the regional scale with Bias value of approximately 50%. The adjustment is very efficient as the Bias drop to 6% for CMORPH-Adj. TMPA-RT adjustment is also positive as Bias value stays lower for all considered classes for TMPA-Adj. PERSIANN-RT adjustment is more contrasted.

RMSE and CC are enhanced by the adjustment for all the classes but increase Bias value over the plain and glacial region.

- CMORPH-Adj is the most accurate SREs to describe annual and monthly rainfall over Pakistan. However, TMPA-Adj is very close with close Bias, RMSE, and CC.
- The daily analysis confirms the positive effect of the adjustments with an increase of POD for all SREs at the regional scale and for all considered classes.

The results suggest that CMORPH-Adj should be used in studies requiring annual to monthly rainfall information. With more than 17 years of the available data set, those products provide valuable information to highlight the main change in rainfall tendencies over the period. Thus, this data has a strong potential for national management regarding the conceivable drought and flood future scenarios damaging billions of people. The potentiality of SREs at daily scale was quickly assessed. However, due to the low density of the rainfall gauges network used, it is not possible to clearly state on SRE ability and more assessments are still needed. In this scope, future studies may indirectly assess SREs' daily estimate by using SREs as an input data for hydrological modeling and compare simulated and observed discharge. Such an approach avoids direct comparison with a scarce gauge network and the subsequent gauge spatial representativeness problem.

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