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ORIGINAL ARTICLE

Automated Landform Classification using SRTM DEM and Satellite Imagery in Belihuloya, Sri Lanka

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ABSTRACT

Belihuloya is a steep and rugged landscape characterized by pronounced elevation gradients and deeply incised valleys. The area is highly susceptible to environmental hazards, particularly landslides and erosion, due to its terrain and high rainfall. The landforms in the Belihuloya area are diverse, highlighting the importance of accurate identification and classification for effective land management and environmental risk assessment. The main objective of this study is to identify and classify landforms in the Belihuloya area using STRM DEM, which aims to gain a comprehensive understanding of the land morphology and landscape diversity of the study area. An automated GIS-based method is used to create a landform classification map using the Topographic Position Index (TPI). TPI is used at different scales for this classification. This study identified and classified the landforms of the Belihuloya area as follows: deep valleys or basins: 6.87 km^2 (11.18%), lower valleys: 15.97 km^2 (25.99%), flat or constant slopes: 19.13 km^2 (31.14%), mountain ranges: 14.16 km^2 (23.05%), and high mountain ranges or peaks: 5.31 km^2 (8.64%). The resulting map was validated through field verification, where four of the five GPS points showed complete agreement with the observed ground conditions. Combining different terrain maps and calculating TPI provide valuable insights into terrain morphology across multiple spatial scales. The study demonstrated that this method provides more accurate results in classifying landforms in mountainous areas compared to traditional techniques. The findings highlight the importance of considering topographical attributes in land management and spatial planning efforts that can facilitate informed decision-making and sustainable land management practices in the Belihuloya region, as well as determine the level of vulnerability to landslides.

1 Introduction

The term “landforms” refers to the natural landforms found on the Earth’s surface and are arranged in a hierarchical order, ranging from relatively small features such as isolated mountains, small-scale features such as badlands, to large-scale ones such as mountain ranges, large plateaus, and floodplains (Roy and Das, 2021). Landform classification is the process of organizing different types of land by how they look, where they are located, and how they have changed over time. New technology such as remote sensing and GIS (Geographic Information System) has changed the way people understand and read landforms. Landforms show how high the land is, and images from satellites show us what is on the land, such as vegetation, and how people use it. This allows us to learn more about landforms than ever before (Mohamed, 2020). Properly understanding and classifying landforms within a region is crucial for effective land management, natural resource management, environmental conservation, and spatial planning (Mashimbye and Loggenberg, 2023).

Digital representations known as Digital Elevation Models (DEMs) have been used to depict the topography of landscapes since the 1970s. These DEMs and associated datasets, which include parameters such as slope, relief intensity, curvature, and elevation, have been effectively used by researchers to investigate geomorphological and geometric features (MacMillan et al., 2003).

TPI has been widely employed in geomorphological and landscape studies to classify landforms based on relative elevation differences from the surrounding terrain surface. TPI quantifies whether a location lies lower or higher than

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the average elevation within a defined neighborhood, enabling the identification of features such as valley bottoms, mid-slopes, and ridge tops (Guisan et al., 1999; Weiss, 2001). Compared to traditional classification methods that rely solely on slope or elevation thresholds, TPI offers several advantages. Traditional slope-based classifications can misidentify landform features because similar slopes may occur on both ridges and valleys, whereas TPI explicitly accounts for relative position with respect to the surrounding landscape (Evans, 2012). TPI measures the difference between the mean elevation of neighboring cells and the central cell, where a positive value indicates a higher terrain, and a negative value indicates a valley or lower terrain (Weiss, 2001). TPI, which is primarily used to classify slopes and landforms through DEM evaluation, is widely used in fields such as geology, geophysics, and hydrology. Various landform features, including slope, relief intensity, curvature, and elevation, are mainly used as landform attributes for landform classification (Prasannakumar et al., 2011).

Despite significant progress, research using advanced geospatial methods to analyze and classify landforms in the Belihuloya region is still lacking. This represents a significant research gap in this context. This study intends to use remote sensing and GIS to develop a landform map based on the TPI and to use the results of the landform classification for land use planning and environmental risk assessment, especially in relation to landslides. Landform analysis is crucial for enhancing environmental data. Through this method, the study aims to provide a comprehensive understanding of landform classification in the study area.

2 Materials and Methods

2.1 Study Area

The study area is in Sri Lanka's Ratnapura District, covering an area of roughly 59 km^2 and reaching elevations between 497 and 1600 m above mean sea level (Fig. 1). It experiences a tropical intermediate-zone climate, with warm and humid conditions throughout the year. Average temperatures generally range between 24 °C and 28 °C, while rainfall is relatively high due to the influence of both monsoon seasons. Belihuloya is a picturesque village enhanced with numerous water bodies and stunning hills. The area is home to significant peaks like the 1,400-meter-high Hawagala, the roughly 1,530-meter-high Baker's Bend, and the 1,500-meter-high Paraviyangala (Wijesooriya et al., 2022). Therefore, Belihuloya has been chosen as the study area.

The data preparation process (Table 1) involved acquiring SRTM DEM data from the USGS website, with a resolution of 30 x 30 meters, specifically for the Belihuloya study area. Landsat-8 surface reflectance data freely available from the United States Geological Survey ((USGS (http://www.usgs.gov/)) is used to prepare a full coverage map of Belihuloya. The Z-factor parameter was adjusted to accommodate the transformation of the DEM into a projected coordinate system, specifically WGS_1984_UTM_Zone_44N.

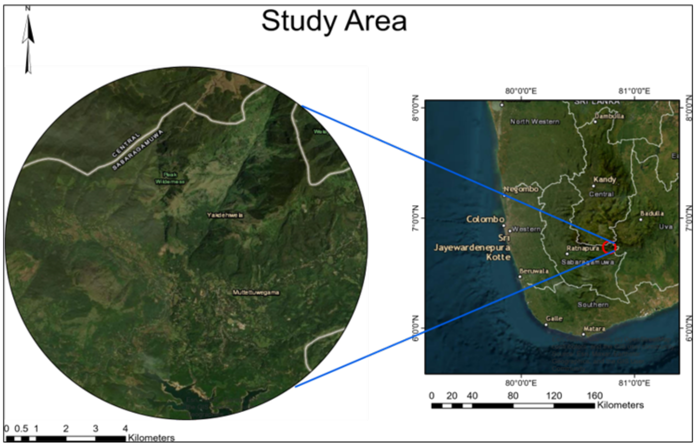

Fig. 1: Map of the study area.

Table 1: Sources of the data used.

Data Source	Resolution	Thematic Layers
Landsat 8 OLI Satellite 2023	30 m	Hydro-geomorphology
SRTM DEM	30 m	Elevation, Contour lines

The methodology shown in Fig. 2 describes the systematic process employed to integrate various geospatial techniques, and the software tools utilized in this study to generate the landform classification map.

2.2 Semi-automated Method

Four main maps were created in the terrain analysis: slope, curvature, elevation, and relief intensity, each of which provides insights into different aspects of the terrain. Adjustments were made to the Z-factor parameter to improve accuracy in visualization and analysis and to align elevation values with linear units (MacMillan et al., 2003). Then, terrain attributes such as slope, curvature, elevation, and relief intensity were calculated from the DEM.

The slope map classifies the terrain into certain classes based on steepness, facilitating terrain interpretation. Similarly, the curvature map classifies the terrain into concave, flat, and convex areas, helping to understand the terrain shape. Elevation and relief intensity maps further characterize terrain features, helping to identify elevation patterns and roughness. Overlaying these maps integrates terrain attributes, providing a comprehensive view of terrain properties, and facilitating terrain classification (Ghosh and Bera, 2023).

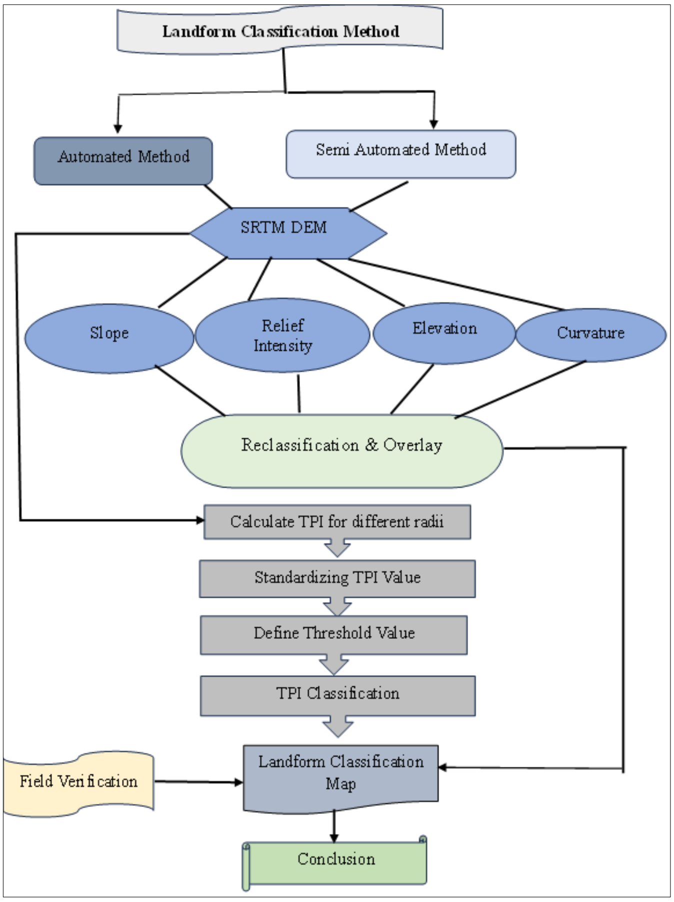

Fig. 2: Methodology of the workflow.

Each map was classified into distinct classes for easy interpretation. Finally, the Cell Statistics tool in ArcGIS 10.5 was used to overlay these maps to create a composite representation that provides a comprehensive view of terrain properties such as slope, curvature, elevation, and relief intensity. This tool is a raster overlay function that performs cell-by-cell mathematical operations on two or more raster layers. This integrated approach aids in terrain classification and terrain characterization, improving understanding of terrain features. The landform classes were generated using a cell-based statistical integration of slope, curvature, elevation, and relief intensity layers, as expressed in Equation (1) (Ghosh and Bera, 2023).

Land from classes = Cellstatistics ("Slope", "Curvature", "elevation", "Relief Intensity") " (1)

2.3 Automated Method

The topography of a large area, such as a basin, plays a significant role in the natural processes, productivity, and diversity of landscapes. It is influenced by various environmental factors, such as climate, geology, and topography. A set of topographic indicators can be used to characterize the topography and capture the diversity of land surface features in an area (Bishop et al., 2012). One such indicator is the TPI, which measures the variation between the elevation at a central point (z_0) and the average elevation ($\hat{z}$) within a given radius (R), taking into account the total number of neighboring points (n) involved in the calculation.

$$\hat{Z} = \left(\frac{1}{nR}\right)\{nR \sum i \in RZ_i\} \tag{2}$$

The TPI was computed using a circular neighbourhood approach in equation (2). For each central cell (z_0), the surrounding elevation values were averaged within a circular window of radius R, where R was varied to analyze terrain characteristics at multiple spatial scales. The number of neighbouring cells (n) included in the calculation depended on the size of the radius.

TPI values are positive when the center point is higher than its surroundings and negative when it is lower. Values outside this range, which typically fall between +1 and -1, may indicate anomalies in the digital elevation model (DEM). In addition, the topographic position standard deviation (DEV) estimates the topographic position of the center point (z_0) using the TPI and the standard deviation (SD) of the elevation as mention in equations (3) and (4) (Weiss, 2001).

$$DEV = \frac{(Z_0 - \hat{Z})}{SD} \tag{3}$$

$$SD = \sqrt{\frac{1}{(nR-1)} \sum_{i=1} (Z_i - \hat{Z})^2} \tag{4}$$

TPI < - focal (x, w = f, fun = function (x . . .) x [5] - mean (x [-5])) (Wilson and Gallant, 2000).

Positive TPI values indicate high areas such as ridges, while negative values indicate low areas such as valleys, and a TPI value of zero indicates flat terrain. The choice of scale (neighborhood values) for TPI calculation affects the results, revealing different insights into the terrain and their relationships, as shown in Fig. 3 (Mokarram et al., 2015).

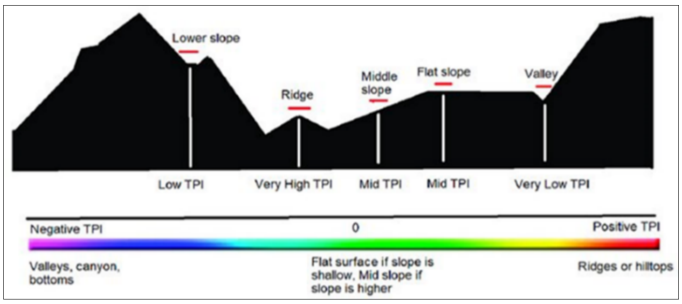

Fig. 3: An illustration of the TPI value in the topography (Source: Abdullah and Abdulrahman).

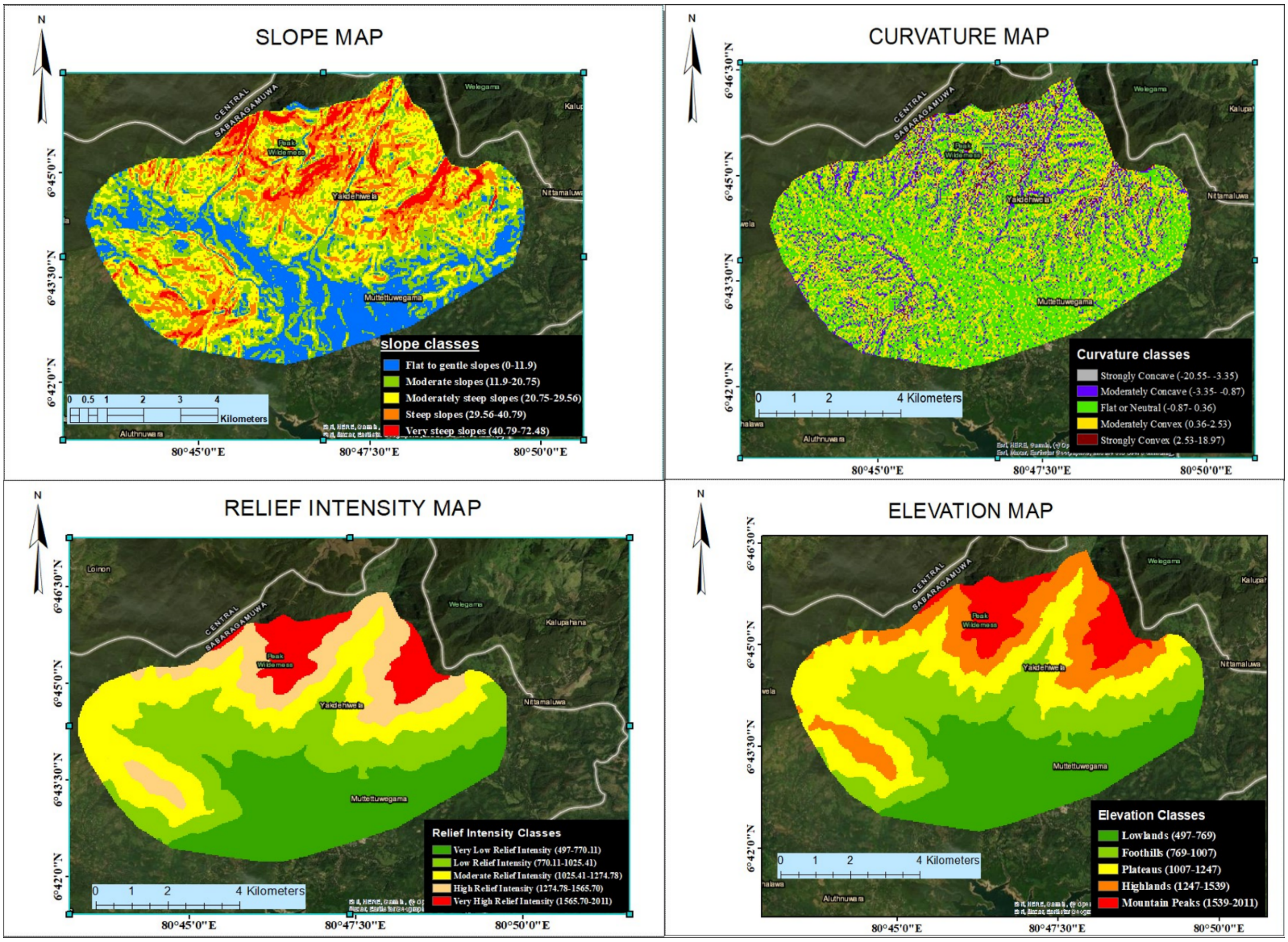

Fig. 4: Terrain characteristics of the study area; left to right and top to bottom: slope, curvature, relief intensity, and elevation.

The next steps in the automated classification process are:

i. Slope Classification: TPI values can be easily classified into slope classes based on their vertex and the slope at each point. TPI values that exceed a certain threshold can be identified as ridge tops or mountain peaks, while values below the threshold can indicate valley bottoms or depressions. TPI values close to 0 are generally classified as flat plains (Garcia and Grohmann, 2019).
ii. Standardization of TPI values: TPI values were standardized by calculating the mean and standard deviation for each radius and then applying normalization techniques to ensure consistency across spatial scales.
iii. Defining Threshold Values: A Python script was used in Google Colab to determine optimal threshold values for terrain classification based on the standardized TPI data.
iv. Reclassification of standard TPI values: The standardized TPI raster was reclassified using the identified threshold values to divide the landscape into distinct landscape types.

The TPI rasters generated for different radii were standardized to the same spatial resolution and extent and then combined using a cell-by-cell overlay (Cell Statistics). This process integrates multi-scale TPI values into a single composite raster, providing a comprehensive representation of landscape variation (Ghosh and Bera, 2023).

3 Result and Discussion

3.1 Landform classification based on semi-automated method

The analysis of topographic attributes within the study area reveals diverse terrain characteristics, including slope, curvature, relief intensity, and elevation as shown in Fig. 4. These topographic attributes collectively contribute to shaping the physical and ecological characteristics of the landscape.

Table 2 summarizes the terrain attribute analysis, providing insights into the topographic characteristics of the study area. It reveals diverse distributions across slope, curvature, relief intensity, and elevation classes. Gentle slopes cover the largest area, representing 21.38%, while moderately steep slopes and moderately steep to steep slopes account for 26.15% and 28.32%, respectively. Curvature analysis shows flat or nearly flat areas dominating the landscape (54.76%) and moderately convex areas covering 28.99%.

Table 2: Terrain attributes.

TERRAIN ATTRIBUTE	CLASSES	AREA (KM^2)	PERCENTAGE (%)
SLOPE	0 - 11.94	12.58	21.38
	11.94 - 20.75	15.38	26.15
	20.75 - 29.56	16.66	28.32
	29.56 - 40.08	10.67	18.14
	40.08 - 72.48	3.53	6.00
CURVATURE	-20.56 - -3.35	0.51	0.87
	-3.35 - -0.87	7.90	13.42
	-0.87 - 0.37	32.22	54.76
	0.37 - 2.54	17.05	28.99
	2.54 - 18.97	1.16	1.97
RELIEF INTENSITY	497 - 770.11	16.50	26.85
	770.11 - 1,025.42	15.55	25.31
	1,025.42 - 1,274.78	15.31	24.92
	1,274.78- 1,565.71	8.94	14.56
	1,565.71 - 2,011	5.14	8.36
ELEVATION	497 - 769	15.62	26.54
	769 - 1,007	14.03	23.84
	1,007 - 1,247	14.69	24.96
	1,247 - 1,539	9.32	15.84
	1,539 - 2,011	5.18	8.81

Relief intensity classification indicates low relief intensity areas (26.85%) and areas with moderate relief intensity (25.31%). Elevation classification delineates lowlands (26.54%), foothills (23.84%), and plateaus (24.96%). These findings offer valuable insights for land management and ecological assessments.

Fig. 5, the landform classification map, identifies five landform classes: high ridges, ridges, flat, lower valleys and deep valleys based on terrain attributes. The northern and northeastern parts of the study area are characterized by high peaks and ridges, while the western and northwestern parts are dominated by ridges and slope areas. The southern and southeastern parts are covered by deep valleys and lower valleys.

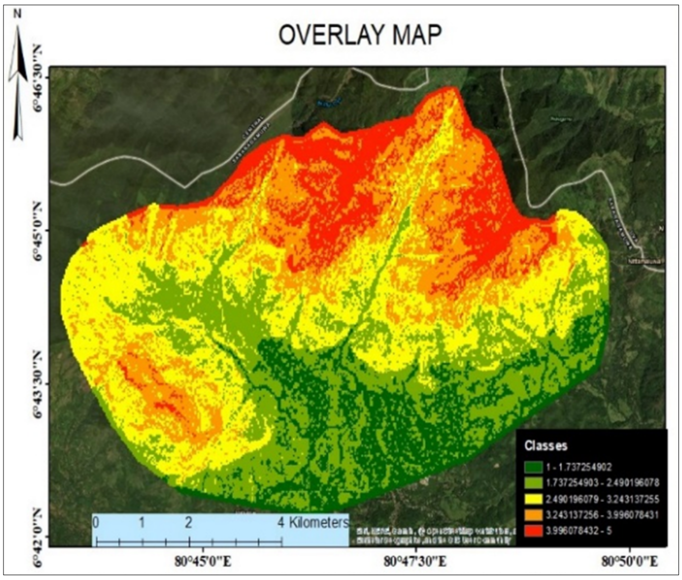

Fig. 5: Landform classification map by semi-automated method.

3.2 Landform classification based on automated method

The calculation of the TPI at various radii gives useful information about the spatial variability of terrain characteristics at different scales within the study area. TPI, a relative topographic position, measures a cell's elevation in respect to its surroundings. In this study, TPI was calculated using five different radii: 10, 20, 30, 40, and 50 m (Fig. 6), allowing for the investigation of terrain features at numerous resolutions. Although the DEM used in this study has a 30-m spatial resolution, the TPI algorithm allows the use of circular neighbourhoods defined by any radius (R). For each radius, ArcGIS includes all DEM cells whose centres fall within the circular window. Thus, a 10 m radius represents only the central pixel, whereas radii of 20–50 m incorporate gradually larger neighbourhoods. These radii were selected to capture terrain characteristics at multiple spatial scales, enabling the identification of both fine-scale and broader landform patterns.

3.3 Defining threshold for standard TPI

The optimal threshold for analyzing the standardized TPI rasters was determined using the Google Colab environment, using Python programming for computational efficiency and flexibility. After conducting experiments and analyses, the best threshold value was identified as 0.6767676768 (Fig. 7). This threshold effectively separated the standardized TPI rasters into different classes representing different landscape features, facilitating further analysis and understanding.

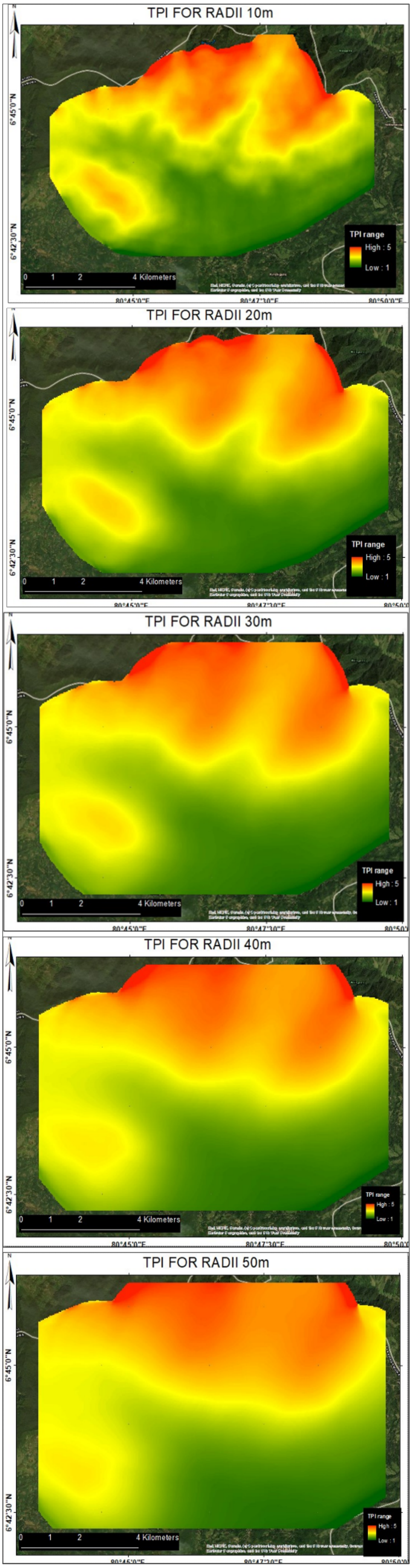

Fig. 6: Different radii for topographic Position Index (TPI).

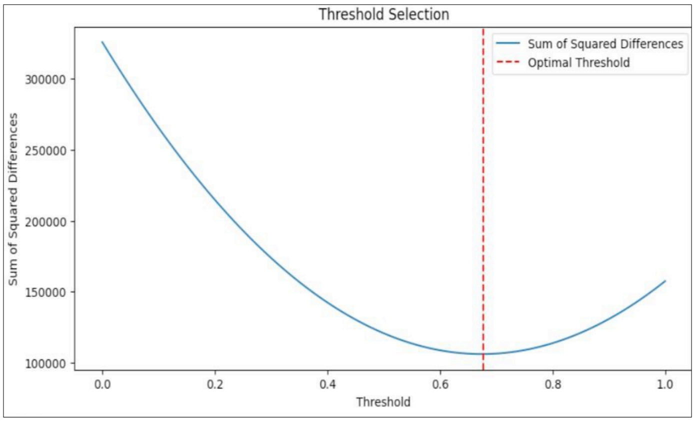

Fig. 7: Plot defining the optimal threshold value.

3.4 Reclassification of standardized TPI

Reclassification of standardized TPI rasters with radii ranging from 10 m to 50 m was performed using an optimal threshold value of 0.6767676768 (Fig. 8). This threshold is critical for distinguishing terrain features within the terrain and for making their classification into meaningful categories.

Values greater than +0.6767 were classified as high ridges or mountain peaks, while values between 0 and +0.6767 represented ridges. Values close to zero (i.e., between –0.6767 and +0.6767) were interpreted as flat or stable slopes. TPI values between –0.6767 and 0 were classified as low valleys, and values less than –0.6767 were categorized as deep valleys or basins. This threshold-based approach ensures consistent and meaningful differentiation of terrain types across all radius-derived TPI rasters.

The classification revealed spatial patterns reflecting the topographic diversity of the study area. High ridges or mountain peaks corresponded to very high TPI values, representing prominent landforms like peaks or hilltops. Ridges were identified in areas with slightly positive TPI values, indicating elevated ridgelines or crests. Flat or constant slopes occurred in regions with minimal elevation differences, indicating plains or gently sloping landscapes. Lower valleys were found in depressions or areas with negative TPI values, representing low-lying valleys or drainage channels. Deep valleys or basins were located in areas with highly negative TPI values, indicating enclosed depressions or basin-like features.

3.5 Landform classification map

The final landform classification map (Fig. 9) provided a detailed overview of terrain characteristics in the study area, categorizing landforms into five primary classes: deep valleys, lower valleys, flat slopes, ridges, and high ridges or mountain peaks. Deep valleys or basins comprised 11.18% of the study area, with significant relief depressions influencing local drainage. Lower valleys, occupying 25.99%, featured gentle slopes between uplands and lowlands. Flat slopes covered 31.14% of the area, suitable for agriculture and urban development.

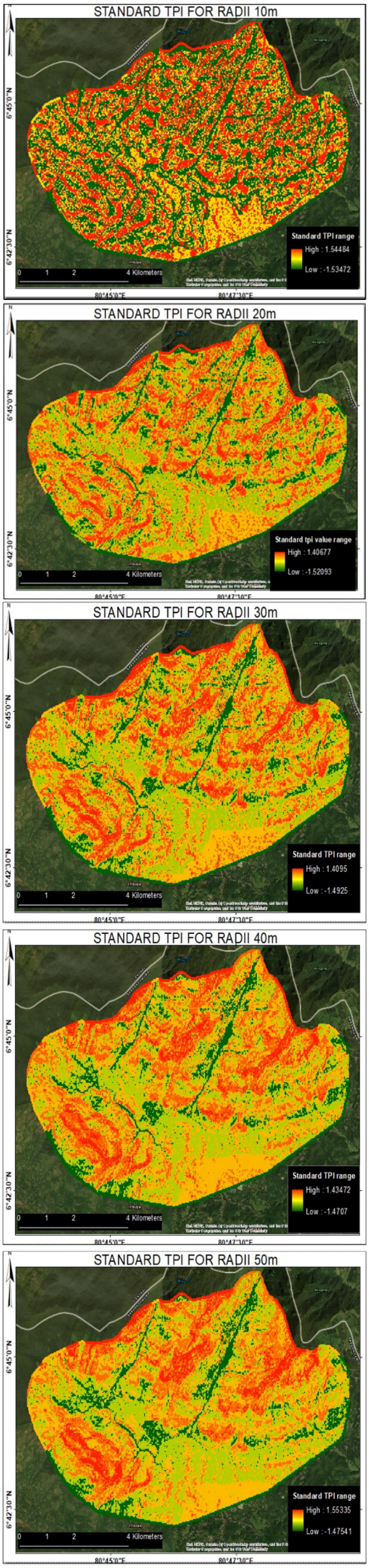

Fig. 8: Standardized TPI for different radii.

Ridges, accounting for 23.05%, shaped local drainage basins, while high ridges or mountain peaks (8.64%) featured rugged terrain and scenic beauty (Table 3).

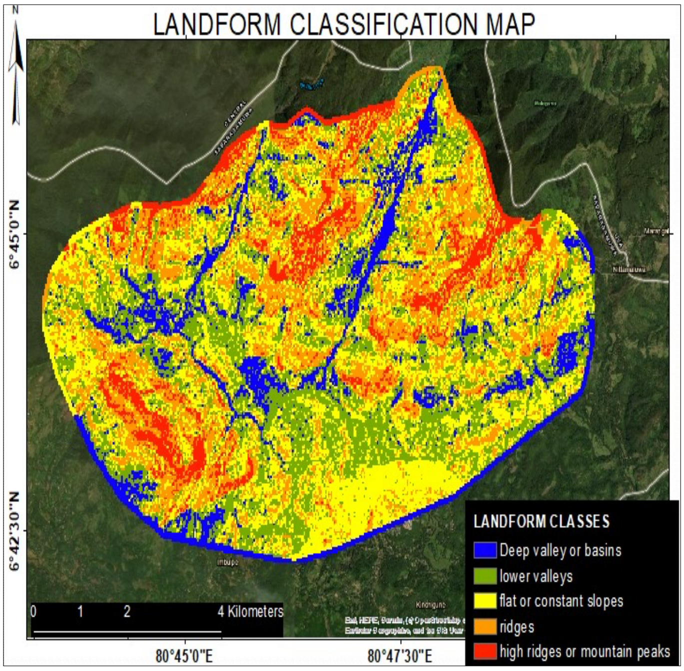

Fig. 9: Final landform classification map.

Table 3: landform classes attributes.

Classes	Area (km^2)	Percentage (%)
Deep valleys or basins	6.87	11.18
Lower valleys	15.97	25.99
Flat or constant slopes	19.13	31.14
Ridges	14.16	23.05
High ridges or mountain peaks	5.31	8.64

3.6 Accuracy Assessment

The accuracy of landform classification is calculated, and the final output of the land classification is visually compared with the ground truth data.

As the first step, this study calculated the accuracy of land form classification. The accuracy assessment, detailed in Table 4, summarizes the classification results, documenting the number of correctly classified instances for each landform class. Overall accuracy stands at 88%, representing the percentage of correctly classified instances out of the total. User's accuracy and producer's accuracy were computed for each class to evaluate classification performance, measuring the proportion of correctly classified instances within each class and relative to the total instances referenced, respectively. The Kappa coefficient, a statistical measure of agreement between classification and reference data, validates the accuracy of the landform classification map, registering at 88.24%.

Table 4: Accuracy assessment of landform class attributes.

	Deep Valleys	Lower Valleys	Flat Slopes	Ridges	High Peaks	Total (producer)
Deep Valleys	39	2	2	0	0	43
Lower Valleys	1	29	2	1	0	33
Flat Slopes	2	0	17	1	0	20
Ridges	1	0	1	27	1	30
High Peaks	0	1	1	2	20	24
Total (producer)	43	32	23	31	21	150

The study randomly selected five site locations, as shown in Fig. 10, and identified the locations using a handheld GPS. It then verified the landform classification map generated by the automated method. The physically existing landforms at the site locations were overlaid and compared with the auto-generated landform classification map. Each location was marked as either agreeing or disagreeing with the system based on visual interpretation. Finally, four GPS points completely matched the real ground conditions.

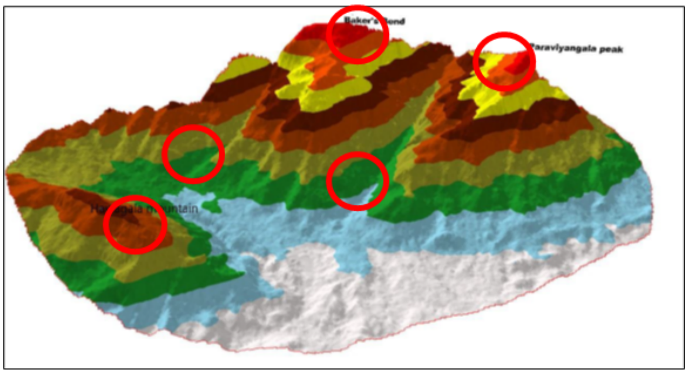

Fig. 10: GCP points locations.

4 Conclusion

This study has presented both automated and semi-automated methods for landform classification mapping using a combined classification approach based on elevation, slope, relief, curvature, and the TPI. The topography attributes and the slope index indicate that these methods are well suited for landscape classification in this region.

The study concludes that the entire Belihuloya region has diverse landscape features that have been formed and modified by multiple geological, geologic, and tectonic processes. The landscape classification map is a valuable tool for understanding the historical evolution of the landscape and managing environmental hazards. The map provides important data and information on landscape ecology, landscape characteristics, forestry, wetlands, and soils.

Furthermore, this study improves the understanding of landscape dynamics and provides a foundation for sustainable land management practices in the Belihuloya region. It contributes to informed decision-making and effective natural resource management, helping to conserve and utilize the ecological diversity of the region. For a more comprehensive understanding of landscape dynamics and geologic processes, future research can investigate additional parameters such as aspect and slope, in addition to existing landscape attributes. Additionally, increasing GPS points for ground truth data collection can improve accuracy by validating terrain features and reducing uncertainties associated with remote sensing techniques.

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Author Contributions

Conceptualization, methodology, analysis, writing - original draft preparation, review and editing, D.S.M. The author has read and agreed to the published version of the manuscript.

Conflict of Interest

The author declares no conflict of interest.

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