Revisiting 2013 Uttarakhand flash floods through hydrological evaluation of precipitation data sources and morphometric prioritization

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ABSTRACT
With advancements in computational technology, data assimilation techniques, high-resolution remote sensing, and complex climate models, numerous precipitation products are available with different spatiotemporal resolutions; however, their evaluation, especially in the Himalayan region, is unexplored. Therefore, this study attempts to assess four sources (gridded observation dataset, reanalysis, satellite, and numerical weather prediction models) of precipitation through hydrological modelling for the catastrophic 2013 floods of Uttarakhand, India. The Upper Ganga Basin located in Western Himalayas is selected as the study area consisting of Alaknanda and Bhagirathi streams in the eastern and western parts. The Hydrologic Engineering Center’s Hydrologic Modeling System (HEC-HMS) is employed for rainfall-runoff modelling. The rainfall from IMD, ERA-5, GPM-IMERG-Final, and WRF model outputs are forced into the calibrated HEC-HMS model for assessing their performance in hydrological simulations. The correlation coefficient of IMD, ERA-5, GPM-IMERG-Final, and WRF simulations with respect to the observed flow is 0.89, 0.88, 0.55, and 0.89, respectively, whereas their corresponding Modified Kling-Gupta Efficiency (KGE) is 0.66, 0.72, 0.48, and 0.71. Flash flood prioritization of the sub-watersheds based on morphometric characteristics suggests that the Alaknanda basin is relatively more vulnerable to flash floods due to their elongated nature, highest relative relief, and high mean slope.

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1. Introduction

The increase in the number of flash floods in recent years, especially over the mountainous regions, has urged developing a reliable flood forecasting system. The climatic changes resulting in the intensification of precipitation extremes cause further damaging consequences to the populace (Mittal et al. 2014; Mishra and Lilhare 2016; Swain, Mishra, Pandey, Dayal 2021; Swain et al. 2021a, 2021b). The repercussions caused by flood events vary from place to place depending on the climatic, morphological, soil, and land use characteristics as well as the hydraulic properties of the streams. For example, a precipitation intensity of above 30 mm/h can cause a flash flood in steep mountainous terrains, while it may lead to pluvial flooding over urbanized surfaces; however, it may not have the pronounced effects on a plain region with a pervious surface (Merz and Blöschl 2003). Therefore, selecting an appropriate hydrological model input forms the most vital component of the flood forecasting system. It not only helps to monitor or predict the extremes, but is also crucial to understand their extent and severity. Amongst all the factors that influence the occurrence of a flash flood, precipitation is the most crucial one (Rozalis et al. 2010) and therefore, it is the key input in hydrological modelling (Arnaud et al. 2011).

Precipitation can be obtained by four methods: in-situ observations at the ground (point data), estimation by radar (Krajewski and Smith 2002), satellite remote sensing estimates (Dinku et al. 2008), and numerical simulations based on the climate models (Kishore et al. 2016). Each method has its own advantages and disadvantages. For example, in-situ observation is considered the most accurate; however, it is highly affected by the surrounding conditions. Its accurate estimation largely depends on the spatial density of rain gauges (Sieck et al. 2007; Swain et al. 2022a). Radar estimates can cover the spatial distribution of precipitation; however, complex terrain and occlusion affect the performance (Krajewski et al. 2010). Satellite-based remote sensing is a relatively lesser-accurate way of estimating precipitation (Saikrishna et al. 2021). Nevertheless, it can collect data at a high temporal resolution, i.e. at sub-hourly scales, and can be employed over the entire globe (Skofronick-Jackson et al. 2017). Further, precipitation is one of the outputs of numerical simulations using complex climate models. Due to the complexities in understanding the process of precipitation, the models still face problems for regional-scale simulations (Bador et al. 2020).

A reliable non-structural measure to reduce the flash flood’s adverse impacts is to develop efficient early warning systems through hydrological modelling frameworks (Dhote et al. 2018). Such frameworks largely depend on the accuracy of the precipitation data. With the advancement in computational technology, data assimilation techniques, remote sensing, complexity in climate models, numerous precipitation products are available with different spatial and temporal resolutions. Many researchers have evaluated the precipitation products (Andermann et al. 2011; Ward et al. 2011; Tan et al. 2015) and their utility in hydrological simulations (Tuo et al. 2016). The increasing number of global and near-real-time products has paved the way for predicting and evaluating hydrological disasters. However, the available precipitation products are still associated with the inherent uncertainties and spatial variabilities that affect the hydrological response of the watersheds, especially in the mountainous regions, e.g. the Himalayas (Ward et al. 2011). Over the Himalayan regions, due to
complex topography and limited in-situ stations, accurate precipitation estimation through radar, satellite, and climate models is quite challenging (Kim et al. 2019).

Uttarakhand is an Indian state located mostly in the Himalayan region. The intense rainfall events linked to the orographic topography of the Himalayas and the high flow velocity due to steep slopes make Uttarakhand particularly vulnerable to flash floods (Thakur et al. 2019; Singh and Pandey 2021). Several flash flood events have occurred over the region in recent years. For example, in 2012, four major cloudburst events occurred, affecting more than 17 villages (Dimri et al. 2017). The glacial lake outburst flood (GLOF) is a unique feature of the region. It occurs with a failure of a dam containing the glacial lake, thereby causing flash floods. During 15–17 June 2013, Uttarakhand and the adjoining state of Himachal Pradesh witnessed one of the most devastating floods (IMD 2013). The Automatic Weather Station (AWS) at Karanpur, Dehradun recorded a total of 575 mm of rainfall from 15 (0030 IST) to 17 June (0830 IST) 2013. Dobhal et al. (2013) reported 326 mm of rainfall during 15–16 June 2013 from the AWS near Chorabari Lake, Kedarnath. During this period, two major flash flood events were reported in the Kedarnath area (around 250 km upstream to Dehradun), first on the evening of 16 June 2013 due to heavy rainfall, and second on the morning of 17 June 2013 due to breach of Chorabari Glacier Lake, Kedarnath (Allen et al. 2016; Ray et al. 2016). The incident killed more than 6000 people and stranded around 100,000 people. It caused massive destruction of roads and bridges and damages to at least 30 hydropower plants (Dobhal et al. 2013). These compound extreme events were unprecedented. To mitigate such disasters, understanding the hydrological response of the watershed is essential, which should be followed by the development of a reliable flood forecasting system. For site-specific flood control measures, the morphometric analysis of a watershed is one of the easiest ways for a data-scarce region.

The hydrological utility of the morphological parameters of a watershed was first illustrated by Horton (1945) and Langbein (1947). Horton’s work was then further extended by many investigators (Miller 1953; Schumm 1956; Melton 1957). These morphometric properties can be related to the flood hydrographs that can be further extended to flood risk mapping (Youssef et al. 2011). In practice, the methodology for identifying high flood regions involves the association and analysis of the morphometric characteristics and flood response hydrograph of the basin (Angillieri 2008; Diakakis 2011; Costache, Hong, et al. 2020, Costache, Țincu, et al. 2020, Costache et al. 2021; Talukdar et al. 2020; Singh et al. 2021). For example, for a high flood potential watershed, the relief and drainage density will be higher than the low flash flood potential watersheds (Patton and Baker 1976; Elkhrachy et al. 2021). One of the advantages of using morphometry is the applicability to the data-scarce regions. With the advancement of the remote sensing and geographic information system, the river and basin characteristics can be quantified using digital elevation models (DEM) (Vincy et al. 2012; Ali et al. 2020; Abedi et al. 2021; Swain et al. 2022b). The integration of watershed characteristics and flood risk mapping is helpful in the implementation of site-specific flood mitigation strategies. Therefore, the main objectives of this article are (a) to present a hydrological evaluation of multi-source precipitation for the disastrous flood event of June 2013; and (b) to identify/prioritize the flash flood-prone sub-watersheds in the basin through morphometric characterization.
outcome of the study will help develop a robust flood forecasting system and provide a base for the potential high flash flood zones, where site-specific mitigation strategies can be applied.

2. Materials and methods

2.1. Study area

The area selected for this study is a part of the Western Himalayas, shown in Figure 1. The basin is commonly known as ‘Upper Ganga Basin’. It covers an area of 23,200 km². The two streams, i.e. Alaknanda from the east and Bhagirathi from the west side, merge at Devprayag to form the Ganges River, which accounts for 25.2% of India’s total water resources (Dadhwal et al. 2012). The event of 15–17 June 2013 caused by the GLOF at Chorabari Lake has led to heavy devastation to the basin, especially to the Kedarnath region. Some of the devastated sites (Rudraprayag to Kedarnath) were visited by researchers from the Indian Institute of Remote Sensing, Dehradun, India in September–October 2013, which are shown in Figure 2.

2.2. Precipitation datasets

1. **IMD**: India Meteorological Department (IMD) provides gridded 0.25° × 0.25° (nearly 25 km × 25 km) daily rainfall dataset from 1901 (Pai et al. 2021). The product uses daily rainfall values from a network of 6995 rain gauge stations from all over India. The interpolation of station data to the gridded format uses inverse distance weighted interpolation (IDW) proposed by Shepard (1968), with modification by Rajeevan et al. (2006).
2. **GPM**: The global precipitation measurement (GPM) provides the half-hourly precipitation estimates. It can measure rainfall rates from 0.2 to 110.0 mm/h and detect snow events (moderate to intense) (Skofronick-Jackson et al. 2017). GPM uses well-calibrated dual-frequency precipitation radar (DPR) and GPM Microwave Imager (GMI) sensors to produce $0.1^\circ \times 0.1^\circ$ (nearly 10 km $\times$ 10 km) half-hourly global precipitation estimates in near-real-time. The rainfall data collected in near-real-time is post-calibrated with respect to rain gauges to improve the quality of the estimates. This post-processed product is also called Integrated Multi-satellite Retrievals for GPM (IMERG) V06 Final run (Skofronick-Jackson et al. 2017), which is recommended superior amongst satellite-based precipitation estimates (Gupta et al. 2021, 2022).

3. **ERA5**: It is a global reanalysis (fifth generation) dataset developed by the European Centre for Medium-Range Weather Forecasts (ECMWF). It is available from 1950 to near-real time with a spatial resolution of around 30 km and hourly temporal resolution. ERA5 utilizes a state-of-art data assimilation system (IFS Cycle 41r2 4D-Var), improved radiance calculation, and uncertainty from an ensemble of 10 members (Hersbach et al. 2020). The data can be downloaded from [https://cds.climate.copernicus.eu](https://cds.climate.copernicus.eu).

4. **WRF**: The Weather Research and Forecasting (WRF) model (Skamarock et al. 2019) is being used in most of the centres to forecast rainfall (Powers et al. 2017). It is being considered for a flood forecasting system using a hydrological model, generally termed as WRF-Hydro. For consistency with all other rainfall products in this study, an uncoupled version of the WRF model version 4.1.2 is used. The model is configured for three nested domains with 9, 3, and 1 km spatial resolution. The output from the 1 km domain at hourly temporal resolution is used in the analysis. More information about the domain configuration and physics options in WRF may be referred from the Supplementary Information (Figure S2 and Table S6). There could be millions of possible combinations of the physics schemes that can simulate the event, which consumes substantial time and computational resources and is out of the scope of this work.

![Figure 2. (a) Post-floods view of Kedarnath from Chorabari lake and (b) Kedarnath town after floods with breached lake seen in upstream area.](image-url)
The total accumulated rainfall from 15 to 17 June 2013 from different precipitation sources is shown in Figure 3. It can be observed that the magnitude of total precipitation is highest for WRF. Also, the time-series of the precipitation measurements from the AWS at Karanpur (Dehradun) for the study duration is presented in Figure S1 in Supplementary Information.

2.3. Discharge

The streamflow data was obtained for Haridwar station from the Central Water Commission (CWC, Ministry of Jal Shakti, Government of India) for research purposes only. The dataset is available at a 2-h time step for the event.

2.4. Watershed terrain processing

The Carto DEM V3R1 (30 m spatial resolution) is downloaded from the website of Bhuvan (https://bhuvan-app3.nrsc.gov.in/data/download/index.php) for the Upper

Figure 3. Total accumulated rainfall during 15–17 June 2013 from (a) IMD 0.25° gridded daily dataset, (b) GPM-IMERG 0.1° gridded half-hourly dataset, (c) ERA5 gridded 0.25° gridded hourly dataset, and (d) WRF-simulated 1-km hourly dataset.
Ganga Basin. A total of 11 tiles are downloaded and merged to obtain the pre-filled DEM. The streams, basins, and sub-basins are generated using the Hydrologic Engineering Center – Geospatial Hydrologic Modeling Extension for Hydrologic Modeling System (HEC-GeoHMS) toolbox through ArcGIS, assigning the outlet at Haridwar. This process resulted in the 55 sub-basins covering an area of 23,177 km² with 1309 km of length of stream channels (shown in Figure 1).

2.5. Land use/land cover and soil maps

The land use/land cover (LULC) information is obtained from the Indian Space Research Organization (shown in Figure 4), and the soil type is procured from the National Bureau of Soil Survey and Land Use Planning (NBSS & LUP), Nagpur. The classified LULC map shown in Figure 4 indicates that the catchment is mostly covered with forests and snow. The LULC and soil type were spatially integrated to generate the curve number (CN) for each sub-watershed.

2.6. Hydrologic model: HEC-HMS

In this study, the Hydrologic Engineering Center’s Hydrologic Modeling System (HEC-HMS) version 4.2 developed by the US Army Corps of Engineers, is used for rainfall-runoff modelling. HEC-HMS allows sub-basins to generate the runoff by representing each hydrologic component. The different hydrologic components include initial losses, base-flow, channel routing, and runoff generation. The model is divided into three sub-models, i.e. the basin model, the precipitation model, and the control model. The basin model controls the basin, routing, and connectivity parameters. The precipitation model handles the rainfall information of the model. The control model

Figure 4. (a) Classified LULC and (b) Soil map of the basin. The B represents the Broadleaf Forest, and N represents the Needleleaf Forest.
contains the timing information of the simulations. The details of the model structure and various processes available are given in the HEC-HMS User’s Manual (Feldman 2020). However, the information on the model’s important processes used in this study is provided below.

HEC-HMS categorizes the land use and land cover into two different surfaces, i.e. impervious and pervious. Precipitation on the impervious surfaces causes direct run-off, whereas it is subjected to losses on previous surfaces. The losses are accounted using the soil conservation service curve number (SCS-CN) method, which estimates the precipitation excess as a function of total precipitation, soil type, LULC, and antecedent moisture using the following equations:

\[ P_e = \frac{(P-I_a)^2}{P-I_a+S} \]  

where \( P_e \) is accumulated precipitation excess at time \( t \), \( P \) is accumulated rainfall at time \( t \), \( I_a \) is the initial abstraction loss, and \( S \) is the potential maximum retention (infiltration occurring after runoff has started). A general relationship between \( I_a \) and \( S \) is \( I_a = 0.2S \) (Feldman 2020). Then, the \( P_e \) is given as:

\[ P_e = \frac{(P-0.2S)^2}{P + 0.8S} \]  

The maximum retention (\( S \)) is determined using the following equation:

\[ S = \frac{(25,400-254CN)}{CN} \]  

where CN is the SCS CN, a value that provides the ability of the surface to generate runoff. It is a function of soil group, LULC, and antecedent moisture conditions. The CN values lie in between 0 and 100. Higher the values of CN, more the runoff generation ability and vice versa.

The SCS unit hydrograph (SCS UH) method is used to estimate direct runoff. The unit hydrograph discharge is given by the ratio of peak discharge (\( Q_p \)) at any time \( t \), and a fraction of time to UH peak (\( T_p \)). The \( U_p \) and \( T_p \) are related as:

\[ Q_p = C \frac{A}{T_p} \]  

where \( A \) is the area of the watershed and \( C \) is the constant (2.08). \( T_p \) is related to the duration of excess precipitation (\( \delta t \)):

\[ T_p = \frac{\delta t}{2} + t_{lag} \]  

where \( t_{lag} \) is the basin lag, defined as the time for which water produced by the rainfall excess remains in the basin. In the case of ungauged basins, the \( t_{lag} \) is related to the time of concentration (\( t_c \)).
The $t_c$ can be estimated as:

$$t_c = t_{sheet} + t_{shallow} + t_{channel} \tag{7}$$

where $t_{sheet}$ is the total time travel of sheet flow over the watershed land surface, $t_{shallow}$ is the total time in shallow flow segments, and $t_{channel}$ is the total time travel in the channel segments.

The baseflow is taken as the monthly average, and the outflow is calculated using the Muskingum-Cunge method. Since no cross-section data were available for the entire watershed, a uniform trapezoidal channel profile is considered. The HEC-HMS model is calibrated for the events in years 2005 and 2006, and validated for the events of 2007. Overall, the model setup is found to have a coefficient of correlation of 0.84. For more information about the calibration and validation of the model over the basin, Patel (2015) may be referred. The calibrated HEC-HMS model is used in simulating the runoff from various precipitation datasets. The correlation coefficient and Modified Kling-Gupta efficiency (KGE) (Gupta et al. 2009; Kling et al. 2012) are used to evaluate the datasets. The KGE is calculated using the following equations:

$$KGE = 1 - \sqrt{(KGE_r - 1)^2 + (KGE_b - 1)^2 + (KGE_g - 1)^2} \tag{8}$$

where $KGE_r$ is the correlation, $KGE_b = \frac{\mu_S}{\mu_O}$, $KGE_g = \frac{CV_s}{CV_o}$, where $\mu$ is the mean values, and $CV$ is the co-efficient of variation for the simulated ($S$) and observed ($O$) values. The best value of KGE is 1. KGE ensures that the bias and variability ratios are not

| Morphometric parameters | Formula | References |
|------------------------|---------|------------|
| Stream order           | Hierarchical rank | Strahler (1957) |
| Stream length          | Length of the stream | Horton (1945) |
| Area                   | Area of the watershed | Aher et al. (2014) |
| Perimeter              | Perimeter of the watershed | Aher et al. (2014) |
| Bifurcation ratio      | Total number of streams of a given order | Schumm (1956) |
| Drainage density       | Total length streams of all order | Horton (1945) |
| Stream frequency       | Total number of streams of all order | Horton (1945) |
| Texture ratio          | Area of the watershed | Horton (1945) |
| Basin length           | 1.312 (Area of the watershed)$^{0.56}$ | Nooka Ratnam et al. (2005) |
| Form factor            | Area of the watershed | Horton (1945) |
| Circulatory ratio      | 4π (Area of the watershed)$^{0.56}$ | Miller (1953) |
| Elongation ratio       | (Perimeter of the watershed)$^{0.56}$ | Schumm (1956) |
| Compactness ratio      | 0.2821 (Perimeter of the watershed)$^{0.56}$ | Horton (1945) |
| Relief                 | Highest elevation – lowest elevation | Aher et al. (2014) |
| Relief ratio           | Relief | Schumm (1956) |
| Relative relief        | Relief | Melton (1957) |
| Ruggedness number      | Relief $\cdot$ drainage density | Melton (1957) |
| Mean basin elevation   | Mean elevation of the watershed | Aher et al. (2014) |
| Mean slope (%)         | Mean slope (percent rise) | Aher et al. (2014) |
| Aspect                 | Mean aspect of the watershed | Aher et al. (2014) |
cross-correlated and therefore, is advantageous in judging the model performances (Kling et al. 2012).

### 2.7. Morphometric analysis

For the morphometric analysis, the sub-watersheds used are the same as that of the hydrological model to maintain consistency among the analyses. For the stream definition, 1 km² threshold is used to define the minimum stream. The morphometric parameters used are shown in Table 1. More details of these parameters are available in Supplementary Information (Section 2). The morphometric prioritization is carried out by the weighted sum approach (WSA). This widely used approach is simple yet effective in prioritizing sub-watersheds (Ali et al. 2020). In WSA, the final ranking of the sub-watersheds is based on the compound factor (CF) calculated by multiplying weightage (W) provided by the cross-correlation matrix of the morphometric parameters (M) and the corresponding morphometric values (Aher et al. 2014). For a sub-watershed, the CF can be written as

\[
CF = \sum_{i=1}^{n} W_i \times M_i
\]

where \(i\) is the morphometric properties taken into consideration.

### 3. Results and discussion

#### 3.1. Inter-comparison of precipitation sources in capturing the extreme event

The cumulative rainfall averaged over the basin is shown in Figure 5 for IMD, ERA5, GPM, and WRF. It can be observed that the IMD and ERA5 cumulative rainfall are closer to each other with amounts 292 and 278 mm, respectively. The WRF-simulated rainfall is the highest (370 mm), followed by GPM-IMERG with 330 mm of rainfall. On 15 June 2013, the rainfall started and continued up to 18 June 2013, which is captured by all the precipitation datasets (Figure 6). Considering the cumulative

![Figure 5. Cumulative rainfall from IMD, ERA5, GPM, and WRF averaged over the watershed.](image)
precipitation amount, GPM showed the highest value amongst all at the start of 16 June 2013, and it was closest to IMD. At the end of 16 June 2013, the GPM estimates were still higher than all the precipitation datasets; however, the WRF-simulated amounts were closer to IMD, while ERA5 showed the least cumulative amount. It is important to note that the rainfall estimates show almost similar duration while different amounts and intensities for the same storm. Also, with the increase in the spatial resolution of the datasets from 25 to 1 km, the total accumulated rainfall has increased consistently. One of its possible reasons could be the ability of the high-resolution datasets to capture rainfall due to the mountainous topography that might get averaged over in the coarse-resolution datasets.

### 3.2. HEC-HMS simulation

The hydrologic simulations are performed using the IMD, ERA5, GPM, and WRF rainfall datasets while keeping all other hydrologic parameters the same. The result from the IMD and ERA5 simulations are shown in Figure 6, while that for GPM and WRF are shown in Figure 7. It is to mention that the 'Haridwar (T)' represents the inflow at Haridwar considering controlled Tehri reservoir outflow while 'Haridwar' represents the virgin flow. Figure 6(a) shows the daily average rainfall (top) from the
IMD dataset over the basin and inflow at Tehri, Rudraprayag, and Haridwar. It can be observed that the peak discharge at Haridwar is 15,798 cubic metres per second (cms), which reduced to 11,347 cms considering Tehri reservoir, i.e. at Haridwar(T). The maximum inflow to the Rudraprayag and Tehri is 6919 and 5072 cms, respectively. In case of ERA5 simulations, the rainfall dataset is available at a 1-h time-step. The basin-averaged hourly rainfall over the watershed peaked at 16 Jun 2013 2300 UTC with a magnitude of 7 mm (Figure 6(b)). The maximum inflow at the Tehri station is observed on 17 Jun 2013 2000 UTC with a magnitude of 7507 cms. The discharge at the Rudraprayag station peaked at 9178 cms on 17 Jun 2013 1500 UTC, due to a larger contributing area than the Tehri. The Haridwar station peaked at 17 Jun 2013 2000 UTC with a discharge of 21,277 cms, while Haridwar (T) peaked at 18 Jun 2013 0000 UTC with 14,594 cms.

The GPM dataset is available at 30-min temporal resolution. The GPM rainfall shows a bimodal system (Figure 7(a)) with a peak of 6.5 mm on 16 Jun 2013 0400 UTC and another 4.7 mm on 17 Jun 2013 0700 UTC. The behaviour of the rainfall is being reflected in the discharge, i.e. two peaks for Rudraprayag and Haridwar stations can be observed. The Tehri station shows a flat discharge curve, where the crest segment starts at 16 Jun 2013 1400 UTC and continues till 17 Jun 2013 0800 UTC with a peak discharge of 7726 cms. The Rudraprayag station shows the maximum discharge of 19,591

![Figure 7](https://example.com/figure7.png)
cms on 17 Jun 2013 1600 UTC, while the second peak of 11,095 cms on 16 Jun 2013 1700 UTC. Similarly, the Haridwar station shows the first peak of 23,166 cms on 16 Jun 2013 1700 UTC and a second peak of 26,856 cms on 17 Jun 2013 1900 UTC.

Figure 7(b) shows the hourly rainfall and discharge at different locations for WRF rainfall estimates. A peak of 29,486 cms is obtained at Haridwar on 17 Jun 2013 2000 UTC. The Rudraprayag station contributed a peak discharge of 16,969 cms on 17 Jun 2013 1500 UTC. The maximum Tehri inflow is 4697 cms at 17 Jun 2013 2100 UTC, the lowest in all the simulations. It can be noted that WRF produces the highest amount of rainfall and highest peak from all considered simulations. The correlation coefficient of IMD, ERA-5, GPM-IMERG, and WRF simulations with respect to the observed flow at Haridwar station (outlet) is 0.89, 0.88, 0.55, and 0.89, respectively, whereas the Modified KGE for these datasets is 0.66, 0.72, 0.48, and 0.71, respectively.

The rainfall datasets viz., IMD and ERA5 have also shown competent performance in hydrological simulations. The encouraging performance of IMD, despite the coarse gridded and daily temporal resolution, could be because it only includes the observed gauges that are interpolated to generate the gridded dataset. Similarly, the advancement in the modelling system and increase in the computational power has led to developing a global rainfall product, i.e. ERA5 with a high spatio-temporal resolution, which produced a reliable runoff estimate. On the other hand, the GPM-IMERG Final run product is unable to produce a competent result for the event over the basin. There could be two possible reasons: a) the non-availability of adequate rain gauge stations for calibration (post-processing) and b) the complex terrain of the Himalayas might be a crucial factor affecting the accuracy of the radar-based estimates. Previous studies (AghaKouchak et al. 2011; Bartsotas et al. 2018; Sunilkumar et al. 2019; Zhang and Anagnostou 2019; Nkunzimana et al. 2020) have shown that the GPM-IMERG precipitation estimates show significant deviation in the rainfall intensities distribution over the mountainous regions. The performance of the WRF is found to be better than the rest of the datasets; however, due to the more rainfall generated over the region, the peak discharge is higher than the rest of the datasets.
Another set of uncertainty in the discharge estimation is the combined impact of different spatial and temporal resolutions from 1 to 28 km and 30 min to daily, respectively. Overall, the study substantiates the utility of integrating the complex numerical weather prediction models with the hydrological models to produce accurate estimates of near-real-time precipitation and streamflow, which is imperative for a robust early warning system for flash floods, especially over the Himalayan region.

### 3.3. Morphometric analysis

For the morphometric analysis, the aggregated results for Alaknanda, Bhagirathi, and Southern Upper Ganga (SUG) sub-basins (shown in Figure 8) are presented in Table 2. The results of each sub-watershed are provided in the Supplementary Information (Tables S1–S5). The three sub-basins, viz., Alaknanda, Bhagirathi, and SUG, cover 44, 31, and 25% of the basin area, respectively. In terms of basin perimeter, 44% falls under the Alaknanda sub-basin, while the Bhagirathi and SUG sub-basins cover 28% each. As the Alaknanda sub-basin covers most of the area, the total stream numbers and stream lengths are also the largest, with 45 and 43% share of the whole Upper

| Morphometric parameter | Stream order | Overall | Alaknanda | Bhagirathi | Southern Upper Ganga |
|------------------------|--------------|---------|-----------|-------------|----------------------|
| Stream number          | 1            | 5065    | 2301      | 1527        | 1235                 |
|                        | 2            | 1107    | 493       | 344         | 269                  |
|                        | 3            | 253     | 111       | 77          | 65                   |
|                        | 4            | 67      | 30        | 21          | 16                   |
|                        | 5            | 21      | 13        | 5           | 3                    |
| Total                  | 6513         | 2948    | 1974      | 1588        | 1588                 |
| Stream length (km)     | 1            | 8206.45 | 3554.9    | 2539.19     | 2109.54              |
|                        | 2            | 3989.29 | 1663.57   | 1259.13     | 1064.2               |
|                        | 3            | 2115.03 | 903.28    | 625.14      | 586.61               |
|                        | 4            | 1357.97 | 561.23    | 358.4       | 438.34               |
|                        | 5            | 372.83  | 204.42    | 140.68      | 27.73                |
| Total                  | 16,041.57    | 6887.4  | 4922.54   | 4226.41     | 4226.41              |
| Area (km²)             | 23,177.67    | 10,234.11 | 7210.29 | 5726.65     |
| Perimeter (km)         | 7382.22      | 3218.64 | 2087.7    | 2059.14     |
| Bifurcation ratio      | 1            | 4.66    | 4.79      | 4.55        | 4.75                 |
|                        | 2            | 4.74    | 4.04      | 4.35        | 4.66                 |
|                        | 3            | 3.86    | 3.91      | 3.44        | 4.21                 |
|                        | 4            | 1.76    | 1.54      | 2.4         | 1.67                 |
| Total                  | 4.12         | 4.15    | 3.93      | 4.41        |
| Drainage density       | 0.7          | 0.67    | 0.68      | 0.75        |
| Stream frequency       | 0.29         | 0.29    | 0.29      | 0.28        |
| Texture ratio          | 0.8          | 0.86    | 0.79      | 0.73        |
| Basin length           | 38.25        | 39.51   | 38.35     | 38.46       |
| Form factor            | 0.27         | 0.26    | 0.27      | 0.26        |
| Circularity ratio      | 0.28         | 0.29    | 0.3       | 0.23        |
| Elongation ratio       | 0.58         | 0.58    | 0.59      | 0.58        |
| Compactness ratio      | 1.94         | 1.89    | 1.86      | 2.13        |
| Relief                 | 3141.27      | 3914.33 | 3191.5    | 1919        |
| Relief ratio           | 93.58        | 103.47  | 106.12    | 52.33       |
| Relative relief        | 26.63        | 30.53   | 30.35     | 13.8        |
| Ruggedness number      | 2150.13      | 2621.21 | 2161.28   | 1433.01     |
| Mean basin elevation (m)| 2784.64     | 3326.39 | 3602.77   | 1073.97     |
| Mean slope (% rise)    | 51.38        | 55.41   | 53.09     | 42.07       |
| Aspect                 | 175.96       | 172.73  | 178.59    | 176.35      |
Ganga Basin, respectively. On the other hand, Bhagirathi and Upper Ganga sub-basins contain 30 and 24% of stream numbers and 31 and 26% of stream lengths, respectively. Interestingly, the drainage density of Alaknanda and Bhagirathi are similar with respective values of 0.67 and 0.68, while for SUG, it is 0.75. Note that a high drainage density of a watershed implies a high runoff potential.

The stream frequency, basin length, form factor, elongation ratio, and aspect show similar values for the sub-basins. The texture ratio is highest for Alaknanda (0.86), followed by Bhagirathi (0.79) and SUG (0.73) sub-basins. It is to mention that the texture ratio depends on the infiltration capacity and relief of the sub-watersheds. Hydrologically, higher values of texture ratio represent the longer lag time (Smith 1950); therefore, the Alaknanda sub-basin has the longest lag time than the other two. It is evident from the values of the Circulatory Ratio, Elongation Ratio, and Form Factor that all the sub-basins are elongated. The Alaknanda sub-basin has the highest relief (3914 m), and SUG has the lowest relief (1919 m). However, the mean elevation of the Bhagirathi sub-basin is the highest (3602 m) and lowest for SUG (1073 m). The Ruggedness Number indicates the structural complexity of the sub-basin, and its higher values indicate higher susceptibility to erosion. The Alaknanda and SUG sub-basins possess the highest (2621) and the lowest (1433) values of Ruggedness Number.

The morphometric analysis of the sub-basins suggests that the Alaknanda covers the maximum area and thus, produces more runoff, which induces flash floods. The elongated nature, highest relief, relative relief, and mean slope of the Alaknanda sub-basin leads to its higher potential for flash floods, which is also reflected in the HEC-HMS simulations in the form of high peak values at the Rudraprayag station. On the contrary, the sub-watersheds contributing to the Bhagirathi have comparatively lower relief, relative relief, and mean slope than the Alaknanda and thus, produced a more flattened hydrograph. The morphometric analysis of the sub-watersheds presented here can be utilized for flash flood prioritization, flood risk, and flood susceptibility mapping.
Figure 9 shows the WSA-based ranking of the sub-watersheds for prioritization. The higher the sub-watershed’s rank/priority, the more vulnerable the sub-watershed. The sub-watersheds downstream of the watershed are more vulnerable than the upstream. On the contrary, sub-watersheds 1, 2, 3, and 17 are more vulnerable than the neighbouring watersheds. The more vulnerable sub-watersheds (high ranking) are due to higher relative relief and stream frequency than the rest. The details of the CF are shown in the Supplementary Information.

3.4. Discussions
The importance of revisiting the catastrophic 2013 floods of Uttarakhand is to understand if the state-of-art technologies or datasets could have been effective to reduce the devastations. Additionally, it was also necessary to understand the spatial variation in effects of the extreme precipitation event due to the physiographical aspects. Considering the limitations of ground-based precipitation data availability, different types of precipitation datasets are evaluated and are forced into a calibrated event-based hydrological model. In terms of efficacy measures for hydrological simulations, WRF outperformed other datasets. It must be noted that WRF possesses superiority over other datasets in terms of spatiotemporal resolutions. Moreover, WRF being a weather prediction model can be utilized for forecasting such extreme precipitation events. Even for the event revisited in this study, it is evident that the WRF-simulated rainfall was the highest, which could have been taken as a warning for floods. Further, owing to the inherent morphometric aspects, viz., elongated nature, highest relative relief, and high mean slope, the Alaknanda basin is found to be relatively more vulnerable to flash floods, which explains the devastating consequences of the event caused therein. Besides, the attenuation in peak flows at Haridwar(T) also highlights the role of reservoirs in flood control. Overall, the information reported in this study can certainly be helpful for disaster monitoring over the Himalayan regions in general, and the Upper Ganga Basin in particular.

The United Nations’ Sustainable Development Goal (SDG) of ‘Climate action’ aims to take urgent collective actions against climate change since 91% of the geophysical disasters between 1998 and 2017 were climate-related, causing 1.3 million human deaths. It can be fulfilled by providing adequate planning towards effective monitoring of disasters through improved models, accurate datasets, and early warning systems. The information reported in this study helps to achieve the same through a detailed study over the Himalayan region, wherein the multi-source datasets are evaluated using a hydrological modelling framework. This study also substantiates the utility of integrating the complex numerical weather prediction models with the hydrological models to produce accurate estimates of near-real-time precipitation and streamflow, which is imperative for a robust early warning system for flash floods, especially over the Himalayan region. Additionally, identifying the flash flood-prone regions through morphometric assessment helps prepare adaptation and mitigation plans to alleviate the vulnerability to flash floods. Lastly, the detailed methodology presented in this study would encourage its replication over other regions of the world, especially the data-scarce mountainous catchments vulnerable to flash floods.
4. Summary and conclusions

Every year flooding causes loss of lives and property across the globe. To mitigate the effects, the first and foremost step is to understand the process behind the flooding, where hydrological modelling and morphometric analysis provides the foundation. Precipitation estimation, the core of hydrological modelling, has witnessed recent advancements due to improved remote sensing techniques, near-real-time observations, and reanalysis datasets. This study attempted to assess the impacts of the different precipitation products (IMD, ERA5, GPM-IMERG, and WRF) for HEC-HMS-based hydrological modelling of the disastrous flash flood event of June 2013 (commonly known as Kedarnath floods) over Western Himalayas, Uttarakhand, India. The results indicated that despite having similar watershed characteristics, the discharge in the three stations varied significantly using different rainfall datasets. The best performance in hydrologic simulations is shown by WRF, whereas ERA5 and IMD also produced competent results. One of the possible reasons could be the higher spatial resolution (1 km) of WRF than the rest of the datasets. On the other hand, the GPM-IMERG Final product did not perform well over the basin. Also, the watershed contributing to the Rudraprayag station is getting more affected by the rainfall than the Tehri station, whereas Haridwar shows the combined characteristics.

The morphometric characterization of the sub-watersheds was also carried out for prioritizing the flash flood-prone zones. The results indicated that the Alaknanda sub-basin is most vulnerable to flash floods due to its higher relief, mean slope, and ruggedness number. These properties might have contributed to the rainfall-dependent high-peak discharge generation in the Alaknanda basin. The study emphasizes the utility of integrating numerical weather prediction model outputs with a hydrological model (e.g. HEC-HMS) to develop a flood forecasting system. The morphometric assessment can generate flood susceptibility and flood risk maps and devise site-specific control measures. The information reported in this study through hydrologic and morphometric analyses can be employed to adopt flash flood mitigation measures over the study area.

The major limitation of the study is the unavailability of the datasets related to the various hydraulic structures, such as hydropower plants, reservoirs, and the limited uncertainty quantification in the rainfall estimations due to the unavailability of the rain-gauge stations. However, the study still provides substantial value in understanding the impact of precipitation in hydrological modelling and watershed characteristics for the given region.

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Data availability statement

The data that support the findings of this study are available from the authors upon reasonable request.

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