

1 Article

2 Comparison and evolution of satellite-based precipitation 3 product for flood-prone Kunhar River basin, Khyber Pakh- 4 tunkhwa (KPK) , Pakistan

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9 **Abstract**

10 Floods are one of the major natural hazards affecting the northern regions of Pakistan.
11 Kunhar River basin lies in the northern territory of Pakistan and is highly vulnerable to
12 flooding due to its steep terrain and heavy monsoon rainfall. Reliable precipitation data
13 is essential for accurate hydrological modeling and flood forecasting. However, ground-
14 based rainfall observations are often limited, making satellite-based precipitation prod-
15 ucts an important alternative. This study focuses on the comparison and evaluation of
16 different satellite-based precipitation datasets for their suitability in the hydrological
17 modeling of the flood-prone Kunhar River basin. Several global products such as Inte-
18 grated Multi-Satellite Retrievals for the Global Precipitation Measurement (GPM) mission
19 and Tropical Rainfall Measuring Mission (TRMM) analyzed and compared with available
20 ground station data. The selected precipitation datasets were applied in the Hydrologic
21 Engineering Center - Hydrologic Modeling System (HEC-HMS) hydrological model to
22 evaluate their role in simulating rainfall-runoff processes. Statistical performance indica-
23 tors including correlation, bias, Root Mean Square Error, and Nash-Sutcliffe efficiency
24 was used to assess their accuracy. Integrated Multi-satellite Retrievals for GPM mission
25 was the most suitable satellite-based precipitation product for enhancing flood prediction
26 and water resource management in the Kunhar River Basin, KPK, Pakistan.

27 **Keywords:** Comparison and evaluation; HEC-HMS; Hydrological modeling; Kunhar
28 River basin; Satellite-based precipitation products.

29

30 **1. Introduction**

31 One of the most disastrous natural hazards is the flooding. Pakistan is one of the
32 countries that experienced floods, as they do not have data to aid in flood management
33 [1]. Flood prediction and reliable hydrological simulation require accurate precipitation
34 data for estimating surface runoff, watershed responsiveness and planning disaster pre-
35 paredness [2,4]. Precipitation fluctuates on an annual and multi-decadal scale, and the
36 alterations in terms of quantity, intensity, frequency, and form (e.g., snow and rain, etc.)
37 impact the environment and society. Light continuous rainfall will penetrate into the
38 ground; can be absorbed by the vegetation. Whereas the same amount of rainfall for a

39 relatively short duration can result in the appearance of local flooding and high runoff
40 thus, leaving the soils considerably drier by the end of the day [3].

41 The presence of unevenly distributed rain-gauge networks decreases the perfor-
42 mance of the conventional ground-based hydrological prediction systems, in particular,
43 during extreme weather conditions when the risk of heavy rainfall, like the 2010, 2016,
44 and 2022 flood seasons, is present [5,11]. In order to address these deficiencies, satellite-
45 derived precipitation products (SPPs) such as the Tropical Rainfall Measuring Mission
46 (TRMM), Global Precipitation Measurement (GPM), and Climate Hazards Group Infrared
47 Precipitation with Station Data (CHIRPS) are gaining more and more importance as the
48 source of observations in remote areas or those with no or less data available. These da-
49 tasetes give real-time high-resolution rainfall data, and have been used in several hydro-
50 logical and climatic analyses in the Himalayan region [6,7,10,11].

51 One of the flood-prone sub-catchments of the Jhelum River system is the Kunhar
52 River basin (KRB) which is found in the Kaghan Valley of Khyber Pakhtunkhwa. Its sharp
53 hills, small valleys and heavy rainfall during monsoons have a major contribution in the
54 production of runoff and flood prone areas [5,11]. Previous researchers indicate that ex-
55 treme rainfall, which lasts a short period, combined with land-use transformation and
56 glacial melt are frequent causes of flash flooding, landslides, and riverbank erosion in the
57 area [13, 22-24]. Like the Swat and Indus basins, KRB had gone through a series of devas-
58 tating floods, which proves how critical it is to have better hydrological modeling and
59 early-warning systems [11, 12]. The varying climate in the region has recently been mag-
60 nified due to haphazard changes in the hydrological processes, like floods [28].

61 Hydrological modeling software like Hydrologic Engineering Center-Hydrologic
62 Modeling System (HEC-HMS) is capable of simulating rainwater-runoff, creating hydro-
63 graphs, and assessing the behavior of a watershed at different inputs of rainfall. HEC-
64 HMS has been extensively applied in Pakistan as well as in other parts of the world in
65 flood forecasting, climate scenario modeling and stormwater management [2, 4, 12]. In
66 mountainous basins such as Kunhar, satellite precipitation combined with HEC-HMS of-
67 fers a viable solution to assess the flood response in a location with the limitation of the
68 gauge data or unreachability. This method is useful in determining the most dependable
69 rainfall product to be used in the operational flood prediction.

70 The HEC-HMS model was developed by the US Army Corps of Engineers [14] and
71 could be used for many hydrological simulations. The HEC-HMS model can be applied
72 to analyze urban flooding, flood frequency, flood warning system planning, reservoir
73 spillway capacity, stream restoration, etc. [16]. The proliferation of personal computers
74 and the development of the HEC-1 model of the U.S. Army Corps of Engineers in 1998 to
75 a GUI (graphical user interface)-based user-friendly HEC-HMS model, which is available
76 in the public domain, have come as another useful tool to the field hydrologists. Unfortu-
77 nately, the HEC-HMS model, or any of the many watershed models for that matter, has
78 not found many takers due to the uncertainty involved in the estimation of parameters of
79 the models [2]. But parameter estimation on a regional scale at least may be possible to
80 switch over to watershed models like the HEC-HMS and take advantage of the high-speed
81 computer programs rather than spreadsheet exercises [15].

82 In this study, the SCS Curve Number method in parts of precipitation loss was used.
83 Required factors for this method are initial abstraction, curve number and the impermea-
84 ble proportion of soil surface. Combining the prepared maps from hydrologic groups (soil
85 texture based) and land use, the average value of CN for the Kunhar watershed was com-
86 puted. Having computed the average value of CN, surface conservation of soil (S) and
87 estimation of the empirical value of initial abstraction are used in several investigations
88 [17,18]. Thus, the comparison of various datasets of satellite precipitations is crucial to
89 making credible hydrological predictions [7, 8, 10].

Some studies have been conducted to point out the advantages and disadvantages of SPPs in mountainous areas. TRMM offers historical views over a long period, but it has been biased in high-altitude places under the influence of snow [8, 9]. GPM has better spatial resolution and better two-frequency precipitation radar features, which is more appropriate in the case of intense convective storms [7, 11]. A CHIRPS is a satellite-based model combining data with climatic stations, which is accurate but unpredictable in rugged areas [10, 11]. Based on past studies in the Himalayas and northern Pakistan, this study would fill a large gap by comparing the accuracy of major satellite rainfall products in particular hydrological modeling of the Kunhar Basin. Although comparable analyses have been carried out in Swat [19], Indus [20] and Jhelum basins [21], not much literature has been carried out on Kunhar catchment. The study will hence help increase accuracy in flood-forecasting, watershed management, and climate-resilience planning in the area.

In contrast to the past research, which majorly entails comparative statistical analysis of rainfalls, the current study assesses the satellite precipitation products in terms of their hydrological response and flood peak generation in a very complex Himalayan basin. The results give basin-related information on the usability of TRMM and GPM products on flood modeling within ungauged and data-sparse mountainous areas of Pakistan. It is expected that this study will determine the optimal satellite data to describe the variability of rainfall and to help estimate floods in the KRB by using the HEC-HMS simulations, statistical metrics of performance (NSE, R2, and RMSE) and sensitivity analysis. Improved rainfall inputs will boost real-time flood monitoring, early-warning systems, and disaster-management plans in accordance with the demands of the communities in the Kaghan Valley.

2. Data and Methods

2.1 Study area

The KRB is situated in the mountainous area, which is to the north of Pakistan and mainly in the Khyber Pakhtunkhwa province. It also starts at Lulusar Lake, adjacent to Babusar Pass, at a height of more than 3,800 meters and drains south of the beautiful Kaghan Valley, where it meets the Jhelum River at Muzaffarabad, Azad Jammu and Kashmir (AJK) [25]. It is located between 34.2°N, to 35.1°N latitude and 73.3°E to 74.0°E longitude, and has an area of around 4,000 km², depending on the area of delineation [26].

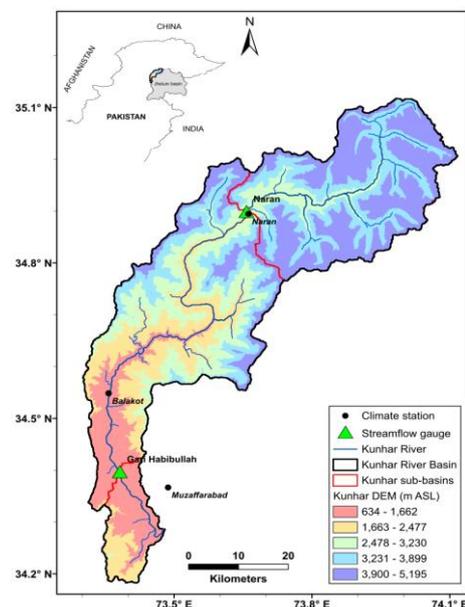
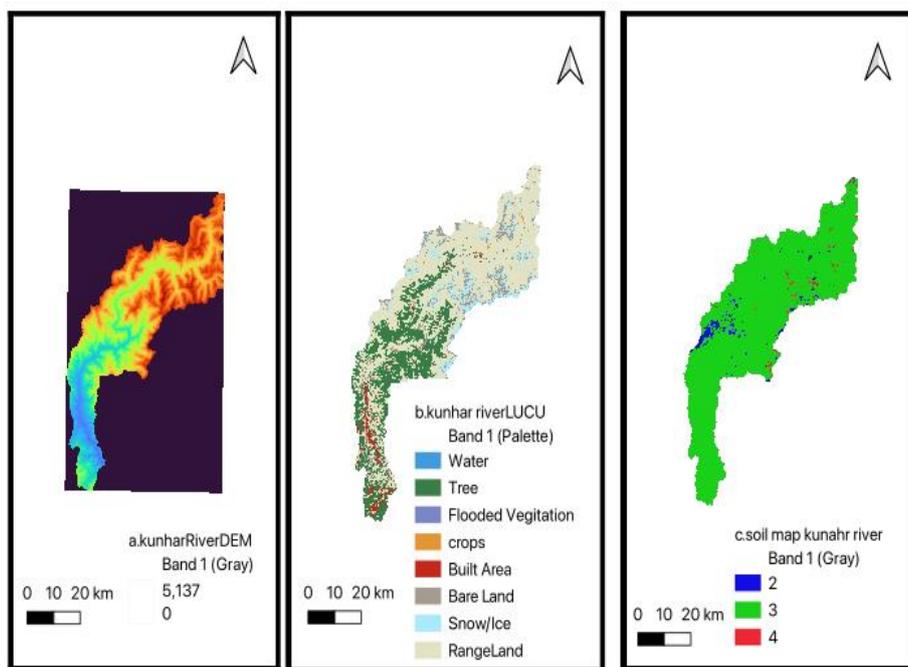


Figure 1. Study area map showing Kunhar River basin along with streamflow & climate stations

123 The basin topography is high and steep mountainous, has deep valleys and high elevation which renders the basin prone to both flash floods and rapid runoff [4] and high
 124 winter snowfalls particularly to settlements along the river such as those found in Balakot,
 125 Kaghan and Naran [27]. The amount of annual precipitation ranges from 800mm to 1600
 126 mm with maximum rainfall occurring during the monsoon, July-August [26]. The steep
 127 inclines combined with deforestation, glaciers melting, and heavy rainfall translate to a
 128 sudden surge in the river discharge [25] and the reason behind this flash floods. The KRB
 129 also presents hydrological complexity and prone to flooding and therefore, it is a key re-
 130 gion to apply hydrology models through satellite precipitation data particularly in regions
 131 with low density of ground-based observation stations [25,27].
 132

133 2.2 Data

134 Ground-based rain gauges data is usually inadequate or inaccurate in remote and
 135 mountainous areas such as the KRB. Consequently, the SPPs are necessary to estimate the
 136 rainfall of extensive and unreachable areas. The prediction of future climate has been a
 137 major worldwide concern given the high carbon emissions practices and owing to signif-
 138 icant diversity in climatic parameters like rainfall and temperatures [29]. This research
 139 utilized a mix of the topographic, land cover, rainfall, and streamflow data to construct
 140 the hydrological model of KRB. The watershed was drawn and slopes and stream net-
 141 works were extracted using a 30-m Digital Elevation Model (DEM) that is crucial in mod-
 142 eling the process of runoff in steep basins of the Himalayas [2, 4]. The SCS Curve Number
 143 (CN) values were calculated on land use/land cover (LULC) data and soil maps to gener-
 144 ate the values that regulate rainfall collected by a surface and surface run-off produced
 145 [9]. Both ground stations and commonly used SPPs were used as rainfall inputs such as
 146 GPM IMERG and TRMM 3B42 due to the extremely low number of rain gauges in the
 147 region and the improved spatial coverage of satellite data in mountainous areas [5, 8, 10,
 148 12]. Streamflow measurements in the basin outlet were observed and model calibration
 149 and validation were conducted and guaranteed the validity of the comparisons between
 150 SPP-based runoff simulations [13, 11]



151
 152 **Figure 2:** a) Digital Elevation model b) Land use and land cover c) soil map of Kunhar River basin,
 153 KPK, Pakistan.

Table 1: Details description of data used in the study including their spatial-temporal resolution and sources

Sr. No.	Data description	Spatial Resolution	Temporal Resolution	Data source
1	Digital Elevation Model	30m	Static (Feb 11-12,2000)	30-meter STRM
2	Land Use and Land Cover Map Soil Map	10m	Annual	ESRI
3	Soil Map	250m	Annual	NASA, USA
4	Precipitation (GPM IMERG)	0.1°	Daily (2010-2014)	NASA, USA
5	Precipitation (TRMM)	0.25°	Data (2010-2014)	NASA, USA

2.3 Methods

The methodology used in this study comprises five large components, i.e., basin delineation, derivation of hydrological parameters, satellite precipitation products selection and processing, setting up of HEC-HMS model, and model calibration-validation. The general processes involved in the workflow are standard hydrological model tasks normally used in mountainous and data poor basins [2, 4, 13, 30]. A methodology chart showing workflow is shown below as Figure 3.

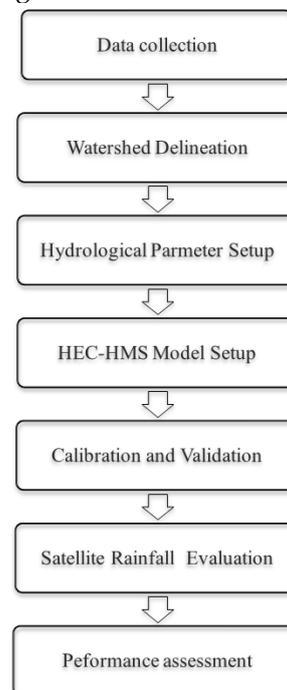


Figure 3. Flowchart illustrating the methodology adopted for evaluating satellite-based precipitation products using the HEC-HMS hydrological model in the Kunhar River basin, KPK, Pakistan.

Watershed Delineation and Physical Parameter Extraction Watershed delineation involves extraction of watershed physical parameter and delineation of watershed in real life situations. The KRB was delineated using a 30-m Digital Elevation Model (DEM) from Shuttle Radar Topography Mission (SRTM) in HEC-HMS [31, 32]. Preprocessing in the form of sink filling, flow direction, flow accumulation, and stream definition using DEM

172 aided in the location of drainage patterns and sub-basin boundaries. The mountainous
173 catchments such as the Himalayas require automated delineation of watersheds because
174 steep slopes play a major role in shaping the nature of the runoff [9]. Smaller sub-basins
175 were combined to have hydrological uniformity and ease of calculation. The sub-baseline
176 features such as the area, slope, centroid; flow length and time of concentration were au-
177 tomatically derived and subsequently utilized to determine basin lag time, a critical vari-
178 able to the SCS Unit Hydrograph

179 The ESA provided LULC data that were compared with high-resolution Google
180 Earth imagery. FAO soil maps formed the basis of hydrologic Soil Groups (HSGs). The
181 SCS Curve Number (CN) technique was chosen as it was used to estimate the potential of
182 infiltration and runoff because of its reliability and frequent application in flood prone
183 basins. In QGIS, the LULC and HSGs were grouped using Zonal Statistics which were
184 then used to compute CN values per sub-basin. The same methods are widely used in the
185 watersheds of the Himalayan region where measurements are restricted on the ground.
186 The common SPPs were chosen, including: GPM IMERG and TRMM 3B42. These datasets
187 have been characterized by high performance in mountainous areas of South Asia espe-
188 cially where the density of rain-gauges is sparse [8], [10], [12]. The rainfall-runoff model
189 was developed in HEC-HMS 4.12 that gives the opportunity to represent the hydrologic
190 processes in detail and is frequently applied in flood prediction [2], [4]. The SCS CN
191 Method was used to estimate a loss. Runoff transformation was processed by referring to
192 the SCS Unit Hydrograph, which was used in terms of the suitability of the method in the
193 small-middle mountainous catchments, recession method for base flow and temperature
194 index method is used for snowmelt. The Muskingum routing method that was used to
195 perform channel routing is an effective simulation of flood wave translation in steep river
196 networks. The measured mean streamflow discharge per day at the basin outlet of Water
197 and Power Development authority (WAPDA) stream gauges, temperature and precipita-
198 tion data of Pakistan Meteorological Department (PMD) gauges was used for model. Dis-
199 charge per day at the basin outlet of WAPDA gauges was taken as reference streamflow
200 data. Each set of precipitation data (GPM, TRMM,) was modeled independently to com-
201 pare the performance of the model on the three-precipitation series and determine which
202 satellite image is best suited to hydrological modeling.

203 The model is said to be calibrated and validated in case both the predictive and ex-
204 planatory accuracy are evaluated and verified. Reliable precipitation data with spatial dis-
205 tribution and temporal variability is vital for accurately representing rainfall inputs into
206 the model. Historical streamflow and precipitation data can be used for model calibration
207 and validation to ensure accurate representation of river flow dynamics [33]. Combined
208 with the manual fine-tuning, and the automated optimization schemes in the HEC-HMS,
209 calibration was done. The calibrated hydrological parameters were assumed to be time-
210 invariant, as they represent the physical characteristics of KBR, including soil infiltration
211 capacity catchment response time, channel routing behavior and base flow processes. The
212 main parameters that are calibrated are: SCS Curve Number, Lag time, temperature index,
213 baseflow, Muskingum K and X parameters. One period (1971-1988) of observed data was
214 used in calibration and an independent dataset in validation (1989-1994) in order to ensure
215 the model reliability. To assess model performance datasets was compared using: Nash
216 Sutcliffe Efficiency (NSE), Coefficient of Determination (R²), Percent Bias (PBIAS) and
217 Root Mean Square Error standard deviation (RMSE Std. Dev). The same parameter set
218 was transferred without modification to satellite era (2010-2014). This approach ensures
219 that differences in stimulated runoff are attributable primarily to the precipitation input
220 source (TRMM vs. GPM) rather than to parameter re-adjustment. The parameter-transfer
221 approach is commonly used in hydrological studies to evaluate alternative forcing da-
222 taset under identical basin condition. These measures are largely suggested to SPP's

evaluation research and hydrological model validation. The most efficient satellite data were chosen on the grounds of reproducing observed discharge patterns as well as peak flows

3. Results and Discussion

After running the HEC-HMS hydrological model using precipitation inputs from TRMM and GPM the following observations were made based on model performance, hydrograph patterns, and statistical evaluation.

Table 2. Statistics for model discharge evaluation at Talhata station.

Time series	Calibration (1971-1988)				Validation (1989-1994)			
Indicators	RMSE (Std dev)	NSE	R ²	PBIAS (%)	RMSE (Std dev)	NSE	R ²	PBIAS (%)
Daily	0.7	0.510	0.52	6.17	0.7	0.492	0.56	3.33

Table 3. Statistics for model discharge evaluation of satellite at Talhata station.

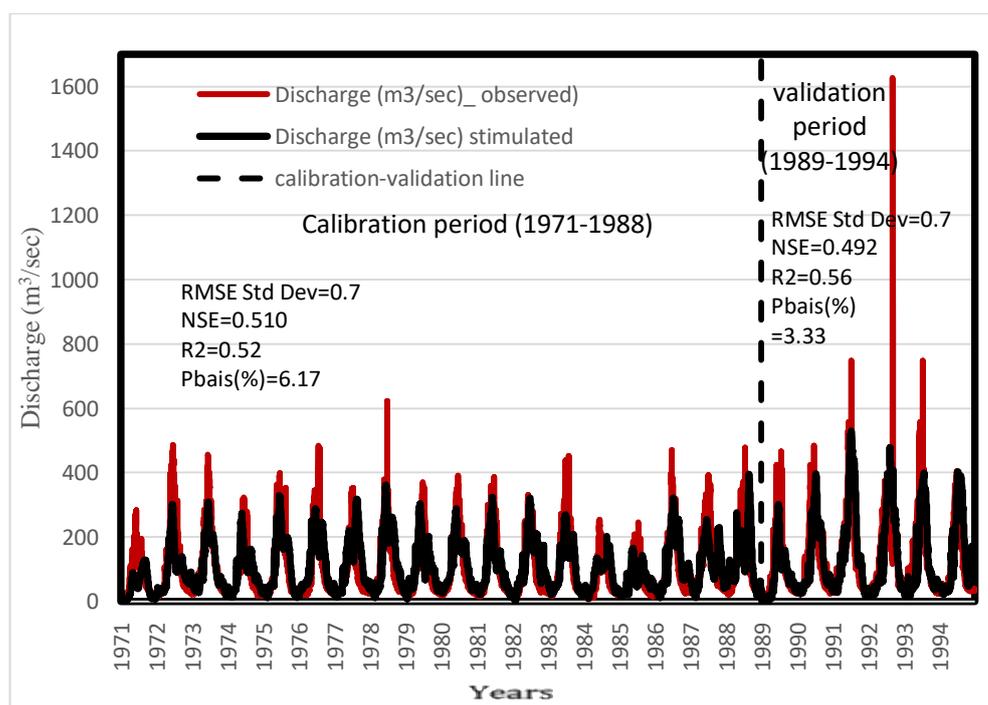
Time series	GPM (2010-2014)				TRMM (2010-2014)			
Indicators	RMSE (Std dev)	NSE	R ²	PBIAS (%)	RMSE (Std dev)	NSE	R ²	PBIAS (%)
Daily	1.0	0.047	0.12	-0.13	1.0	0.009	0.31	-45.81

In this study the various precipitation records were tested to determine whether they are suitable in hydrological modeling. Collaborating with WAPDA and NASA ensures a robust dataset, enhancing our understanding and forecasting capabilities. The HEC-HMS model was calibrated and validated for the Kunhar River basin using observed discharge data from Gari Habibullah station. The model performance was evaluated for each dataset using statistical metrics including Nash–Sutcliffe Efficiency (NSE), Root Mean Square Error (RMSE) Std. dev, PBIAS, and coefficient of determination (R²). Calibration was performed using the SCS Curve Number method, SCS Unit Hydrograph, Temperature index, Recession and Muskingum routing parameters. To make sure that a physically consistent model is made KRB was hydrologically modeled in 1971-1988 and validated in 1989-1994 based on the measured discharge. In calibration, the model performed good with Nash-Sutcliffe Efficiency (NSE) of 0.51 and a coefficient of determination (R²) of 0.52 which clearly shows a good model performance and good simulation of rainfall-runoff response of the basin. The Percent Bias (PBIAS) of 6.17 indicates a slight overestimation of the volume of runoff, which is within the acceptable prediction limits of hydrological models especially in steep mountainous catchments where there is an inherent level of uncertainty presented by the variability of precipitation and snowmelt processes. The standard deviation (RMSE = 0.7) is relatively small, which also indicates the credibility of the calibrated model.

Validation showed good agreement between simulated and observed hydrographs, indicating that the model reliably captures the rainfall–runoff processes in the basin [12, 2, 9]. The model validation output was similar to the calibration phase, with an NSE of 0.49 and an R² of 0.56 indicating that the set of calibrated parameters is stable over time and not weak. The increased PBIAS of 3.33% in the validation period shows that the systematic error is less and that model parameters are sufficient in capturing the physical aspects of the basin over varying time periods. Such findings justify a transfer of calibrated parameters to the satellite age and make them useful to assess the satellite-based precipitation products when subjected to the same hydrological condition [35].

261 The fixed calibrated parameter set was then used to assess the hydrological perfor-
 262 mance of satellite precipitation products in the period 2010-2014. These findings indicate
 263 that both GPM and TRMM precipitation products have low predictive power of hydro-
 264 logical applications in the mountainous complex terrain of the Kunhar River basin. In the
 265 case of GPM-driven simulation, the model had a slightly positive NSE of 0.047 which was
 266 marginally better than the average observed discharge. Nevertheless, the low correlation
 267 coefficient (R2) value of 0.12 indicates that there is a weak association between simulated
 268 and observed variability in the flow, especially in terms of predicting the occurrence of
 269 the highest flow. Although this is a weakness, the near-zero PBIAS (-0.13) indicates that
 270 GPM has been found to replicate the total volume of runoff, which indicates its relative
 271 capability of estimating cumulative discharge and flood volume.

272 Conversely, the attempt to simulate with TRMM led to a low NSE of 0.009 which
 273 implies a bad overall model performance. Though TRMM had a relatively higher R2 of
 274 0.31, which implies a better correlation in time and recognition of flow patterns, the PBIAS
 275 of it, though negative, was dramatically large in magnitude -45.81, indicating a significant
 276 underestimation of the magnitude of runoff. Such a high degree of negative bias suggests
 277 that TRMM does not capture heavy precipitation events in the Kunhar River basin, which
 278 results in a high underestimation of the highest floods. This is a major limitation to the
 279 application of TRMM in flood hazard mapping in the study area since the main require-
 280 ment of flood modeling is proper representation of discharge magnitude



281
 282 **Figure 4.** Observed vs. stimulated discharge for calibration (1971-1988) and validation (1989-1994)
 283 at Gari Habibullah station, Kunhar River, KPK, Pakistan.

284 The comparative analysis of GPM and TRMM points out that R2 is not sufficient to
 285 consider hydrological performance especially where large volume bias is involved.
 286 TRMM has high temporal correlation, but its serious underestimation of runoff under-
 287 mines its usefulness in flood modeling. On the other hand, GPM demonstrates relatively
 288 high hydrological consistency, in the sense of representation of runoff volume, although
 289 it is weak on the ability to simulate the timing of discharge.

Altogether, the findings suggest that although satellite precipitation products are useful because of their high spatial coverage in data-deficient mountainous areas, their direct application in hydrologic modeling is still closely related to significant uncertainty. Of the compared datasets, GPM is slightly better than TRMM especially in estimating the runoff; nonetheless, all products need reasonable bias corrections and local adjustments to improve the performance of the models in flood forecasting in the Kunhar River basin. Accurate satellite precipitation data are essential in the Kunhar River basin due to steep topography and monsoon-driven rainfall, which can produce flash floods with significant socio-economic impacts [6, 13, 36]. The findings suggest that high-resolution, bias-corrected satellite precipitation datasets such as GPM IMERG are recommended for flood forecasting and hydrological modeling in the region.

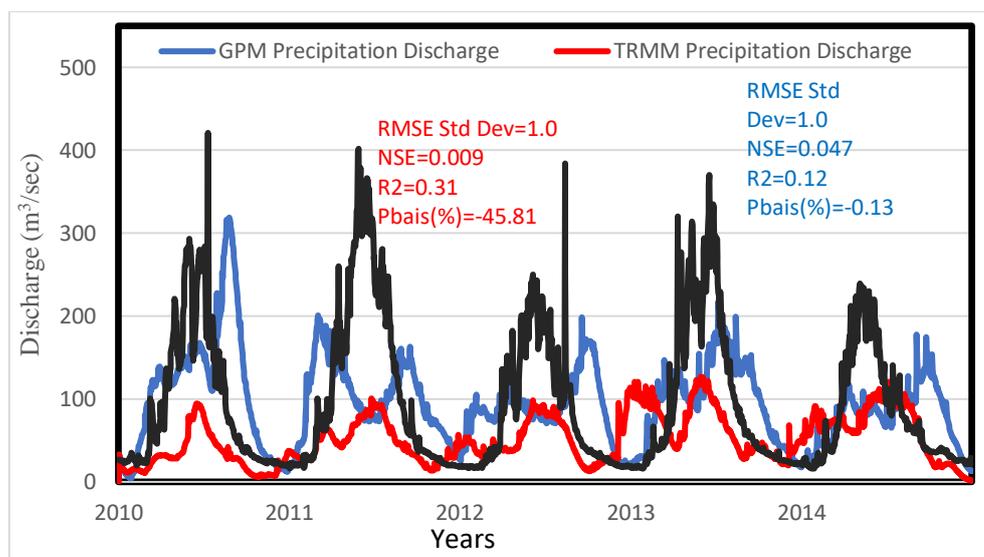


Figure 5. Comparison of discharge at Talhata station for GPM precipitation vs. TRMM precipitation and the observed one from 2010 to 2014.

4. Conclusions

This study evaluated the performance of two satellite-based precipitation products TRMM and GPM for hydrological modeling of the flood-prone Kunhar River basin in Pakistan using the HEC-HMS model compared to station data. Through the findings of the present research, the GPM satellite precipitation product was superior to TRMM and recorded precipitation data to use in hydrological modeling. GPM exhibited lower values of errors, acceptable bias and had better efficiency indicators, which makes it more useful in hydrological simulations. The TRMM data was characterized by strong underestimation as well as negative model efficiency limiting its direct application to hydrological models. TRMM data would have to be biased out so as to make credible simulations.

To conclude, GPM can be suggested as the best satellite precipitation dataset of the considered datasets to be used in terms of hydrological modeling, especially in areas with limited data, but TRMM must be applied with precautions and corrected accordingly. The study also demonstrates that HEC-HMS, when properly calibrated, can effectively simulate streamflow using remote sensing rainfall input. In the future, it is suggested to apply ground rain-gauge data to adjust the biases in satellite rainfall estimates which will aid in minimizing uncertainty in the simulation of runoff. The newer satellite products like GPM IMERG final run and blended radar-gauge rainfall data should also be experimented with because they could give a more accurate estimate of precipitation. The next round of study can be used to combine machine learning methods and physically calculated hydrological

324 models to enhance satellite precipitation correction and flood forecasting in multifaceted
325 mountainous basins. The proactive approach, guided by AI models, will emphasize prac-
326 tical preventive measures at individual and governmental levels, fostering a resilient com-
327 munity ready to mitigate flood impacts. The given research is limited to the comparative
328 analysis of satellite precipitation products in one of traditional HEC-HMS frameworks.
329 Moreover, model calibration by using machine learning methods will enhance parameter
330 forecasting and increase the accuracy of flood forecasting particularly in mountainous ba-
331 sins where sufficient data is unavailable. This study will serve as the baseline for hydro-
332 logical modeling using satellite-based precipitation products for similar basins and will
333 help managing water resources especially in the northern areas of Pakistan [37, 38,39].

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336 **Conflicts of Interest**

337 The authors declare no conflicts of interest.

338 **Ethics Approval**

339 It does not apply. Meanwhile the work has not been published elsewhere.

340 **References**

- 341 [1]Waleed, M., and Sajjad, M. (2025). High-resolution flood susceptibility mapping and exposure assessment in Pakistan: An
342 integrated artificial intelligence, machine learning and geospatial framework. *Machine Learning and Geospatial Framework*.
343 *Int. J. Disaster Risk Reduct*, 121, 105442.
- 344 [2] Beven, K. (2012). *Rainfall-Runoff Modelling: The Primer*. Wiley-Blackwell.
- 345 [3] Trenberth, K.E., (2011). Changes in precipitation with climate change. *Climate research*, 47(1-2), pp.123-138.
- 346 [4] Dingman, S. L. (2015). *Physical Hydrology* (3rd Edition). Waveland Press.
- 347 [5] Ahmad, S., Ali, A., & Khan, M. (2018). Evaluation of precipitation in Northern Pakistan. *Atmospheric Research*, 207, 136–
348 150. <https://doi.org/10.1016/j.atmosres.2018.03.014>
- 349 [6] Bookhagen, B., & Burbank, D. (2010). Topography, relief, and TRMM-derived rainfall variations. *Journal of Geophysical*
350 *Research*, 115(F3). <https://doi.org/10.1029/2009JF001426>
- 351 [7] Kidd, C., & Huffman, G. (2011). Global precipitation measurement. *Meteorological Applications*, 18(3), 334–353.
352 <https://doi.org/10.1002/met.289>
- 353 [8] Huffman, G. J., Bolvin, D. T., & Adler, R. F. (2007). TRMM and other data precipitation estimation. *Journal of Hydromete-*
354 *orology*, 8(1), 38–55. <https://doi.org/10.1175/JHM560.1>
- 355 [9] Kummerow, C., et al. (1998). The Tropical Rainfall Measuring Mission (TRMM) sensor package. *Journal of Atmospheric*
356 *and Oceanic Technology*, 15(3), 809–817. [https://doi.org/10.1175/1520-0426\(1998\)015<0809:TTRMMT>2.0.CO;2](https://doi.org/10.1175/1520-0426(1998)015<0809:TTRMMT>2.0.CO;2)
- 357 [10] Funk, C., Peterson, P., Landsfeld, M., et al. (2015). The Climate Hazards InfraRed Precipitation with Stations (CHIRPS)
358 dataset. *Scientific Data*, 2, 150066. <https://doi.org/10.1038/sdata.2015.66>
- 359 [11] Ali, A., ul Hassan, M., Sharif, M., et al. (2017). Evaluation of satellite rainfall products in Pakistan’s mountainous regions.
360 *Hydrological Sciences Journal*, 62(7), 1123–1138. <https://doi.org/10.1080/02626667.2016.1266345>
- 361 [12] Nadeem, M. U., Anjum, M. N., Afzal, A., Azam, M., Hussain, F., Usman, M., & Majeed, F. (2022). Assessment of multi-
362 satellite precipitation products over the Himalayan mountains of Pakistan. *Sustainability*, 14(14), 8490.
363 <https://doi.org/10.3390/su14148490>
- 364 [13] Sharif, M., ul Hassan, M., & Yaseen, M. (2019). Performance of TRMM and GPM precipitation products in the Indus Basin,
365 Pakistan. *Water*, 11(11), 2330. <https://doi.org/10.3390/w11112330>
- 366 [14] A.D. Feldman *Hydrologic Modeling System HEC-HMS, Technical Reference Manual* (2000).
- 367 [15] Descheemaeker, K., Poesen, J., Borselli, L., Nyssen, J., Raes, D., Haile, M., ... & Deckers, J. (2008). Runoff curve numbers
368 for steep hillslopes with natural vegetation in semi-arid tropical highlands, northern Ethiopia. *Hydrological Processes: An*
369 *International Journal*, 22(20), 4097-4105.
- 370 [16] U.S. Army Corps of Engineers, 2008
- 371 [17] Baltas, E.A., N.A. Dervos and M.A. Mimikou, (2007). Technical note: Determination of SCS initial abstraction ratio in an
372 experimental watershed in Greece. *Hydrology and Earth System Sciences*, 11: 1825-1829.

- 373 [18] Lim, K.J., A. Bernard, E. Suresh and J. Horbor, (2006). Effects of initial abstraction and urbanization on estimated runoff
374 using CN technology. American Water Resource Association, pp: 629-643.
- 375 [19] Anjum, M. N., Ding, Y., Shangguan, D., Ijaz, M. W., & Zhang, S. (2016). Evaluation of High-Resolution Satellite-Based
376 Real-Time and Post-Real-Time Precipitation Estimates during 2010 Extreme Flood Event in Swat River Basin, Hindukush
377 Region. *Advances in Meteorology*, 2016(1), 2604980.
- 378 [20] Khan, A.J., Koch, M. and Chinchilla, K.M., (2018). Evaluation of gridded multi-satellite precipitation estimation (TRMM-
379 3B42-V7) performance in the Upper Indus Basin (UIB). *Climate*, 6(3), p.76.
- 380 [21] Muhammad, U., Farooq, G. H., Sajjad, H., Ammara, N., & Shahid, M. (2021). Application of precipitation products for
381 flood modeling of transboundary river basin: a case study of Jhelum Basin. *Theoretical and Applied Climatology*, 143(3-4),
382 989-1004.
- 383 [22] Dar, T., & Aziz, K. (2025). Assessment and Management of Flash Floods in the India Himalayas: Challenges, Strategies,
384 and Solutions. *Water Resources Management in Mountain Regions*, 301-317.
- 385 [23] Riaz, K., Aslam, H. M. S., Yaseen, M. W., Ahmad, H. H., Khoshkonesh, A., & Noshin, S. (2022). Flood frequency analysis
386 and hydraulic design of bridge at Mashan on river Kunhar. *Archives of Hydro-Engineering and Environmental Mechanics*,
387 69(1).
- 388 [24] Sohail, M., & Mahmood, S. (2024). Flood susceptibility modeling using geo-morphometric ranking approach in Jhelum
389 River basin, Pakistan. *Natural Hazards Research*, 4(2), 187-193.
- 390 [25] Ansari, M. Z., Ahmad, I., Rautela, K. S., Goyal, M. K., & Singh, P. K. (2023). Hydrological modelling using HEC-HMS and
391 estimation of the flood peak by Gumbel's method. In *Ecosystem restoration: towards sustainability and resilient development*
392 (pp. 173-190). Singapore: Springer Nature Singapore.
- 393 [26] Rasul, G. (2010). Climate data and modeling for the Upper Indus Basin. Pakistan Meteorological Department.
- 394 [27] Hussain, Z., et al. (2021). Evaluation of flood hazard in the Kunhar River Basin using GIS and remote sensing. *Natural*
395 *Hazards and Earth System Sciences*.
- 396 [28] Mahmood, R., Jia, S., & Babel, M. S. (2016). Potential impacts of climate change on water resources in the Kunhar River
397 Basin, Pakistan. *Water*, 8(1), 23.
- 398 [29] Nguyen, D. T., Ashraf, S., Le, M., Trung, L. Q., & Ali, M. (2023). Projection of climate variables by general circulation and
399 deep learning model for Lahore, Pakistan. *Ecological Informatics*, 75, 102077.
- 400 [30] Ali, M., Raziq, U., Qureshi, A., Zaid, M., Qaseem, U., & Ali, U. (2025). Integrating SWAT and HEC-RAS models for en-
401 hanced flood risk mapping in Swat River, KPK, Pakistan. *Fusion Journal of Engineering and Sciences*.
- 402 [31] Farr, T. G., Rosen, P. A., Caro, E., (2007). The Shuttle Radar Topography Mission. *Reviews of Geophysics*, 45(2), RG2004.
403 <https://doi.org/10.1029/2005RG000183>.
- 404 [32] Aslam, M. N., Ashraf, S., Shrestha, S., Ali, M., & Hanh, N. C. (2024). Climate change impact on water scarcity in the Hub
405 River Basin, Pakistan. *Groundwater for Sustainable Development*, 27, 101339.
- 406 [33] Ashraf, S., Ali, M., Shrestha, S., Hafeez, M. A., Moiz, A., & Sheikh, Z. A. (2022). Impacts of climate and land-use change
407 on groundwater recharge in the semi-arid lower Ravi River basin, Pakistan. *Groundwater for Sustainable Development*, 17,
408 100743.
- 409 [34] Rahman, M. A., Ali, M., Mojid, M. A., Anjum, N., Haq, M. E., Kainose, A., & Dissanayaka, K. D. C. R. (2023). Crop coeffi-
410 cient, reference crop evapotranspiration and water demand of dry-season Boro rice as affected by climate variability: A case
411 study from northeast Bangladesh. *Irrigation and Drainage*, 72(1), 148-165.
- 412 [35] Ahmad, I., Ali, M., Asghar, H., Okamoto, M., Shirayama, Y., Talha, Z., ... & Yuasa, M. (2025). The Impact of Temperature,
413 Humidity, and Precipitation on COVID-19 Cases: A Study Across National and Subnational Levels in Pakistan. *J*, 8(3), 21.
- 414 [36] Ali, M., & Ali, U. (2025). Remote sensing of seasonal variation of LAI and fAPAR in Pakistan under changing climate
415 using machine learning. *Fusion Journal of Engineering and Sciences*.
- 416 [37] Hussain, A., Ashraf, S., Shrestha, S., Ali, M., & Khanh, N. T. M. (2025). Climate Change Impact on Water Resources and
417 Hydropower in Satpara Basin, Pakistan. *Earth Systems and Environment*, 1-19.
- 418 [38] Ali, M., Gillani, S. H., & Ali, U. (2024). Flash Drought Monitoring in Pakistan Using Machine Learning Techniques and
419 Multivariate Drought Indices. *Technical Journal of University of Engineering & Technology Taxila*.
- 420 [39] Ali, M., Taha, M., Aziz, M. S., Ahmed, H., & Ahmed, H. (2024). Flash Flood prediction of Panjkora River, KPK, using
421 Artificial Neural Networks (ANN) and Support Vector Machine (SVM). *Technical Journal of University of Engineering &*
422 *Technology Taxila*.