GAU Research Journal **49** (2) : 146-159 (July 2024)

Integrating GIS and DEM for Hydrological Parameter Analysis in Geo-Environmental Research

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Received : June, 2024 Accepted : July, 2024

ABSTRACT

Hydrological modeling is essential for diverse scientific research applications, including species distribution, ecological assessments, agricultural suitability, climatological studies, and disaster prediction models such as floods, flash floods, and landslides. Despite significant advancements, existing studies often lack comprehensive frameworks that integrate topography-driven hydrological factors into hazard modeling. This gap highlights the need for refined methodologies to better understand the dynamic interplay between topography and hydrological processes, particularly for geo-environmental hazard mapping.This study aims to bridge this gap by detailing systematic methods for deriving critical hydrological indices, including Topographic Wetness Index (TWI), Terrain Ruggedness Index (TRI), Stream Power Index (SPI), Sediment Transport Index (STI), and Topographic Position Index (TPI) from Digital Elevation Models (DEMs) using Geographic Information Systems (GIS). Physically-based techniques were implemented in ArcMap 10.4 software, utilizing freely accessible SRTM DEM data to ensure reproducibility and accessibility.The findings underscore the significance of hydrological parameters in deciphering landscape dynamics and improving hazard modeling accuracy. This research provides a valuable methodological contribution to geo-environmental sciences and lays the groundwork for future studies focusing on integrating hydrological and topographical analyses into predictive hazard models.

Keywords : Digital Elevation Model, Hydrological Parameters, GIS, RS, Modelling

INTRODUCTION

Hydrological processes are essential for comprehending and modeling various environmental phenomena, particularly those involving geo-environmental hazards (Chen, Chen *et al*. 2024). Accurately representing hydrological conditions is vital for creating effective models to predict and mitigate risks associated with floods (Elsadek and Almaliki 2024, Khan and Jhamnani 2024, Solaimani, Darvishi et al., 2024), flash floods (Bordoloi, Bora *et al*. 2024, Prince, Bhatt *et al*. 2024), and landslides (Dey, Ojha et al. 2024, Halder, Srivastava et al. 2024, Moayedi, Xu et al., 2024, Youssef, El-Haddad et al., 2024). Topography, a key determinant of

hydrological processes, significantly influences water flow, infiltration, and erosion patterns (Pandey and Kumari 2024). As a result, deriving hydrological factors from Digital Elevation Models (DEMs) has become a crucial aspect of many environmental studies (Ndabula, Iguisi et al., 2017, Xiong, Yang *et al*., 2024). Hydrological modelling provides a framework for simulating the movement and distribution of water within the environment. By integrating various data sources and employing sophisticated algorithms, these models can predict the behavior of water systems under different scenarios, including extreme weather events and long-term climatic changes. Effective hydrological models are indispensable tools for managing water resources, planning urban development, and formulating policies for disaster risk reduction.

Topography is a primary control on hydrological processes. The shape and features of the Earth's surface dictate how water flows across and infiltrates into the ground, influencing erosion patterns, sediment transport, and the formation of water bodies (Sarkar, Alshehri et al., 2024). High-resolution topographic data are essential for capturing the nuances of these processes. Digital Elevation Models (DEMs), which represent the Earth's surface in a gridded format, are widely used to derive topographic and hydrological information. DEMs serve as the foundation for calculating various hydrological factors, such as slope, aspect, flow accumulation, and watershed boundaries. Digital Elevation Models (DEMs) have revolutionized the way hydrological and topographic data are analyzed. DEMs provide a detailed representation of the terrain, which is crucial for hydrological modeling. When processed using Geographic Information Systems (GIS), DEMs can be used to extract a multitude of hydrological factors that are vital for environmental studies. GIS tools enable the visualization, manipulation, and analysis of spatial data, making it possible to conduct complex hydrological analyses with relative ease and accuracy (Chowdhury 2023).

Several key hydrological factors can be derived from DEMs using GIS, each providing valuable insights into the behavior of water in the landscape. The Topographic Wetness Index (TWI) quantifies the effect of topography on the location and extent of saturated areas, influencing soil moisture and surface runoff. The Terrain Ruggedness Index (TRI) measures the variability in elevation, which is critical for understanding erosion and sediment transport. The Stream Power Index (SPI) represents the potential erosive power of flowing water, while the Sediment Transport Index (STI) estimates the potential for sediment movement. The Topographic Position Index (TPI) differentiates between ridge tops, valley bottoms, and slopes, aiding in the classification of terrain (Ahmad, Dar et al., 2019).

Hydrological models and the factors derived from DEMs have a wide range of applications in environmental science. In flood and flash flood modeling, these factors help identify areas at risk of inundation and inform the design of mitigation measures such as levees and retention basins. In landslide susceptibility mapping, they contribute to understanding the conditions that trigger slope failures, guiding land use planning and hazard mitigation efforts. Additionally, hydrological factors are used in ecological modeling to study habitat suitability and

species distribution, in agricultural suitability assessments to optimize land use, and in climate change studies to predict the impacts of changing precipitation patterns on water resources (Mansour and Abdelkareem 2024, Youssef, El−Haddad et al., 2024).

The primary objective of this study is to explore the application of Geographic Information Systems (GIS) in conjunction with SRTM DEM to derive key hydrological factors that are essential for geo-environmental hazard mapping. By processing DEMs using GIS, the study aims to generate and analyze critical hydrological indices such as the TWI, TRI, SPI, STI, and TPI. These indices are crucial for understanding landscape dynamics and developing models that predict and mitigate risks associated with floods (Satapathy and Mishra 2024), flash floods, and landslides (Poddar and Roy 2024). This research seeks to highlight the significance of hydrological factors in environmental studies and provide methodologies for future research in geo-environmental sciences (Jaafari, Mafi-Gholami et al., 2024).

STUDY AREA AND DATA USED

Study area:

The Panam River watershed, a substantial tributary of the Mahi River in Gujarat, India, served as the study area. Encompassing approximately 2400 square kilometers, the watershed exhibits a tropical climate characterized by distinct wet and dry seasons with an annual rainfall of 945 mm. This combination of geographical and climatic factors renders the Panam watershed an ideal location to investigate hydrological processes.

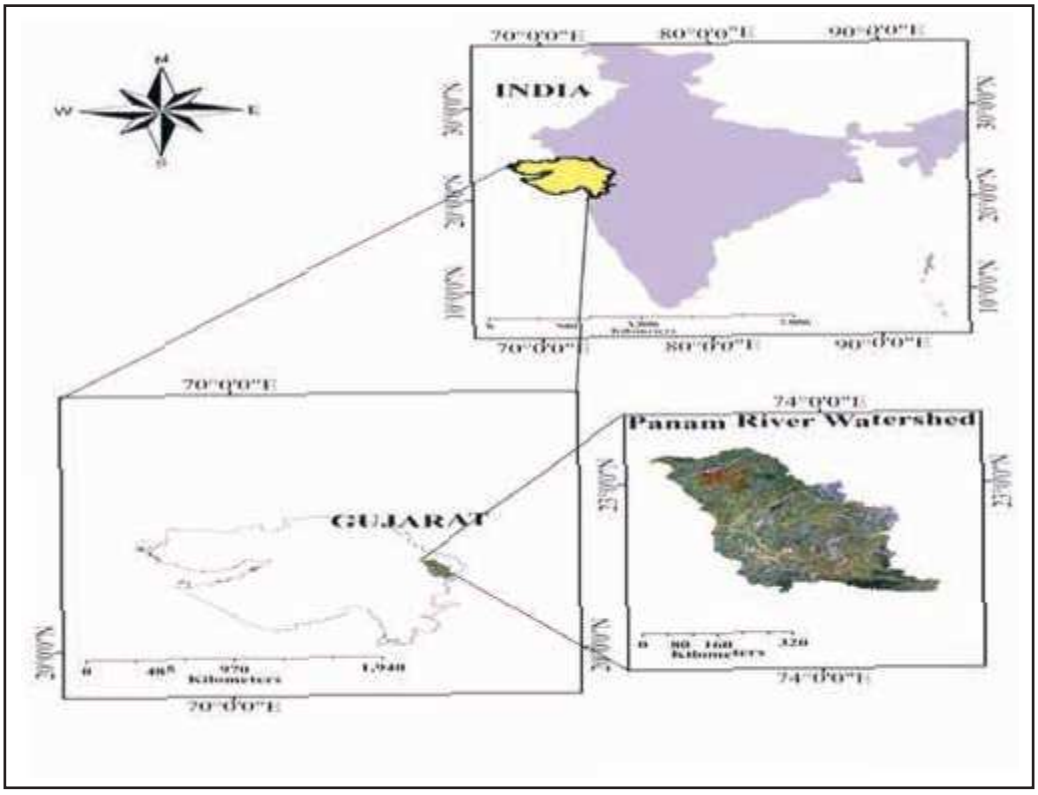


Fig. 1 Digital Elevation Model of Panam river watershed

Data used:

To accurately characterize the watershed's topography, the Shuttle Radar Topography Mission (SRTM) Digital Elevation Model (DEM) was utilized. This dataset, developed through a joint effort between NASA and the National Geospatial-Intelligence Agency (NGA), provides elevation data at a resolution of 1 arc-second (~30 meters at the equator), making it suitable for regional-scale topographic and hydrological studies. The SRTM DEM is referenced to the EGM96 vertical datum and WGS84 horizontal datum, ensuring consistency and compatibility with other geospatial datasets.

The SRTM data was acquired using dual radar antennas on board the Space Shuttle Endeavour during an 11-day mission in February 2000. This innovative approach captured elevation data with a vertical accuracy of ±16 meters and a horizontal accuracy of ±20 meters. The dataset was preprocessed to remove voids and noise, ensuring high-quality elevation information.

In this study, the SRTM DEM served as the foundational dataset for deriving hydrological indices such as slope, flow direction, flow accumulation, and watershed delineation. Its fine resolution allowed for a detailed representation of the Panam watershed's terrain, capturing key features such as ridges, valleys, and drainage patterns.

METHODOLOGY

In this study, various hydrological indices, including the Topographic Wetness Index (TWI), Terrain Ruggedness Index (TRI), Stream Power Index (SPI), Sediment Transport Index (STI), and Topographic Position Index (TPI), were derived using GIS tools to analyze and characterize the Panam River Watershed. These indices provide valuable insights into the watershed's hydrological behavior, terrain complexity, water accumulation potential, and sediment transport dynamics. GIS-based processing enabled the efficient calculation and visualization of these indices, facilitating a comprehensive assessment of the watershed's topographic and hydrological characteristics essential for understanding erosion risk, water flow patterns, and land management strategies.

TOPOGRAPHIC WETNESS INDEX (TWI)

The Topographic Wetness Index (TWI) is a hydrological parameter that quantifies the influence of topography on soil moisture and surface water accumulation. It is derived from the slope and catchment area of a given location, reflecting the propensity of a site to retain water. The flow chart to calculate TWI is illustrated in figure 2 using ArcMap. Higher TWI values indicate areas where water is more likely to accumulate due to favorable topographic conditions, such as depressions or low-gradient slopes. This index is crucial for understanding the distribution of wet areas within a landscape, which has implications for vegetation growth, soil moisture content, and flood risk assessment. In environmental studies, TWI helps identify zones prone to waterlogging and contributes to effective land management and conservation strategies. TWI can be calculated using equation 1 (Beven and Kirkby 1979).

$$TWI = \ln(a/tan\beta) \quad (1)$$

here α is upslope catchment area divided by contour length and β is slope of catchment.

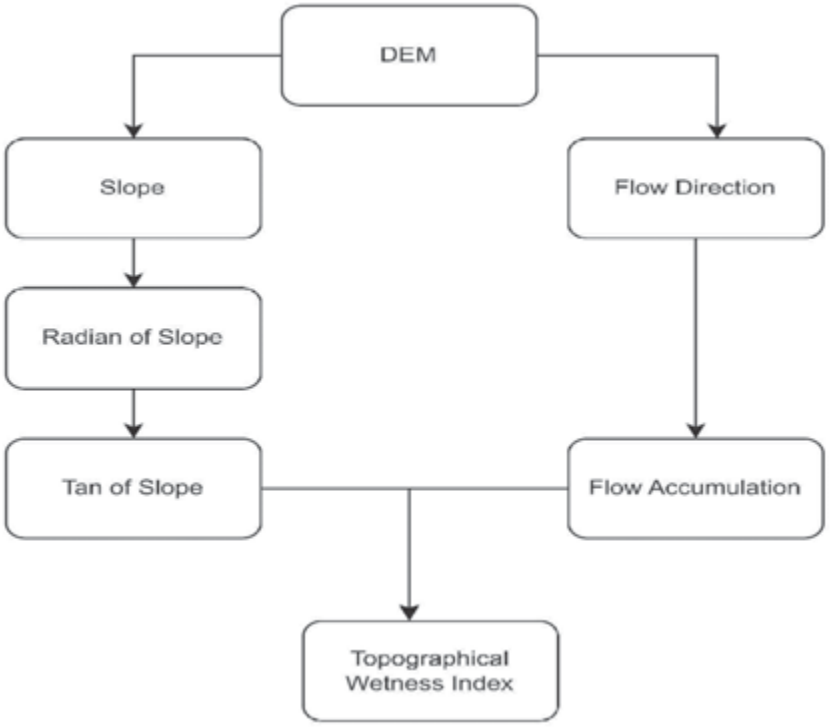


Fig. 2 : Flowchart to calculate Topography Wetness Index

Terrain Ruggedness Index (TRI)

The Terrain Ruggedness Index (TRI) measures the variability in elevation within a given area, providing insight into the roughness or ruggedness of the terrain. It is calculated by assessing the differences in elevation between a cell and its surrounding cells within DEM. High TRI values denote areas with significant elevation changes, such as hills or valleys, which can influence erosion rates, water flow patterns, and habitat suitability. TRI is an important factor in hydrological modeling as it affects sediment transport and erosion processes. Understanding terrain ruggedness is essential for applications such as land use planning, environmental impact assessments and infrastructure development (Whitehouse 2023). TRI can be calculated using equation 2 given by (Riley, DeGloria et al., 1999).

$$TRI = 1/cos(\tan\beta \times \pi/180) \quad (2)$$

Stream Power Index (SPI)

The Stream Power Index (SPI) evaluates the potential erosive force of flowing water based on the slope and contributing area of a given location. It is calculated by combining the slope of the terrain with the flow accumulation data, indicating the capacity of a stream to erode and transport sediment (Jaafari, Najafi *et al.*, 2014). Higher SPI values correspond to locations with greater potential for erosion and sediment movement, which are typically found in steeper and more active areas. SPI is vital for predicting sediment transport, identifying erosion-prone regions, and designing effective erosion control measures. In hydrological studies, SPI contributes to understanding stream dynamics and managing water quality in river systems (Mohebzadeh 2024). SPI is calculated using equation 3 given by

(Rahmati, Kalantari *et al*. 2019). The Flow chart to calculate Stream Power Index calculation is depicted in figure 3.

$$SPI = a \times (tan\beta) \quad (3)$$

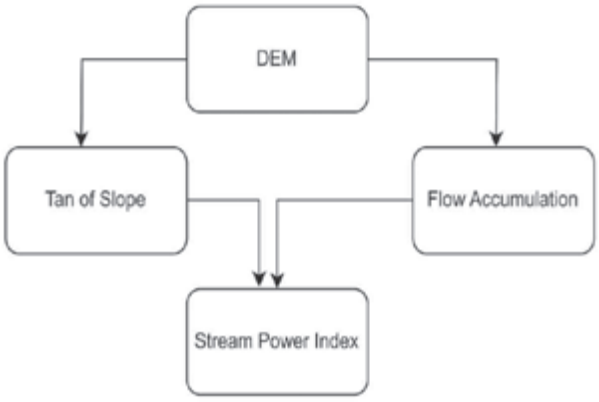


Fig. 3 Flow chart to calculate Stream Power Index calculation

Sediment Transport Index (STI)

The Sediment Transport Index (STI) estimates the potential for sediment movement within a landscape by integrating factors such as slope, land cover, and flow accumulation. STI assesses how likely sediments are to be transported by surface runoff and streamflow based on topographic and environmental conditions. High STI values indicate areas with a high potential for sediment movement, which can affect soil fertility, water quality, and the stability of streambanks. This index is particularly useful for land management practices aimed at reducing soil erosion and controlling sedimentation in water bodies. STI is a key component in sediment budgeting and erosion control strategies. STI can be calculated using equation 4 (Ahmad, Dar *et al.*, 2019).

$$STI = \left(\frac{a}{22.13}\right)^{0.06} \times \left(\frac{\sin\beta}{0.0896}\right)^{1.3} \quad (4)$$

Topographic Position Index (TPI)

The Topographic Position Index (TPI) classifies the position of a location relative to its surrounding topography, distinguishing between features such as ridges, slopes, and valleys. It is calculated by comparing the elevation of a cell with the average elevation of its neighbors, indicating whether the cell is positioned on a high point, low point, or slope. TPI is valuable for understanding landscape features and their hydrological implications, such as the distribution of water flow and sediment deposition.

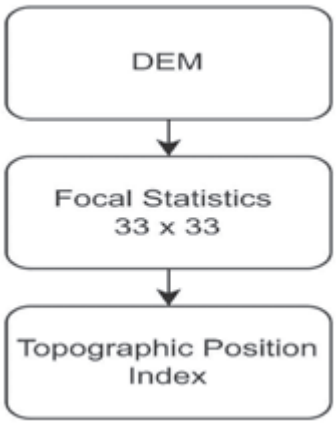


Fig. 4 (a) Flow chart to calculate Topographic Position Index

Within ArcMap, the TPI can be computed using a equation 5 that calculates the difference between a cell's elevation and the mean elevation of its neighboring cells as illustrated in figure 4.

$$TPI = zero/near - zero - flat\ or\ a\ near\ continuous\ slope \quad (5)$$

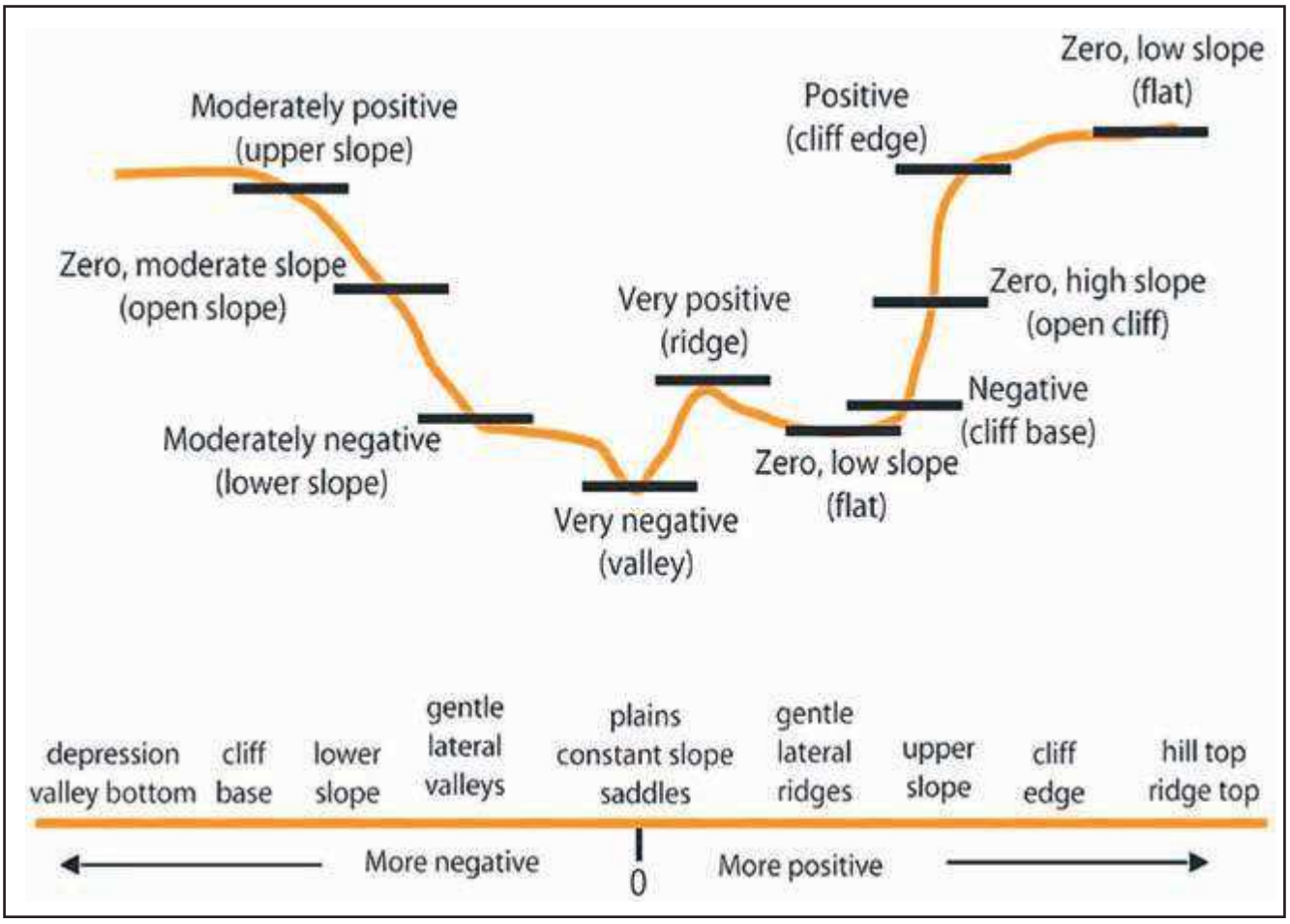


Fig. 4 (b) TPI vs slope (Weiss 2001).

As illustrated in figure 4-b, the TPI map reveals distinct spatial patterns of topographic position. Positive TPI values indicate elevated areas such as ridges and peaks, while negative values correspond to depressions and valley bottoms. Areas with TPI values close to zero represent relatively flat or gently sloping terrain (Heni, Shofiyatul et al., 2022).

RESULT AND DISCUSSION

The present study delved into the intricate relationships between topography and hydrological processes through the derivation and analysis of key hydrological factors. By employing a series of GIS-based operations on a high-resolution DEM, we successfully generated flow direction, flow accumulation, slope, TWI, TRI, SPI, and TPI maps.

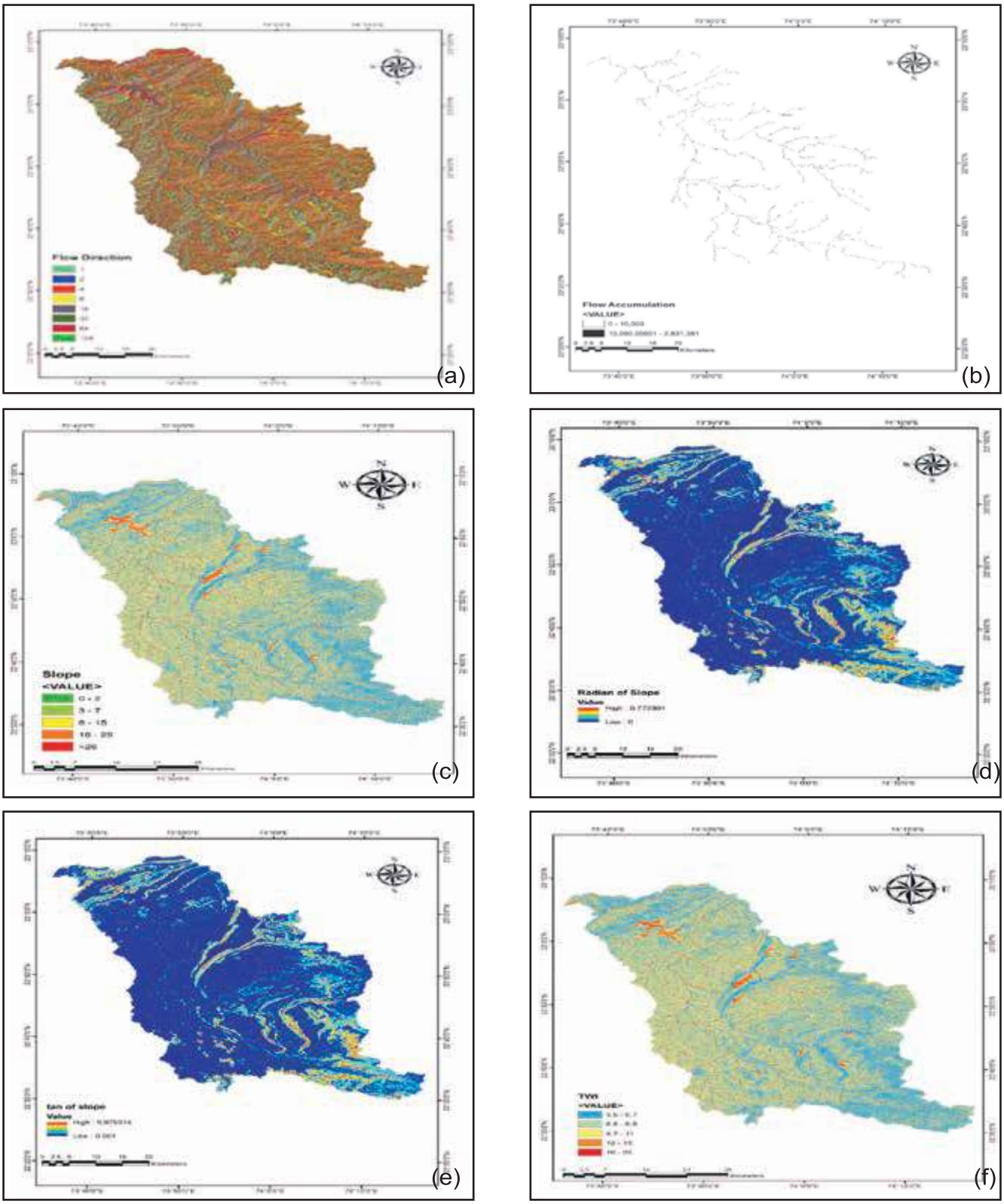


Fig. 5 (a) Flow Direction Map (b) Flow Accumulation Map (c) Slope Map (d) Radian Slope Map (e) Tangent Slope Map (f) Topographic Wetness Index (TWI) Map

The flow direction map (Figure 5-a) delineated the pathways of water movement across the landscape, providing insights into drainage basin formation. The flow accumulation map (Figure 5-b) quantified the cumulative upstream contributing area, highlighting potential channel networks and areas prone to concentrated runoff. The slope map (Figure 5-c) revealed the spatial variability of terrain steepness, a critical factor influencing erosion and sediment transport.

To enhance computational efficiency and subsequent analyses, the slope was converted to radians (Figure 5-d) and then to the tangent of the slope (Figure 5-e). The resulting TWI map (Figure 5-f) effectively captured areas susceptible to waterlogging and saturated conditions, crucial for understanding hydrological response and potential flood hazards.

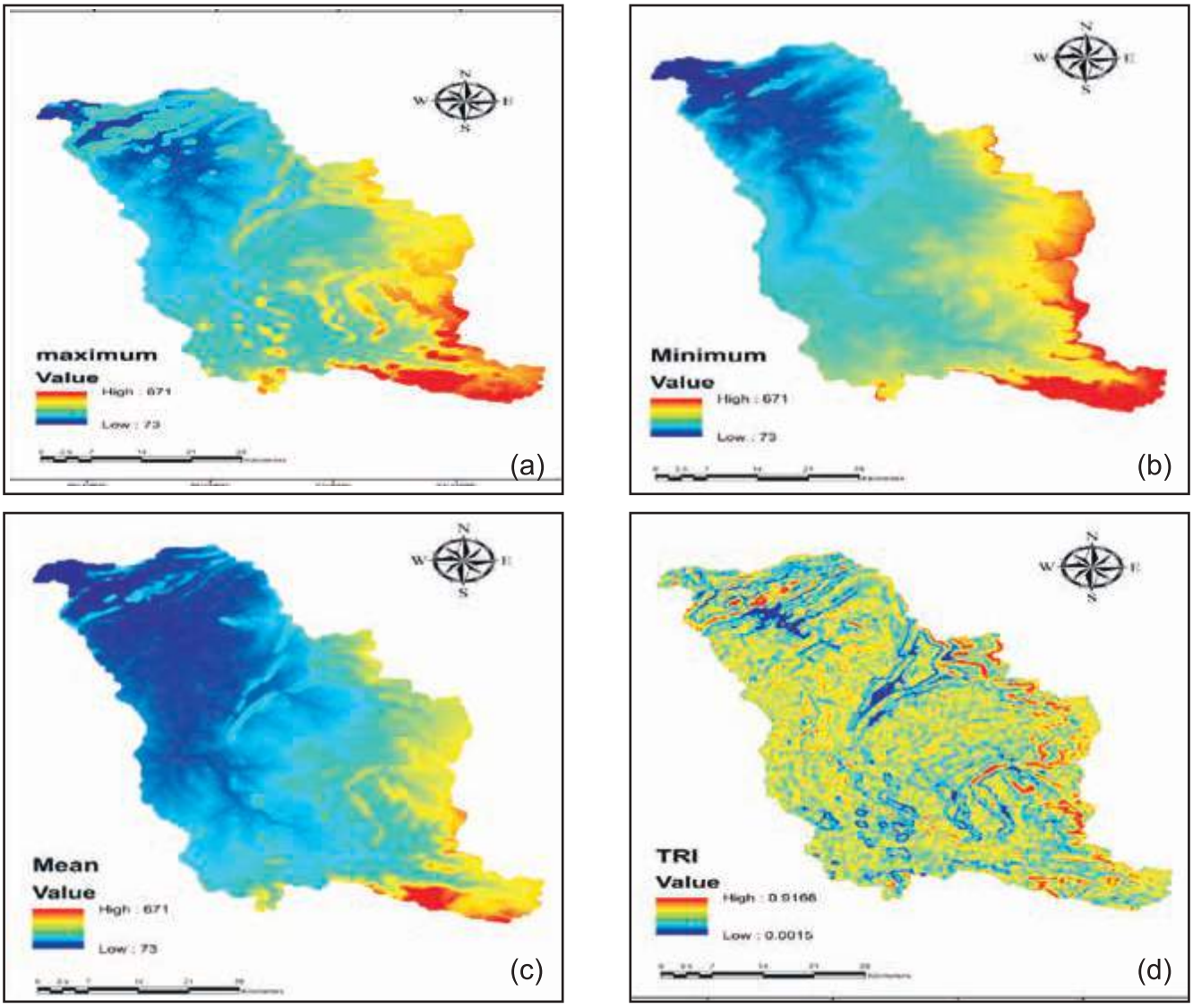


Fig. 6 (a) Focal Statistics maximum value (b) Focal Statistics minimum value (c) Focal Statistics mean value (d) Topography Roughness Index

The Terrain Ruggedness Index (TRI) was computed to quantify surface variability within the study area by calculating the mean, maximum, and minimum elevation values within a specified neighborhood for each grid cell. Figures 6-a, 6-b, and 6-c illustrate the maximum, minimum, and mean elevation, respectively, which provided the foundation for calculating the TRI (Figure 6-d). The TRI served as a quantitative measure of surface roughness, highlighting its influence on erosion and sediment yield. Rugged terrain with higher TRI values exhibited a greater potential for erosion and sediment transport, while smoother landscapes with lower TRI values were less prone to erosive forces. TRI values are influenced by factors such as elevation differences, slope gradient, aspect, geological structure, human activities (e.g., agriculture, mining, and construction), and climatic conditions (e.g., wind erosion, rainfall intensity, and temperature fluctuations), all of which can alter terrain roughness and influence TRI values over time.

The SPI (Figure 7) assessed the erosive power of flowing water, revealing areas prone to channel incision and bank erosion. This index is a product of flow accumulation and slope The SPI map reveals distinct spatial patterns of erosive power. Higher SPI values, concentrated primarily within river channels and steep slopes, indicate areas with greater potential for erosion. Conversely, lower SPI values are associated with flatter terrain and reduced erosive forces. These results align with the theoretical underpinnings of the SPI, which posits that the erosive capacity of a stream is directly related to its discharge and slope gradient.

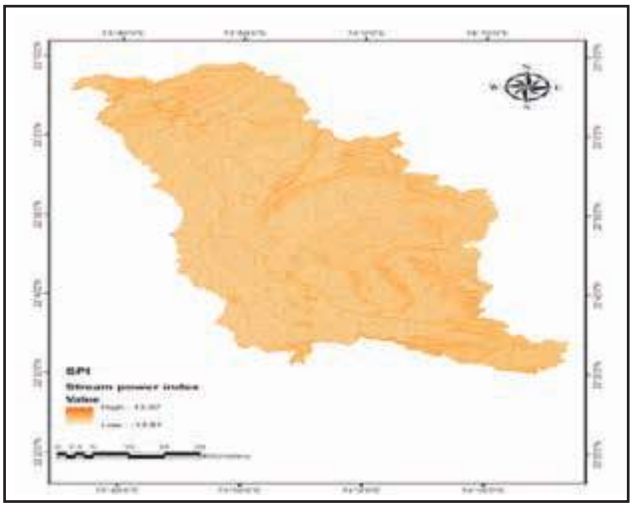


Fig. 7 Stream Power Index

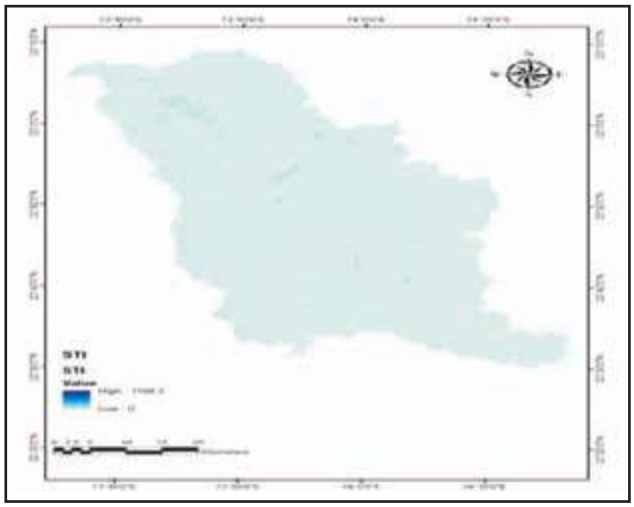


Fig. 8 Sediment Transport Index

The Sediment Transport Index (STI) was calculated to assess the potential for sediment transport within the study area. This index is a function of flow accumulation and slope, as illustrated in Figure 5-b and Figure 5-c, respectively. The derived STI map is presented in Figure 8. Higher STI values indicate areas with greater potential for sediment transport due to increased water flow and steeper slopes. Conversely, lower STI values correspond to areas with reduced erosive forces and lower sediment transport capacity. The spatial distribution of STI reveals areas susceptible to erosion and sediment yield.

The Topographic Position Index (TPI) was calculated to quantify the relative position of each grid cell within its surrounding landscape. This index is derived by comparing the elevation of a cell to the mean elevation of its neighboring cells. The resulting TPI map is presented in Figure 9. The TPI map reveals distinct spatial patterns of topographic position. Positive TPI values indicate elevated areas such as ridges and peaks, while negative values correspond to depressions and valley bottoms. Areas with TPI values close to zero represent relatively flat or gently sloping terrain.

The derived hydrological factors provide a robust foundation for understanding the complex interplay between topography, hydrology, and geomorphology. The results highlight the importance of considering multiple factors when assessing environmental impacts and developing management strategies. For instance, identifying areas with high SPI and TRI values can inform targeted erosion control measures, while mapping TWI and TPI can aid in flood risk assessment and land-use planning.

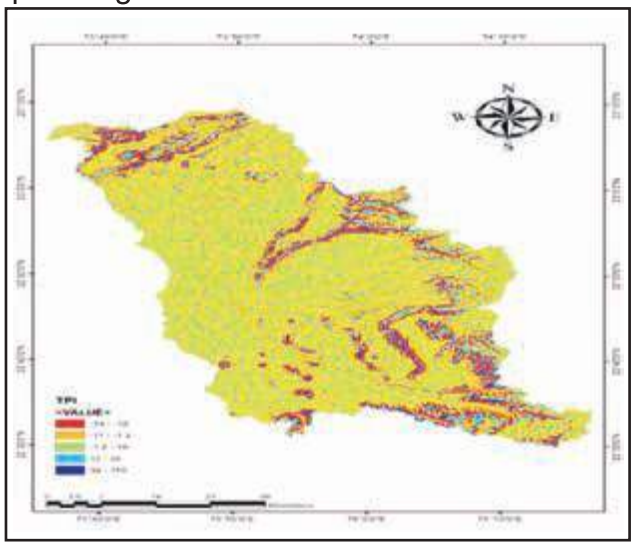


Fig.9 Topography Position Index

CONCLUSION

This study presents a methodological approach for deriving hydrological factors from open-source Digital Elevation Models (DEMs) using Geographic Information Systems (GIS), demonstrated through a detailed case study. The hydrological parameters derived, including Topographic Wetness Index (TWI), Terrain Ruggedness Index (TRI), Stream Power Index (SPI), Sediment Transport Index (STI), and Topographic Position Index (TPI), are crucial for effective hazard assessment, particularly in the context of landslides, floods, and flash floods. Our findings underscore the significance of GIS in extracting and analyzing these hydrological factors from DEM, providing a more comprehensive understanding of landscape dynamics. Furthermore, the combined use of these indices can effectively identify soil erosion-prone zones. Areas with high TWI, SPI, and STI values, coupled with lower TPI and higher TRI values, are more likely to experience soil erosion due to water accumulation, sediment transport, and terrain roughness. These indices, when integrated, offer a robust framework for pinpointing vulnerable regions and informing targeted erosion control and mitigation strategies. The study also highlights the importance of considering the interplay between these indices to enhance the accuracy and reliability of hazard modeling. However, the research reveals the influence of DEM resolution and GIS software on the precision of these hydrological parameters. To ensure optimal outcomes, careful attention must be paid to these factors when

conducting hydrological and hazard assessments, paving the way for more effective geo-environmental hazard mapping and risk management strategies.

DECLARATIONS

Funding

The authors declare that they received no funding for this research and there are no any potential conflicts of interest in this paper.

Author Contribution

All authors contributed to the development and finalization of this manuscript. A.V. Memon conceptualized the study, designed the methodology, and drafted the initial manuscript. N.V. Shah and Y. S. Patel provided expert guidance, oversaw the research process, and contributed to data interpretation.

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Competing interests

The authors declare that they have no competing interests

ACKNOWLEDGEMENT

We are grateful to the U.S. Geological Survey (USGS) Earth Explorer (https://earthexplorer.usgs.gov/) for offering access to DEM, which played a crucial role in our analysis.

REFERENCES

Ahmad I., Dar M.A., Teka A.H., Gebre T., Gadissa E., Tolosa A.T. (2019). Application of hydrological indices for erosion hazard mapping using Spatial Analyst tool, *Environmental Monitoring and Assessment*, 191 (8), 482.

Beven K.J., Kirkby M.J. (1979). A physically based, variable contributing area model of basin hydrology / Un modèle à base physique de zone d'appel variable de l'hydrologie du bassin versant, *Hydrological Sciences Bulletin*, 24 (1), 43-69. DOI: 10.1080/02626667909491834.

Bordoloi B., Bora K., Choudhury S., Sonowal K., Sahu S., Hazarika D., Deka P. (2024). Flood hazard mapping and monitoring in the Kamrup District of the Lower Brahmaputra Valley, Assam: A geospatial appraisal, *Flood Risk Management: Assessment and Strategy*, Springer, 375-400.

Chen H.-W., Chen C.-Y., Yang P.-Z. (2024). Using drone-based multispectral imaging for investigating gravelly debris flows and geomorphic characteristics, *Environmental Earth Sciences*, 83 (8), 247.

Chowdhury M.S. (2023). Modelling hydrological factors from DEM using GIS, *MethodsX*, 10, 102062.

Dey N., Ojha B., Das P. (2024). Landslide susceptibility analysis by frequency ratio model and analytical hierarchical process in Mirik and Kurseong, Darjeeling Himalaya, India, *Landslide:*

Susceptibility, Risk Assessment and Sustainability: Application of Geostatistical and Geospatial Modeling, Springer, 183-218.

Elsadek W.M., Almaliki A.H. (2024). Integrated hydrological study for flash flood assessment using morphometric analysis and MCDA based on hydrological indices—Al-Sail Al-Kabir, KSA, *Natural Hazards*, 120 (7), 6853-6880.

Halder K., Srivastava A.K., Ghosh A., Das S., Banerjee S., Pal S.C., Chatterjee U., Bisai D., Ewert F., Gaiser T. (2024). Improving landslide susceptibility prediction through ensemble Recursive Feature Elimination and meta-learning framework.

Heni M., Shofiyatul A., Indria K., Umi A. (2022). Community survival strategy for environmental sustainability as adaptation in landslide threatened area: Evidence from Malang, Indonesia, *KnE Social Sciences*, 7 (16). DOI: 10.18502/kss.v7i16.12147.

Jaafari A., Mafi-Gholami D., Yousefi S. (2024). A spatiotemporal analysis using expert-weighted indicators for assessing social resilience to natural hazards, *Sustainable Cities and Society*, 100, 105051.

Jaafari A., Najafi A., Pourghasemi H.R., Rezaeian J., Sattarian A. (2014). GIS-based frequency ratio and index of entropy models for landslide susceptibility assessment in the Caspian forest, northern Iran, *International Journal of Environmental Science and Technology*, 11 (4), 909-926. DOI: 10.1007/s13762-013-0464-0.

Khan Z.A., Jhamnani B. (2024). Development of flood susceptibility map using a GIS-based AHP approach: a novel case study on Idukki district, India, *Journal of Spatial Science*, 69 (2), 409-442.

Mansour A.M., Abdelkareem M. (2024). Climate change and risk assessment of the Red Sea region, Egypt, *Oceanographic and Marine Environmental Studies around the Arabian Peninsula*, 289.

Moayedi H., Xu M., Naderian P., Dehrashid A.A., Thi Q.T. (2024). Validation of four optimization evolutionary algorithms combined with artificial neural network (ANN) for landslide susceptibility mapping: A case study of Gilan, Iran, *Ecological Engineering*, 201, 107214.

Mohebzadeh H. (2024). Ephemeral gully erosion mapping and modeling using topographic indices, machine learning, and hydrological/water quality modeling, *University of Guelph*.

Ndabula C., Iguisi E., Jidauna G., Oyatayo K., Nyomo D. (2017). Analysis of spatio-temporal patterns of hydro-geomorphic sensitivity areas and desertification status in a part of Borno-Yobe semi-arid zone of Nigeria, *FUDMA Journal of Sciences*, 1 (1), 144-160.

Pandey S., Kumari N. (2024). Assessment of morphology and soil erosion risk in agrarian watershed of Jharkhand India using RUSLE, GIS and MCDA-AHP, *Journal of the Indian Society of Remote Sensing*, 1-20.

Poddar I., Roy R. (2024). Application of GIS-based data-driven bivariate statistical models for landslide prediction: a case study of highly affected landslide prone areas of Teesta River basin, *Quaternary Science Advances*, 13, 100150.

Prince H.C., Bhatt C., Roy A., Kumari S., Raghubanshi A.S., Singh R.P. (2024). Entropy-based modelling for flash flood hazard mapping in Uttarakhand Himalaya, *Journal of the Indian Society of Remote Sensing*, 52 (1), 127-138.

Rahmati O., Kalantari Z., Samadi M., Uuemaa E., Moghaddam D.D., Nalivan O.A., Destouni G., Tien Bui D. (2019). GIS-based site selection for check dams in watersheds: Considering geomorphometric and topo-hydrological factors, *Sustainability*, 11 (20), 5639.

Riley S.J., DeGloria S.D., Elliot R. (1999). Index that quantifies topographic heterogeneity, *Intermountain Journal of Sciences*, 5 (1–4), 23-27.

Sarkar S.K., Alshehri F., Shahfahad, Rahman A., Pradhan B., Shahab M. (2024). Mapping groundwater potentiality by using hybrid machine learning models under the scenario of climate variability: A national level study of Bangladesh, *Environment, Development and Sustainability*, 1-29.

Satapathy D.P., Mishra B.P. (2024). Flood susceptibility modeling by integrating tree-based regression with metaheuristic algorithm, BWO, *Transactions in GIS*.

Solaimani K., Darvishi S., Shokrian F. (2024). Assessment of machine learning algorithms and new hybrid multi-criteria analysis for flood hazard and mapping, *Environmental Science and Pollution Research*, 1-22.

Weiss A. (2001). Topographic position and landforms analysis, *Poster presentation, ESRI User Conference*, San Diego, CA.

Whitehouse D.J. (2023). *Handbook of Surface Metrology*, Routledge.

Xiong H., Yang S., Tan J., Wang Y., Guo X., Ma C. (2024). Effects of DEM resolution and application of solely DEM-derived indicators on groundwater potential mapping in the mountainous area, *Journal of Hydrology*, 636, 131349.

Youssef A.M., El-Haddad B.A., Skilodimou H.D., Bathrellos G.D., Golkar F., Pourghasemi H.R. (2024). Landslide susceptibility, ensemble machine learning, and accuracy methods in the southern Sinai Peninsula, Egypt: Assessment and mapping, *Natural Hazards*, 1-32