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RESEARCH PAPER

Quantifying Tectonic Influence on Himalayan Glacio-Fluvial Systems: Integrating Morphological Analysis and AI Modeling

Ruchira Ghosh[1] · Goutami Das[1] · Harshada Patil[1] · S. Umamaheswari[2] · P. Jayashri[3]

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Abstract

The Himalayan region is known for its dynamic tectonic activity, presenting significant challenges for geoscientists in detecting and understanding the active tectonic plates behavior. This study proposes the development of a generalized AI model to calculate key geomorphological parameters within the glacial-fluid river basins of the Himalayas. The motivation stems from the critical need to connect artificial intelligence with machine learning techniques to enhance the understanding of tectonic processes in this complex geological setting by analyzing geomorphological data acquired from a research paper Bali et al. (2012) and other sources. This research specifically focuses on the Pindari glacio-fluvial basin in and its sub basins, a region characterized by rugged terrain and high tectonic activity. The drainage network and geomorphological attributes of this basin provide a suitable testbed for modeling due to its varied elevation, complex hydrology, and well-documented tectonic features. Unlike traditional methods that rely on mathematical approaches, such as the morphological law of Horton's and Strahler's stream order laws, our approach focuses on developing a data-driven model capable of automatically extracting essential parameters including area, perimeter, length, and other metrics without manual calculations. By employing AI algorithms, the process of geomorphological analysis is streamlined, enabling researchers to efficiently identify and quantify the characteristics of glacial-fluid river basins associated with active tectonic activity. This innovative approach promises to revolutionize the field by providing a more accurate and comprehensive understanding of geomorphic features indicative of tectonic plate movement in the Himalayan region. This research is anticipated to significantly advance geoscience, with applications in natural hazard assessment, resource management, and infrastructure planning in tectonically active regions. It ultimately aims to deepen the understanding of the interplay between tectonic processes and geomorphological features in the Himalayas, enabling more informed decision-making and enhanced risk mitigation strategies.

✉ S. Umamaheswari
umamaheswari.suk@vit.ac.in

Ruchira Ghosh
ruchira.ghosh2023@vitstudent.ac.in

Goutami Das
goutami.das2023@vitstudent.ac.in

Harshada Patil
harshada.rajendra2023@vitstudent.ac.in

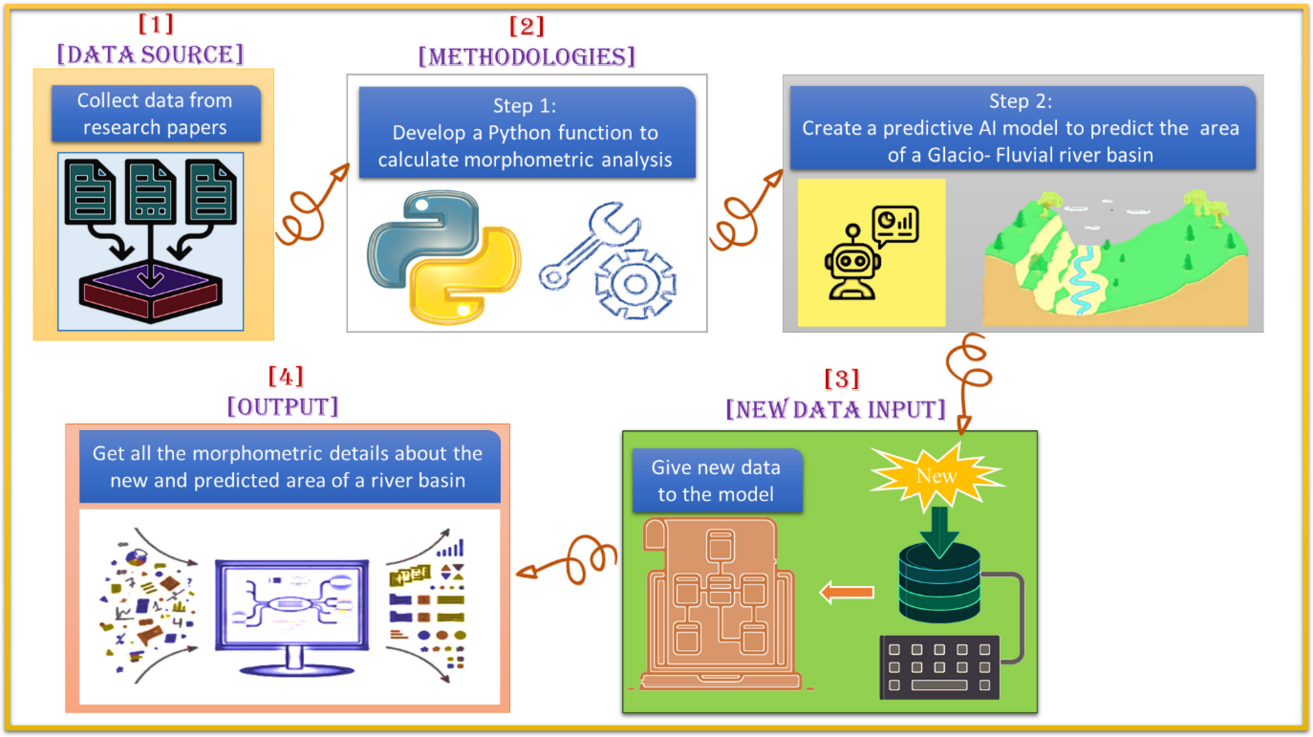
P. Jayashri
jayashri.p2020@vitstudent.ac.in

[1] PG Student, Department of Mathematics, School of Advanced Sciences, Vellore Institute of Technology, Chennai, Tamil Nadu, India

[2] Assistant Professor (Sr), Department of Mathematics, School of Advanced Sciences, Vellore Institute of Technology, Chennai,Tamil Nadu, India

[3] Research Scholar, Department of Mathematics, School of Advanced Sciences, Vellore Institute of Technology, Chennai, Tamil Nadu, India

Graphical Abstract



Highlights

- A thorough approach was created to examine drainage basins in the Himalayan area, emphasizing locating characteristics linked to active tectonic activity. Application of basic and sophisticated modeling methods to improve comprehension of how tectonic processes sculpt the topography. A focus on closely examining the data and stressing how important each parameter is to comprehend the features of the basin. Detailed perspective of basin characteristics that takes into account both intricate elements like physiography and drainage networks, as well as more fundamental details like size and form.
- Introduction of structured AI models to capture different types of relationships—linear or nonlinear—within the dataset. Metrics like Mean Squared Error (MSE) and R-squared (R^2) are used to evaluate the efficacy of models and offer insightful data. Possibility of a revolutionary influence on our understanding of the Himalayan tectonic processes and landscape characteristics. Significant effects on resource use, infrastructure design, and natural hazards management in tectonically active areas.
- In the event of natural catastrophes, a strong basis for informed decision-making and risk reduction is established by combining data-driven methodologies with field experience.

Keywords/Phrases: Drainage Density · Himalayan Glacio-Fluvial · Horton's and Strahler's stream order laws · Morphological study · Tectonic activity

Mathematical Subject Classifications 62R07 · 68T09

Introduction

The formation of the Himalayan mountains resulted from the ongoing collision between the Indian and Eurasian plates, which began during the Eocene epoch. In the early stages of this continental convergence, a prominent suture zone developed between the colliding plates, giving rise to one of the most tectonically dynamic regions on Earth. The Himalayas, renowned for their complex geological structures and diverse environmental conditions, present a compelling setting for interdisciplinary research. From accelerating glacial retreat and shifting river dynamics to frequent tectonic activity, the region confronts a multitude of interrelated challenges that demand thorough scientific

investigation. Despite the geological and environmental significance of the Himalayan region, there remains a notable gap in detailed studies focused on morphological characteristics, drainage density forecasting, and tectonic activation analysis, particularly within its glacial-fluvial basins. Bridging these knowledge gaps is crucial for understanding the region's vulnerability to natural hazards, anticipating landscape evolution, and developing effective mitigation strategies.

This study adopts a dual-faceted approach that combines traditional geomorphological techniques with artificial intelligence (AI)-driven modeling to assess the tectonic influence on glacio-fluvial systems. By examining the morphology of drainage networks and employing AI algorithms for predictive analysis, the research aims to streamline and enhance the accuracy of geomorphological assessments. To ground this analysis in a concrete geographic context, the study focuses on the Pindari glacio-fluvial basin, located in the Kumaon Himalayas of Uttarakhand, India. The Pindari basin is an ideal case study due to its steep elevation gradients, varied lithological characteristics, and well-documented tectonic features. Influenced by both glacial and fluvial processes, the basin serves as a representative system for understanding the geomorphic expressions of active tectonics. By investigating its drainage patterns, basin geometry, and morphometric indices, the study aims to draw broader inferences about tectonic processes in similar Himalayan settings.

To evaluate both historical and ongoing tectonic activity, the study incorporates the analysis of active landform features such as faults, uplift zones, skewed alluvial fans, river terraces, channel migrations, and evidence of river capture. Notably, tectonic signals have been recorded throughout the Himalayan arc over the last 35–40 thousand years, further emphasizing the relevance of morphometric investigation. Drainage evolution in the region is controlled by a complex interplay of climatic variables, lithology, slope, precipitation, topography, and both endogenic and exogenic forces. Tectonic activity has been shown to shape not only the origin and structure of drainage basins but also their morphometric characteristics and hydrological behavior. To identify zones of heightened tectonic deformation, geomorphic indices such as bifurcation ratio, stream length ratio, drainage density, and elongation ratio have become essential analytical tools.

In addition to quantifying basin morphology and tectonic influence, morphometric analysis provides insights into flood hazards, hydrological responses to climate change, and long-term landscape development. These parameters help detect physical alterations in drainage systems resulting from both anthropogenic disturbances and natural events. Variations in drainage patterns—governed by relief, structure, slope, climate, and vegetation—are further indicators of active tectonic shaping. By incorporating AI into this workflow, the study seeks to automate the extraction and analysis of critical parameters, enabling faster, scalable, and more objective assessments. This data-driven methodology enhances our ability to recognize subtle yet significant tectonic signatures embedded in basin morphometry. In summary, this research aims to advance the understanding of tectonic-geomorphic interactions in the Himalayas through a combination of traditional morphological metrics and AI-based predictive modeling. By focusing on the Pindari glacio-fluvial basin, the study provides a high-resolution case that contributes to broader efforts in hazard management, regional planning, and environmental sustainability in tectonically sensitive mountain terrains.

Literature Review

Bali et al. (2012) studied the Pindari glacio-fluvial basin in the Himalayas using measurements of the river system (morphometry) to understand the influence of glacial till deposits. They looked at stream frequency, drainage density, and drainage texture to assess how easily water infiltrates the ground. These parameters were linked to the characteristics of the glacial till, which allows for efficient infiltration of snowmelt and rainwater. Additionally, the study used the shape of the river basins (form factor) to identify areas more likely to experience flash floods. Finally, by analyzing abnormalities in these measurements, they aimed to pinpoint zones of active tectonic movement in the region.

Luirei et al. (2015) encompass the examination of topographic maps (1:50,000) from the Survey of India, as well as high-resolution 1.5-arc-second ASTER-DEM images and satellite imagery (Google Earth). These have been applied to the delineation of lineaments by the computation of morphometric indices in conjunction with field evidence of tectonic activity. Topographic maps with a 20-m contour spacing have been used to calculate steam-gradient (SL) indices, slope profiles, and longitudinal profiles of streams. Nie et al. (2021) described the impact of climate change on glaciers in the Himalaya-Karakoram Mountain ranges. Rising temperatures are melting glaciers at an unsustainable rate, reducing ice storage and initially increasing summer meltwater runoff. This is causing changes in streamflow patterns, leading to more frequent glacial lake outburst floods and unpredictable water availability. The paper concludes that improved monitoring is crucial to predict future water resources and hazards in the region.

Qazi et al. (2020) discussed the critical role of the Himalayas as a water source for nearly 1.3 billion people in surrounding countries. The melting ice and snow (cryosphere)

in the Himalayas significantly impact the Indus, Ganges, and Brahmaputra (IGB) river basins. However, our understanding of exactly how much water comes from glaciers and snowmelt, and when it flows, is limited due to a lack of research and data sharing. The authors call for more investigation and collaboration to improve water resource management in the region. Singh et al. (2022) described the geomorphic features, or shapes created by glaciers, of the Gangotri Glacier in the Himalayas. It examines the rock formations underlying the glacier and identifies lateral moraines, ridges left behind by past glacier movements, as the most common feature. The study suggests that these features are influenced by natural disasters and temperature fluctuations. Finally, the paper highlights the role of past ice ages in shaping the current glacial landscape.

Dar et al. (2022) examined the Rambiara River basin, a sub-basin of the Upper Indus. The basin contains many landforms created by glaciers, indicating past glacial activity was much more extensive than today. During the Last Glacial Maximum, glaciers were thicker and flowed much further. Today, the river has a wide channel that was likely formed by the larger glacial meltwater flows of the past. The paper concludes that glaciers in the basin have receded significantly due to reduced snowfall and warming trends. Azam et al. (2021) highlighted the importance of the Himalayan-Karakoram (HK) rivers for water resources in South Asia. With climate change impacting these rivers, understanding their current state and future changes is vital for water management. The study reveals that glaciers and snow melt are key contributors, especially for the Indus basin. While river runoff and meltwater are expected to rise until the 2050s, significant uncertainties remain due to knowledge gaps. The authors emphasize the need for improved data collection methods to better predict future water availability in the region.

Comparative Analysis

Author(s)	Technique	Advantages	Disadvantages	Remarks
Pandey and Sharma (2019)	Satellite imagery, lineament extraction	Automated extraction of geological features, correlation with geological formations	May miss subtle geological features, dependent on image resolution	Useful for mapping recent geological movements and tectonics
Misra et al. (2020)	SRTM DEM, SPIM model, chi analysis	Combines multiple techniques for robust analysis	Complex requires expertise in multiple methods	Effective for identifying continuous deformation along faults
Bisht et al. (2021)	In SAR, GNSS baseline shortening analysis	Accurate deformation pattern prediction	High-tech, expensive equipment required	Effective for precise tectonic movement studies
Maciuk et al. (2021)	Plate motion calculator, GIS	Analytical approach to tectonic effects on administrative regions	Dependent on the accuracy of plate motion data	Useful for understanding tectonic impacts on national borders
Ghosh and Sivakumar (2024)	Tectono-Geomorphic Anomaly Index (TGAI)	New method for assessing earthquake risk, considers future seismic potential	Requires extensive data and validation	Innovative approach to earthquake risk assessment
Paul et al. (2024)	Geological field studies, remote sensing	Discovery of unique glaciotectonic landform, insights into glacial processes	Specific to Shyok Valley, may not apply elsewhere	Significant for understanding glaciotectonic interactions
Chaubey et al. (2024)	GIS, remote sensing	Efficient analysis of geomorphology and tectonic influence	Limited to the Ukhma River Basin	Demonstrates regional tectonic activity influence on geomorphology
Mohaimen et al. (2024)	Digital elevation models, satellite data	Analysis of neotectonics influence on terrain	May not capture all tectonic activities, depending on data quality	Important for understanding neotectonics landscape shaping

Workflow

See Fig. 1.

Methodology

This section describes the methodology that has been used to –

- Data Description
- Developing Python Function for Morphometric Analysis
- Developing AI Model for Analysis and Predict the Parameter for Morphological Study.
- Data Description.

Data Description

The geomorphological data for the Pindari glacio-fluvial basin and its sub-basins were obtained by scanning Survey of India (SOI) topographical maps. Morphometric parameters such as drainage density, stream length, and basin area were quantitatively analyzed using Arc View 3.2 GIS software. This approach enabled accurate digitization and computation of drainage network characteristics essential for subsequent modeling. All data were derived from secondary sources and processed digitally without relying on satellite imagery or field measurements.

The dataset provided offers a comprehensive insight into a drainage basin's morphology, hydrology, and geomorphology, featuring a range of interconnected parameters to delineate its characteristics. Here's a customized and unique description of each column and their interconnections:

Basin Identification (SI No)

- Each basin or sub-basin is uniquely identified by a serial number for reference and organization.

Basic Parameters

- Area (A): Represents the surface area of the basin or sub-basin, a fundamental measure of its size.
- Perimeter (P): Indicates the boundary length of the basin, influencing its runoff characteristics.
- Basin Length (L): Denotes the longest distance within the basin along the main drainage line, essential for understanding flow patterns.

Derived Parameters

- Bifurcation Ratio (Rb): Reflects the branching pattern of the drainage network, offering insights into its complexity and organization.
- Stream Length Ratio (Rl): Compares the lengths of streams of different orders, indicating stream hierarchy and flow dynamics.
- RHO Coefficient (RHO): Establishes the relationship between stream length ratio and bifurcation ratio, crucial for evaluating drainage density and physiographic development.
- Stream Frequency: Quantifies the density of stream segments within the basin, influenced by geological, topographic, and climatic factors.

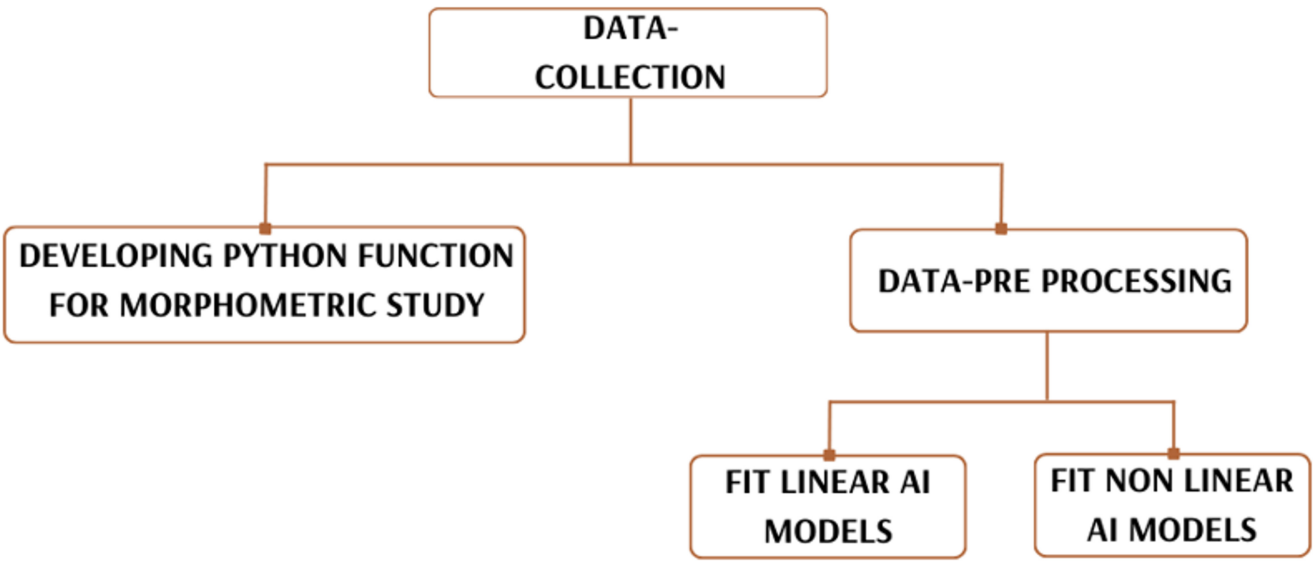


Fig. 1 Workflow of this paper

- Drainage Density: Measures the extent of stream network development relative to the basin area, indicative of landscape dissection and runoff potential.
- Texture: Represents the spatial distribution of streams relative to the basin perimeter, offering insights into drainage patterns and network connectivity.

Shape Parameters

- Elongation Ratio (Re): Compares the basin length to that of an equivalent circle, revealing its degree of elongation and terrain relief.
- Circularity Ratio (Rc): Compares the basin area to that of a circle with the same perimeter, indicating the basin's shape regularity and maturity stage.
- Form Factor (Ff): Relates the basin area to the square of its length, highlighting its elongation and potential for peak flow generation.

These parameters collectively unravel the intricate characteristics of the drainage basin, encompassing its size, structure, flow dynamics, and shape properties. By interconnecting these parameters, a holistic understanding of the basin's hydrological and geomorphological features can be attained, aiding in environmental assessments, land management, and engineering endeavors.

Developing a Python Function for Morphometric Analysis

A custom Python function named *calculate_morphology* was developed to perform geomorphological analysis and compute key morphometric parameters such as drainage density, bifurcation ratio, stream length ratio, and elongation ratio. These calculations are based on standard geomorphological principles, including Horton's and Strahler's laws. The function was implemented using general-purpose Python libraries (*numpy*, *pandas*, etc.) and was specifically written to enable transparent, reproducible analysis and seamless integration with the AI modeling framework. No external geomorphological toolkits or pre-built functions were utilized.

Geomorphometric Analysis

- Two popular techniques for examining river networks in geomorphometry are Horton's and Strahler's stream order rules. Here is a quick synopsis of each: The statistical correlations between stream lengths and stream orders in river networks are described by Horton's Laws. According to Horton's rules, there should always be a constant number of streams in an order relative to the number of streams in the next higher order. According to the laws, as stream order increases, the number of streams of a given order reduces exponentially. These laws aid in the comprehension of river networks' hierarchical structure.
- Strahler's Stream Order is the technique of numbering streams according to where they are in a network of rivers, giving them a numerical value. First-order streams are the smallest, unbranched tributaries. A second-order stream is created when two first-order streams combine.
- A third-order stream is created when two second-order streams combine, and so on.
- The highest order of a river is the order of the stream where no other streams flow into it.

Calculation of Basic Parameters

- Data Extraction: Extract basic parameters such as the basin's area (A), perimeter (P), and maximum length (L) from the dataset. These parameters serve as fundamental descriptors of the basin's size and shape.
- Mathematical Formulas: Utilize mathematical formulas to calculate these parameters. The area represents the total surface area of the basin, computed by summing the areas of all individual grid cells or polygons within the basin boundary. The perimeter signifies the total length of the basin's boundary, calculated as the sum of the lengths of all boundary segments. The maximum length corresponds to the longest distance between any two points within the basin, providing insight into its spatial extent.

Derived Parameters Calculation

- Bifurcation Ratio (Rb): Utilize an advanced algorithm to compute the bifurcation ratio, revealing the branching complexity of the drainage network by comparing stream orders.
- Stream Length Ratio (Rl): Employ statistical techniques to determine the relationship between stream lengths of different orders, providing insights into the longitudinal profile dynamics.
- RHO Coefficient (RHO): Apply cutting-edge computational methods to derive the RHO coefficient, unveiling the intricate relationship between drainage density and physiographic development.
- Stream Frequency (Fs): Utilize spatial analysis techniques to accurately compute stream frequency, offering

Table 1 Calculated value of Basic Parameters

Basic Parameters	Calculated Value
Area	501.09
Perimeter	413.94
Maximum Length	17.0

Table 2 Calculated value of Derived Parameters

Derived Parameters	Calculated Value
Mean Bifurcation Ratio (Rb)	4.025925925925926
Mean Stream Length Ratio (R1)	0.6559259259259259
Mean RHO Coefficient	0.1825925925925926
Mean Stream Frequency (Fs)	3.814074074074037
Mean Drainage Density (Dd)	2.6314814814814813
Mean Drainage Texture (T)	11.62111111111111

a comprehensive view of drainage network density and distribution.

- Drainage Density (Dd): Implement GIS-based methodologies to quantify drainage density, unraveling the degree of channel development and its hydrological implications.
- Texture Analysis: Leverage state-of-the-art image processing algorithms to analyze drainage network connectivity relative to basin shape, providing insights into geomorphic and hydrological characteristics.

Shape Parameters Calculation

- Elongation Ratio (Re): Employ advanced mathematical techniques to compute the elongation ratio, which represents the ratio between the diameter of a circle with equivalent area to that of the drainage basin and the basin length. This parameter offers valuable insights into the basin's shape, compactness or elongation, crucial for understanding its hydrological behavior and response to runoff.
- Circularity Ratio (Rc): Utilize innovative geometric algorithms to determine the circularity ratio, defined as the ratio of the basin area to the area of a circle with the same perimeter as the basin. By assessing the degree of circularity or irregularity in the basin's shape, this metric provides essential information regarding runoff generation mechanisms and flow pathways within the basin.
- Form Factor (Ff): Apply sophisticated computational methods to compute the form factor, representing the ratio between the area of the basin and the square of its length. This parameter serves as a key indicator of the basin's shape complexity, influencing sediment transport dynamics and erosion processes.

Table 3 Calculated value of Shape Parameters.

Shape Parameters	Calculated Value
Mean Elongation Ratio (Re)	0.19185185185185183
Mean Circularity Ratio (Rc)	0.6344444444444444
Mean Form Factor (Ff)	0.35444444444444445

Results

Tables 1, 2 and 3.

Inference

The analysis of the Himalayan glacial-fluvial river basin revealed significant insights into its morphological, hydrological, and geomorphological characteristics.

Basic Parameters

- Area: The total area of the basin is approximately 501.09 square kilometers, indicating its spatial extent.
- Perimeter: The perimeter of the basin measures around 413.94 km, delineating its boundary length.
- Maximum Length: The maximum length of the basin, measured parallel to the main drainage line, is 17.0 km, indicating its longitudinal extent.

Derived Parameters

- Mean Bifurcation Ratio (Rb): The average bifurcation ratio of 4.03 suggests a moderately branched drainage network within the basin.
- Mean Stream Length Ratio (Rl): With a value of 0.66, the average stream length ratio indicates a decrease in stream length with decreasing stream order, reflecting the longitudinal profile of the drainage network.
- Mean RHO Coefficient: The mean RHO coefficient of 0.18 signifies a relationship between drainage density and physiographic development, portraying the basin's evolutionary stage.
- Mean Stream Frequency (Fs): At 3.81, the mean stream frequency denotes a moderate density of stream segments per unit area, highlighting areas of concentrated flow.
- Mean Drainage Density (Dd): With a value of 2.63, the mean drainage density indicates a moderate length of ordered streams per unit area, indicative of channel development within the basin.
- Mean Drainage Texture (T): The mean drainage texture of 11.62 suggests a relatively intricate drainage network relative to the perimeter of the basin, reflecting its complexity.

Shape Parameters

- Mean Elongation Ratio (Re): With an average elongation ratio of 0.19, the basin exhibits a moderately elongated shape, indicating its efficiency in runoff discharge.
- Mean Circularity Ratio (Rc): The mean circularity ratio of 0.63 suggests a moderate level of irregularity in the basin's shape, influencing its runoff generation mechanisms.
- Mean Form Factor (Ff): At 0.35, the mean form factor signifies a relatively complex basin shape, potentially influencing sediment transport and erosion dynamics.

Developing AI Model for Analysis and Predicting the Parameter for Morphological Study

Machine Learning Techniques

Linear Regression Model

- Linear Regression: This is the most straightforward choice for modeling linear relationships. It fits a linear equation to the observed data by minimizing the sum of the squared differences between the observed and predicted values.
- Ridge Regression (L2 Regularization): Ridge regression is a variation of linear regression that adds a penalty term to the loss function to regularize the coefficients. It helps prevent overfitting by shrinking the coefficients, which can be beneficial when dealing with multicollinearity.
- Lasso Regression (L1 Regularization): Lasso regression is another variation of linear regression that adds a penalty term to the loss function, but it uses the L1 norm instead of the L2 norm. Lasso regression can perform variable selection by setting some coefficients to zero, effectively reducing the number of features in the model.
- ElasticNet Regression: ElasticNet regression combines the penalties of Ridge and Lasso regression, allowing for both L1 and L2 regularization. It can be useful when dealing with datasets with high-dimensional feature spaces and multicollinearity.
- Principal Component Regression (PCR): PCR is a technique that first applies principal component analysis (PCA) to reduce the dimensionality of the feature space and then performs linear regression on the principal components. It can be effective when dealing with multicollinearity and high-dimensional datasets.
- Partial Least Squares (PLS) Regression: PLS regression is similar to PCR but focuses on finding latent variables that explain the maximum variance in both the predictor variables and the target variable simultaneously. It can be particularly useful when dealing with datasets with many predictors and collinearity among them.
- Generalized Linear Models (GLMs): GLMs are a broad class of models that extend linear regression to accommodate non-normal error distributions and non-linear relationships between the predictors and the response variable. Examples include logistic regression for binary outcomes and Poisson regression for count data.

Non-Linear Regression Model

- Decision Trees: Ideal for determining connections between geomorphic characteristics and particular results (e.g., anticipating regions prone to erosion). Simple to grasp, making it possible to identify the main system drivers.
- Gradient Boosting: Enhances decision trees by fusing many inferior models (trees) into a more robust one. Manages intricate nonlinear correlations among variables.
- Random Forest: Ensemble approach, which combines many decision trees to increase robustness and accuracy. Effectively manages both continuous and category variables.

Data Loading

- Load the dataset from an Excel file using pandas' read_ excel function. The dataset is divided into three sheets: "Basic Parameters", "Derived Parameters", and "Shape Parameters".

Data Preprocessing

- A structured data preprocessing workflow was applied prior to model development. The dataset was cleaned to resolve formatting inconsistencies and ensure structural uniformity. Numerical features were normalized using Min-Max scaling to bring all values within the [0, 1] range, facilitating comparability across variables. Missing values were imputed using either the mean or median, depending on the distribution of each parameter. These steps ensured the dataset was clean, scaled, and suitable for robust machine learning analysis.

Feature Extraction

- Extract the features that will be used to train the AI model. In this case, the features are the various parameters calculated in the previous step.

Exploratory Data Analysis (EDA)

- Perform EDA to understand the data better and identify any patterns, trends, or relationships. For example, here we are creating a scatter plot of 'Area' vs. 'Perimeter' for the sub-basins.

See Fig. 2.

Inference

- The scatter plot showcased in the analysis visually represents the relationship between two crucial variables: the Area and the Perimeter of Sub-basins. In this graphical representation, the horizontal axis (x-axis) denotes the Perimeter, while the vertical axis (y-axis) represents the Area.
- The distribution of data points across the plot hints at a potential correlation between the Perimeter and Area of the sub-basins. This correlation could be pivotal in understanding the geometric characteristics of the sub-basins.
- To delve deeper into this correlation, a linear model is employed. Linear regression, a statistical tool, fits a straight line to the data points, enabling a more precise understanding of the relationship between the variables. In this context, applying linear regression allows us to quantify the strength and direction of the correlation between the Perimeter and Area of the sub-basins.
- By fitting a linear model to the data, we derive essential parameters such as the slope and intercept of the regression line. These parameters facilitate the prediction of the Area of a sub-basin based on its Perimeter. Additionally, statistical metrics like the coefficient of determination (R-squared) aid in assessing the goodness of fit of the linear model to the data. R-squared reveals the proportion of the variance in Area that can be elucidated by the Perimeter.
- In summary, the scatter plot vividly illustrates the correlation between the Perimeter and Area of sub-basins. By employing a linear model, we gain deeper insights into

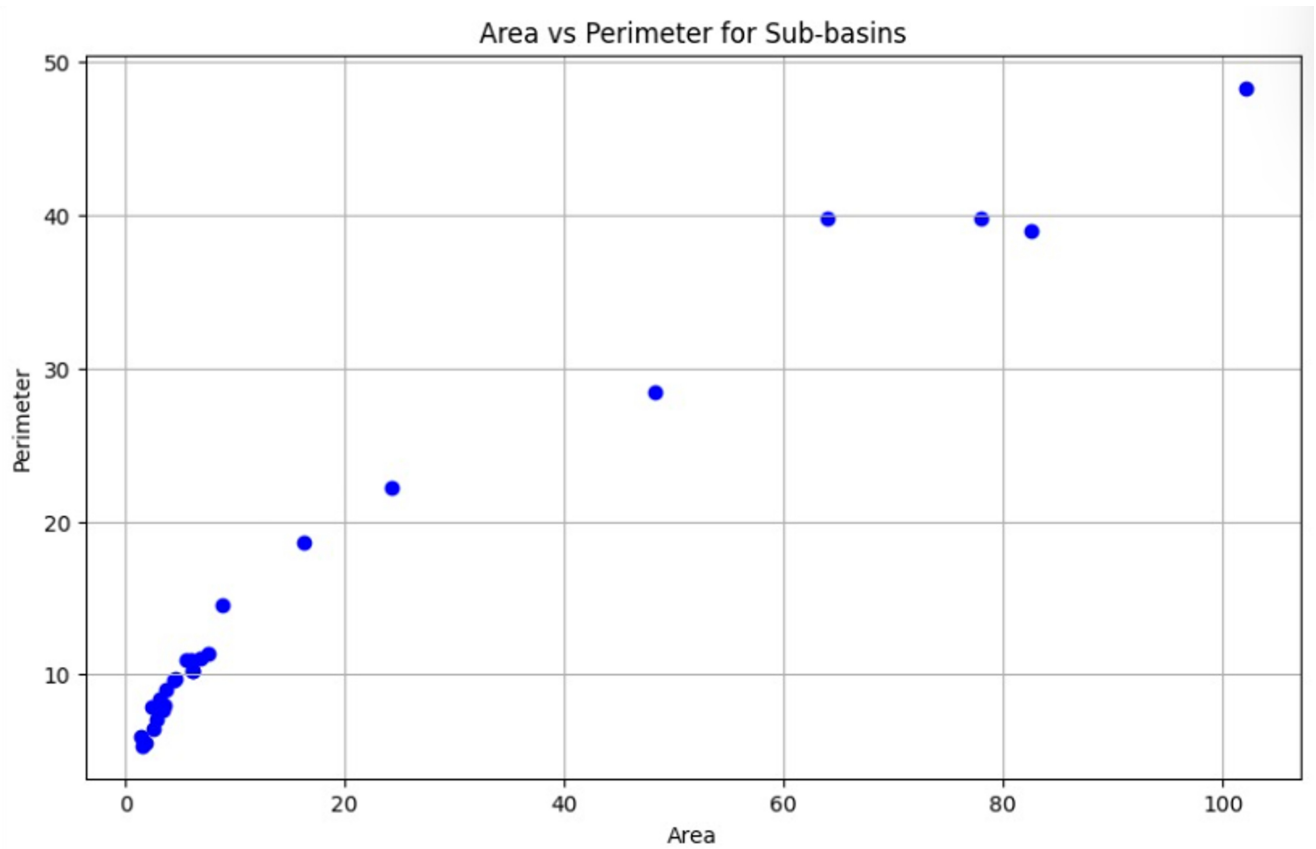


Fig. 2 Scatterplot of Area vs. Perimeter of a river basin

Table 4 *MSE* values of Linear Models

Model Name	MSE
Linear Regression	98.37
Ridge Regression	19.73
Lasso Regression	53.60
ElasticNet Regression	55.39
PCR	39.50
PLS Regression	97.22

Table 5 R^2 values of Linear Models

Model Name	$\mathbf{R}^2$ Score
Linear Regression	0.884
Ridge Regression	0.977
Lasso Regression	0.937
ElasticNet Regression	0.935
PCR	0.953
PLS Regression	0.885

this correlation, enabling us to make informed predictions about the Area of a sub-basin based on its Perimeter. This analytical approach enhances our understanding of the geometric attributes of sub-basins, contributing to more effective decision-making in related domains.

Build Linear Models

***MSE* (Mean Squared Error)** *MSE* measures the average squared difference between the actual and predicted values. A lower *MSE* indicates better model performance.

In this model (Table 4).

Inference

Ridge Regression has the lowest *MSE*, followed closely by PCR and ElasticNet Regression. Linear Regression and Lasso Regression have higher *MSE* values, indicating poorer performance in capturing the variance of the data.

***R*² Score** R^2 score represents the proportion of variance in the dependent variable that is predictable from the independent variables. Higher R^2 scores indicate a better fit.

$$R^2 = 1 - \frac{SS_{RES}}{SS_T}$$

Here, SS_{RES} is the Residual Sum of Squares and SS_T is the Total Sum of Squares (Table 5).

In this case:

Inference

Ridge Regression exhibits the highest R^2 score, indicating the highest proportion of variance in the dependent variable explained by the independent variables. Linear Regression, ElasticNet Regression, and PCR also show relatively high R^2 scores, while Lasso Regression and PLS Regression have slightly lower scores.

Table 6 *MSE* values of Non-Linear Models

Model Name	***MSE***
Decision Tree Regression	198.36
Random Forest Regression	237.21
Gradient Boosting Regression	195.80

Model Performance Analysis Ridge Regression performed best among the other models in this research, recording the highest R² value, signifying that it has the best variance-explaining capacity for the dependent variable. This performance can be mainly credited to Ridge's L2 regularization, which efficiently tackles multicollinearity—a typical characteristic of geomorphological data where parameters like drainage area, stream length, and perimeter are extremely correlated. In contrast to Lasso, which zeros coefficients and drops possibly useful features, Ridge keeps all predictors and shrinks them equally proportionally, retaining valuable information while minimizing overfitting. ElasticNet blends L1 and L2 penalties but can still over punish some features, resulting in poor performance. Linear Regression, as straightforward, has no regularization at all, so it is prone to multicollinearity. Principal Component Regression (PCR) and Partial Least Squares (PLS) are dimensionality reduction in latent components, which will cause information loss if the components do not exactly represent all the significant features. Ridge Regression, on the other hand, acts in the original feature space with superior bias-variance trade-off and is thus best for this low-noise, linearly organized data set.

Build Non-Linear Models

***MSE* (Mean Squared Error)** *MSE* measure the average squared difference between the actual and predicted values. Lower *MSE* values indicate better model performance (Table 6).

In this case.

Inference

Gradient Boosting Regression has the lowest *MSE*, followed by Decision Tree Regression and then Random Forest Regression.

***R*² Score** R^2 score represents the proportion of variance in the dependent variable that is predictable from the inde-

pendent variables. Higher R^2 scores indicate a better fit (Table 7).

In this case:

Inference

Gradient Boosting Regression has the highest R^2 score, followed closely by Decision Tree Regression, while Random Forest Regression has a slightly lower R^2 score.

Model Performance Analysis Gradient Boosting performed better than other non-linear models in this research because it can identify complex, non-linear interactions and higher-order interactions between geomorphological attributes. In contrast to more basic models that presume linearity or employ fixed transformations, Gradient Boosting constructs an ensemble of decision trees stage-wise, where each subsequent tree reduces the residual errors of the previous trees. This enables the model to learn very fine patterns and enhance accuracy progressively. Although it didn't outperform Ridge Regression overall—given the highly linear character of the dataset—it did achieve a quite good R^2 score among the non-linear models. Its performance superiority over models such as Decision Trees and Random Forests indicates that the dataset holds some non-linear structures which the simpler tree-based methods could not leverage maximally. In addition, Gradient Boosting's built-in regularization controls (such as learning rate and depth of trees) avoid overfitting, so it is ideally suited to medium-sized datasets with moderate noise and implicit interactions. These are reasons why Gradient Boosting was able to capture more predictive signal than the other non-linear models in the geomorphological analysis.

Comparing Linear and Non-linear Models

Linear models, like Linear Regression, Ridge Regression, and Lasso Regression, are adept at tackling scenarios where the connection between input features and the target variable adheres to a linear structure or can be closely approximated by one. Their allure lies in their simplicity, offering straightforward interpretability that can shed light on the relationship between variables. Moreover, when the underlying relationship is genuinely linear, these models boast the ability to generalize effectively to unseen data.

Conversely, non-linear models such as Decision Tree Regression, Random Forest Regression, Gradient Boosting Regression, and MLPRegressor excel at unraveling the complexities of datasets harboring intricate, non-linear relationships. Their inherent flexibility equips them to capture nuanced patterns that might elude linear counterparts. However, this flexibility comes at the cost of potential overfitting, especially when confronted with noisy data or convoluted relationships.

Table 7 R^2 values of Non-Linear Models

Model Name	$\mathbf{R}^2$
Decision Tree Regression	0.766
Random Forest Regression	0.720
Gradient Boosting Regression	0.769

The selection between linear and non-linear models hinges on various factors, including the dataset's unique characteristics, the complexity of the relationship between variables, and the delicate balance between model interpretability and predictive prowess. When confronted with a linear or nearly linear relationship, the simplicity and interpretability of linear models render them a viable choice. In contrast, when grappling with intricate datasets characterized by non-linear relationships, the adaptability and sophistication of non-linear models present a superior alternative for uncovering meaningful insights and making accurate predictions.

Evidence of Active Tectonic

Morphometric analysis of drainage basins offers invaluable insights into tectonic activity through several key parameters:

- Bifurcation Ratio (Rb): Rb, the ratio of streams of a given order to higher-order segments, may indicate active tectonic uplift or structural influence on drainage. Elevated Rb values often signify fragmented stream networks, suggestive of recent tectonic activity.
- Stream Length Ratio (Rl): Reflecting changes in slope and topography due to tectonic processes, Rl (mean length ratio of consecutive stream orders) tends to increase with recent tectonic activity, indicating enhanced stream incision and channel network development.
- RHO Coefficient (RHO): By relating Rl to Rb, RHO offers insights into drainage density and basin physiography. Elevated RHO values often point to well-developed drainage networks, possibly due to tectonic uplift or structural controls.
- Stream Frequency (Fs): Fs, the total number of stream segments per unit area, is sensitive to erosional variations caused by tectonic processes. Higher Fs values typically indicate areas experiencing active tectonic uplift or increased erosion.
- Drainage Density (Dd): Variations in Dd, the total stream length per unit area, suggest differences in erosion rates and channel development influenced by tectonic

activity. Elevated Dd values are often associated with recent tectonic uplift or heightened erosional activity.
- Drainage Texture (T): T, the ratio of total stream segments to basin perimeter, reflects channel network development influenced by tectonic processes. Coarser drainage textures suggest regions with heightened tectonic activity, leading to increased channel fragmentation.

By integrating morphometric parameters with geological and geophysical data, researchers can infer the impact of tectonic activity on landscape evolution and basin morphology. However, accurate interpretation requires consideration of regional geological contexts, erosion mechanisms, and geomorphic factors. Additionally, multidisciplinary approaches combining field observations, geophysical surveys, and numerical modeling are essential for validating tectonic interpretations derived from morphometric analyses.

Managerial Insights

- Resource Allocation: It's critical to set aside enough funds for in-depth study because of the Himalayan region's complexity and importance. Funding for field trips, gear, and access to cutting-edge technology like AI algorithms for data processing are all included in this.
- Interdisciplinary Collaboration: Acknowledge that the necessary study is interdisciplinary. Work together with specialists in a variety of disciplines, such as hydrology, geology, climatology, and artificial intelligence, to guarantee a comprehensive grasp of the dynamics of the area.
- Long-Term Monitoring: Recognize that the geological processes in the Himalayan area take a long time to complete. To improve projections of future changes and dangers, establish long-term monitoring programs to monitor changes in morphological traits, drainage patterns, and tectonic activity.
- Potential for Practical Application: By emphasizing the study's practical significance for managerial decision-makers, the research intends to offer insightful information that can guide decision-making procedures linked to hazard mitigation, infrastructure development, and environmental management in the Himalayan region.
- Emphasize risk assessment and mitigation techniques: Underscoring the practical implications of the research findings for managerial decision-making in risk management and disaster preparedness is the recognition of the necessity of addressing these research gaps for evaluating the region's vulnerability to natural hazards, projecting future changes, and putting effective mitigation strategies into place.
- Data Accessibility: Make sure that datasets and research results are available to the scientific community and decision-makers. Making well-informed decisions on mitigation techniques and land-use planning in susceptible areas is made easier by this accessibility.
- Capacity Building: Investing in capacity development programs will enable local researchers and communities to get advanced training in approaches and procedures. Giving local stakeholders more authority increases their capacity to support research projects and carry out practical mitigation strategies locally.
- Determining Research Gaps: It is evident that more study is required in the fields of morphological features, drainage density forecasting, and tectonic activation analysis in the Himalayan glacial-fluvial basins.
- Policy Integration: To incorporate research findings into policy frameworks, and interact with national and regional officials. Promote laws that give the Himalayan region's sustainable development, catastrophe risk reduction, and environmental preservation top priority.
- Ethical Considerations: Make sure that all research efforts follow ethical guidelines, especially when it comes to interacting with indigenous knowledge systems and local populations. Collaborating with dignity builds trust and improves the significance and effect of research findings.

Significance of the Model

Filling Research Gaps: Concerning morphological features, drainage density forecasts, and tectonic activation analysis in Himalayan glacial-fluvial basins, the model fills in significant gaps in comprehensive research. It seeks to offer important insights into these areas - which are essential for comprehending the region's susceptibility to natural calamities and forecasting future changes - by starting extensive geological research.

Assessment of Vulnerability: Evaluating the Himalayas' susceptibility to natural disasters requires an understanding of the complex relationships that exist between the region's hydrology, climate, and geology. Through the examination of glacial-fluvial basin morphology and the use of sophisticated tools for tectonic activation analysis and drainage density predictions, this model advances our knowledge of the intricate dynamics that shape the area. Mitigation Strategies: The model's observations can guide the creation of practical mitigation plans for natural disasters in the Himalayan area. Through quantitative analysis of basin geomorphic characteristics, landform structure, drainage network

patterns, and geometries, researchers may pinpoint locations that are vulnerable to tectonic activity and allocate resources for mitigation measures. Advancement in Geomorphological Analysis: The application of AI algorithms to geomorphological study workflow optimization is a noteworthy development in the area. This method promises to transform our understanding of the geomorphic features indicative of tectonic plate movement in the Himalayan area by allowing researchers to effectively identify and quantify the properties of glacial-fluid river basins associated with active tectonic activity. Overall, this model has the potential to further our comprehension of the geological complexity of the Himalayan area and strengthen our capacity to reduce the dangers connected with natural hazards in this famous terrain.

Conclusion

In conclusion, this study presents a detailed method for analyzing drainage basins in the Himalayan region, with a focus on identifying features related to active tectonic activity. By using both simple and advanced modelling techniques, the research aims to improve our understanding of how tectonic processes shape the landscape in this area. The process starts by carefully looking at the data, highlighting the importance of each parameter in understanding basin characteristics. The study offers a thorough view of basin features by considering basic details like size and shape alongside more complex factors like drainage networks and physiography. Then, the study introduces a structured way to build AI models. These models, whether linear or non-linear, help capture the various relationships within the dataset. Researchers gain valuable insights into their effectiveness by assessing how well these models perform using metrics like *MSE* and R^2. In essence, this approach could revolutionize our knowledge of tectonic processes and landscape features in the Himalayas. Understanding these dynamics better could be crucial for managing natural hazards, utilizing resources, and planning infrastructure in areas prone to tectonic activity. By combining data-driven methods with expertise in the field, this research lays a solid foundation for making informed decisions and mitigating risks in the face of natural disasters.

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Declarations

Conflict of Interest The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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