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Topographic Analysis for Landform Classification Using Geographic Information System: A Case Study of Kirkuk City, Iraq

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ABSTRACT

Landform classification is the process of identifying and grouping different types of landforms based on their physical characteristics. This study investigated the use of Digital Elevation Models (DEMs) to classify landforms in Kirkuk City, Iraq. The study used two different DEMs: the Shuttle Radar Topography Mission (SRTM), the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) Global DEM (GDEM). It used three different landform classification models: the Topographic Position Index (TPI), Support Vector Machine (SVM), and Convolutional Neural Network (CNN). The results of this study showed that the CNN model was the most effective at classifying landforms. The CNN model achieved an overall accuracy (OA) of 88.91% and a kappa of 0.883. The SVM model was the second most effective model, with an OA of 79.81% and a kappa coefficient of 0.781. The TPI model was the least effective model, with an OA of 67.12% and a kappa of 0.658. The field verification results showed that the CNN model was also the most accurate in terms of field mapping. The results of this study suggest that the CNN model is a promising tool for landform classification.

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التحليل الطبوغرافي لتصنيف التضاريس باستخدام نظام المعلومات الجغرافية: دراسة حالة لمدينة كركوك، العراق

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الملخص

تصنيف التضاريس هو عملية تحديد وتجميع أنواع مختلفة من التضاريس على أساس خصائصها الفيزيائية. تناولت هذه الدراسة استخدام نماذج الارتفاعات الرقمية (DEMs) لتصنيف التضاريس في مدينة كركوك، العراق. استخدمت الدراسة نموذجين مختلفين من نماذج DEM: بعثة طبوغرافيا الرادار المكوكية (SRTM)، ومقياس إشعاع الانبعاث الحراري والانعكاس الحراري المتقدم المحمول في الفضاء (ASTER)، ومقياس DEM العالمي (GDEM). واستخدمت ثلاثة نماذج مختلفة لتصنيف التضاريس: مؤشر الموقع الطبوغرافي (TPI)، وآلة ناقل الدعم (SVM)، والشبكة العصبية التلافيفية (CNN). وأظهرت نتائج هذه الدراسة أن نموذج CNN كان الأكثر فعالية في تصنيف التضاريس. حقق نموذج CNN دقة إجمالية (OA) قدرها 88.91% وكابا 0.883. كان نموذج SVM هو النموذج الثاني الأكثر فعالية، حيث بلغ 79.81٪ ومعامل كابا 0.781. كان نموذج TPI هو النموذج الأقل فعالية، حيث بلغ OA 67.12% وكابا 0.658. وأظهرت نتائج التحقق الميداني أن نموذج CNN كان أيضًا الأكثر دقة من حيث رسم الخرائط الميدانية. تشير نتائج هذه الدراسة إلى أن نموذج CNN يعد أداة واعدة لتصنيف التضاريس.

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Introduction

The applications in the field of geomorphology require geospatial information about landforms as it defines the boundary conditions for the underlying processes operative in this field. According to Jacek (1997), a landform is a specific geomorphic feature on the Earth's surface. These features can be large-scale (such as plains or mountain ranges) or small-scale (such as individual hills or valleys), and they can also be composed of other landforms, such as hilltops, valley bottoms, exposed ridges, flat plains, or upper or lower slopes. Large-scale features and small-scale topography on the Earth's surface are examples of landforms that have an impact on human behavior in terms of habitation patterns.

In geomorphological research, landform classification categorizes the surface of the Earth into several geomorphological kinds. Therefore, characterizing the topographic features of a particular place and comprehending their internal geomorphological development processes rely on proper landform classification. However, because of the complexity and dynamics of internal and external factors, landform types are not necessarily distinct from one another. On the surface of the Earth, transitional landforms with gradually altering surface morphologies are also extensively distributed. It is difficult to categorize these intricate and transitional landforms in this context using conventional landform classification.

This study deals with automatic landform classification from remote sensing data based on advanced techniques such as deep learning. this research focused on developing new methods for the extraction of landforms based on deep learning techniques (multiscale CNN).

The proposed model will be capable of identifying large-scale features and small-scale features through multiscale feature learning. The CNN architecture to be designed will also support efficient contextual feature learning and accurate classification of different landform types from DEM data.

The methods of automated landform classification can be grouped into unsupervised and supervised classifications. Unsupervised landform classification (e.g., Irvin et al. 1997, Burrough et al. 2000, Adediran et al. 2004) can be conducted without a priori knowledge, while supervised classification (e.g., Brown et al. 1998, Hosokawa et al. 2002) requires it. DEM is the most common data required in landform classification tasks. Tunçay et al. (2014) used DEM to classify the Beypazari area (northern Turkey) landform. The DEM data were analyzed to determine landform classes. A strong correlation was found between landforms and land cover. The Landform classification with DEM analyses was very successful except for the narrow valleys located in hilly areas. To separate or identify narrow colluvial valleys in these hilly areas, the different resolutions and window sizes for neighboring must be tested for the landform classification. Higher spatial resolution (< 30 m) and multi-temporal data were needed especially in narrow valleys where irrigated areas and trees were not separated successfully.

For the purpose of classifying landforms, supervised approaches have been developed to overcome the drawbacks of unsupervised methods. Prima et al. (2006) created a quantitative technique to categorize landforms using four morphometric parameters from slope and topographic openness thematic raster images obtained from DEMs. These factors may result in a genetic interpretation of topography since the many surficial processes and phases in the formation of slopes produce landscapes with various morphologies. The slope and topographic openness raster maps for Northeast Honshu, Japan, were created from 50-m DEMs. The Jennes algorithm was assessed for landform categorization in the salt dome of Korsia of Darab plain, Iran, in research by Mokarram et al. (2015). By employing least squares to fit a quadratic polynomial to a specified window size, Jennes' method employs a multi-scale approach. A 3x3 and 10x10 window was employed in the investigation. DEM with a resolution of 30 m serves as the input data for classifying landforms. The findings demonstrated that the assessed approach can be useful for geology's predictive mapping.

In recent works, deep learning methods were developed for landform classification. In the Chinese Loess Plateau, Li et al. (2020) created a deep-learning model for the automatic classification of landforms from DEM. Integrated data sources were used to train the algorithm to recognize and extract landform features. Different combinations of images, DEMs, and terrain derivatives are present in these integrated data sources. In order to compare how well the suggested deep learning system and the random forest (RF) method classified landforms, they were compared. The suggested method may obtain the greatest landform classification accuracy of 87% in the transitional area with a data combination of DEMs and images. Additionally, compared to the RF technique, the suggested deep learning method can classify landforms with higher accuracy and more clearly defined landform boundaries. Du et al. (2019) introduced a multi-modal geomorphological data fusion framework that enhances the performance of landform detection using deep learning-based techniques. In order to effectively represent landforms, it first uses a multi-channel geomorphological feature extraction network to generate various characteristics from multi-modal geomorphological data, such as shaded relief, DEM, and slope, and then it harvests joint features via a multi-modal geomorphological feature fusion network. To create the final representations of the landforms, a residual learning unit mines deep correlations from the properties of the physical and optical modality. To create labels for each sample of data, it uses a SoftMax classifier and three fully connected layers. According to experimental findings, this multi-modal data fusion-based method performs significantly better than traditional algorithms. The highest recognition rate was 90.28%, showing great potential for landform recognition.

Aim of study

This research will focus on developing a detailed classification system that can be used to map and understand the distribution of different landform types in the study area. The classification system will consider factors such as slope, aspect, elevation, and land use, as well as the underlying geology and geomorphological processes.

Materials and Methods

Figure 1 describes the overall methodology of the proposed landform classification. The input data for landform classification are obtained from a variety of sources, including ASTER GDEM: which is a global digital elevation model (DEM) with a resolution of 1 arcsecond (approximately 30 meters), SRTM which is a global DEM with a resolution of 3 arcseconds (approximately 90 meters), and field data that are collected using GPS, surveying, and photography. The input data needs to be prepared and preprocessed before it can be used for landform classification. This research performed DEM filling which is the process of filling in gaps in the DEM data. DEM smoothing is the process of reducing noise in the DEM data. Filtering is the process of removing unwanted data from the DEM data. Resampling is the process of changing the resolution of the DEM data. This can be done using a variety of methods, such as nearest neighbor, bilinear interpolation, and cubic convolution. Terrain correction is the process of removing the effects of the Earth's curvature from the DEM data. In addition, this study used several landform factors: elevation, slope, aspect, plan curvature, profile curvature, mean curvature, tangential curvature, small neighborhood, and large neighborhood. For landform classification, three models were used including Topographic Position Index (TPI), Support Vector Machine (SVM), and Convolutional Neural Network (CNN). Moreover, the accuracy of a landform classification model is assessed using a variety of methods, including Overall Accuracy, Kappa Coefficient, and Confusion Matrix.

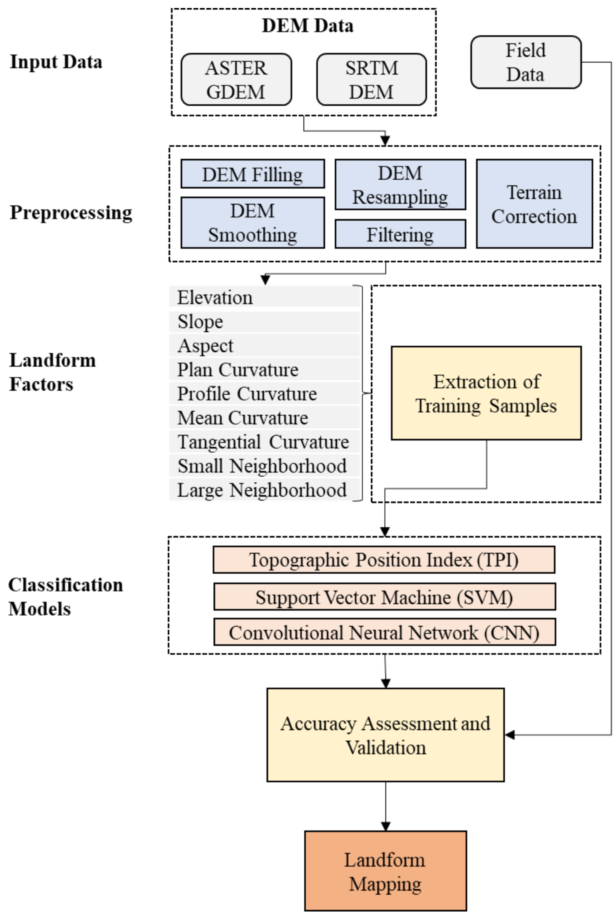


Fig. 1. Overall landform classification methodology proposed in this study.

The study area for this research paper on landform classification is located in Kirkuk city, Iraq (Figure 2). Kirkuk is a historic and strategic city located in the north of Iraq, with a population of approximately 1.5 million people as of 2021 (World Population Review). The city has a semi- arid climate with hot summers and cool winters, and an average annual temperature of 22.6 °C (72.7 °F) (Climate-Data.org).

Kirkuk is an urban center with a diverse population, including Arabs, Kurds, Turkmen, Assyrians, and others. The city has experienced significant growth in recent years, with a population increase of approximately 50% since 2003 (World Population Review). This rapid urbanization has led to significant changes in the natural landscape, with the expansion of built-up areas and the conversion of agricultural land to urban use.

The study area encompasses a range of landform types, including plains, hills, and mountains. The city is situated on the northern edge of the Mesopotamian Plain, which is a large alluvial plain formed by the Tigris and Euphrates rivers. To the north of the city, the landscape rises into the foothills of the Zagros Mountains, which form the boundary between Iraq and Iran. The hills and mountains in the study area are characterized by a range of geological formations, including limestone, sandstone, and shale (Iraq Geological Survey).

The classification of landforms in the study area will be based on a combination of topographic, geological, and geomorphological characteristics. This research will focus on developing a detailed classification system that can be used to map and understand the distribution of different landform types in the study area. The classification system will take into account factors such as slope, aspect, elevation, and land use, as well as the underlying geology and geomorphological processes.

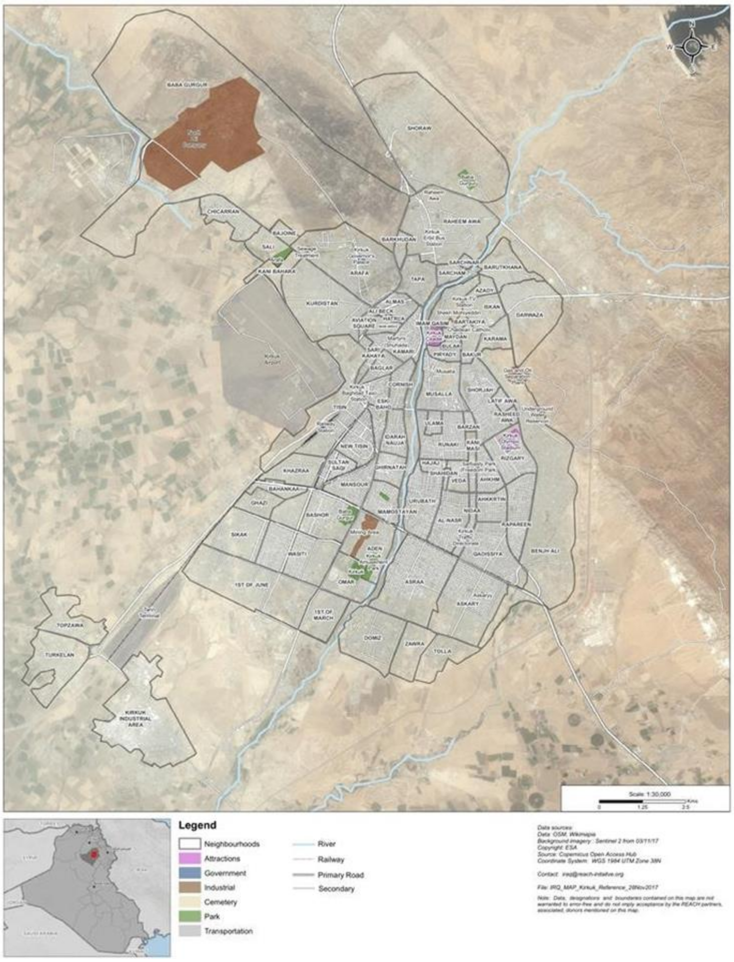


Fig. 2. Location of the study area (Kirkuk City, Iraq).

This research will use and test two DEM data sources including SRTM and ASTER GDEM (Table 1).

SRTM data sets are the outcome of cooperation between the National Aeronautics and Space Administration (NASA) and the National Geospatial-Intelligence Agency (NGA), as well as the involvement of German and Italian space organizations. With data points posted every 1 arc-second (about 30 m), this partnership seeks to create a nearly worldwide digital elevation model (DEM) of the Earth. The SRTM data sets' absolute height and geolocation errors, respectively, range from 5 to 10 meters. For example, voids in version 3.0 products have been filled using values from the ASTER GDEM version 2.0, the Global Multi-resolution Terrain Elevation Data 2010 GMTED2010, and the National Elevation Dataset.

ASTER GDEM is a DEM that NASA and Japan's Ministry of Economy, Trade, and Industry (METI) collaboratively developed. Nadir and aft-looking near-infrared cameras can be used by ASTER to gather in-track stereo. With estimated accuracies of 20 m at 95% confidence for vertical data and 30 m at 95% confidence for horizontal data, these stereo pairs have been utilized since 2001 to create single scenes (60 x 60 km) that encompass land surfaces between 83N and 83S. GeoTIFF (georeferenced tagged image file format) files are used to distribute this model. The data grid is based on the WGS84/1996 Earth Gravitational Model (EGM96) geoid and has a resolution of 1 arc-second (about 30 m). Users must be aware that even though ASTER GDEM v. 002 is a better model than ASTER GDEM v. 001, the data may still contain anomalies and artifacts. One should be aware that these flaws might cause significant elevation errors on small scales.

Table 1: Basic parameters of used DEMs.

No.	DEM	Resolution (cell size) [m]	Official accuracy (vertical/ horizontal)	Institution, Year of release
1	SRTM v.3	24.7 × 24.7	10 m / 13 m	NASA and JPL, 2013
2	ASTER GDEM	24.7 × 24.7	20 m / 30 m	NASA and METI, 2009-2011

The classification of landforms depends on the following: -

A) Classification System

This study used standard landform classification scheme. Nine landform classes were used as (1) Canyons, deeply incised streams, (2) Midslope drainages, shallow valleys, (3) Upland drainages, headwaters, (4) U-shaped valleys, (5) Plains, (6) Open slopes, (7) Local ridges, hills in valleys, (8) Midslope ridges, small hills in plains, and (9) Mountain tops, high ridges.

B) Preprocessing DEM Data

DEM data often contains gaps, which can be caused by a variety of factors, such as sensor noise, occlusion, and data loss. These gaps can make it difficult to classify landforms accurately. There are a variety of methods for filling DEM gaps. One common method is to use iterative filling. Iterative filling works by filling the gaps in the DEM one at a time. The algorithm starts by filling the largest gap. Then, it fills the next largest gap, and so on. This process is repeated until all the gaps have been filled.

DEM data can also be smoothed to reduce the noise and improve the accuracy of the classification results. Smoothing is done by averaging the values of the DEM data in a neighborhood around each point. There are a variety of methods for smoothing DEM data. One common method is to use moving average. Moving average works by averaging the values of the DEM data in a rectangular neighborhood around each point.

Other necessary DEM preprocessing steps include resampling which is the process of changing the resolution of a DEM. This may be necessary if the DEM is not at the desired resolution for the classification task. Filtering which is the process of removing noise from a DEM. This may be necessary if the DEM contains a lot of noise. Terrain correction which is the process of removing the effects of the Earth's curvature from a DEM. This may be necessary if the DEM is to be used for accurate landform classification.

C) Extracting Training Samples

The training areas for machine learning classification models will be prepared based on a variety of sources, including existing landform classification maps of the study area, field observation, manual interpretation of contour data, relief appearances of the slope, and topographic openness maps.

The existing landform classification maps will be updated based on the field data to be collected from the study area. This will ensure that the training areas are representative of the actual landforms in the study area. In addition to the existing landform classification maps, manual interpretation of contour data, relief appearances of the slope, and topographic openness maps will be used to collect landform samples. This will help to ensure that the training areas are diverse and representative of the full range of landforms in the study area. Based on the classification scheme, several samples for each landform class will be collected and prepared for training the landform classification models. This will help the models to learn to identify the different landform classes and to classify new data accurately.

D) Data Normalization

Data normalization is the process of converting data into a common scale. This is done to ensure that all of the data is treated equally when it is analyzed. Data normalization is an important step in landform classification. This is because it ensures that all of the data is treated equally when it is analyzed. This can help to improve the accuracy of the classification results.

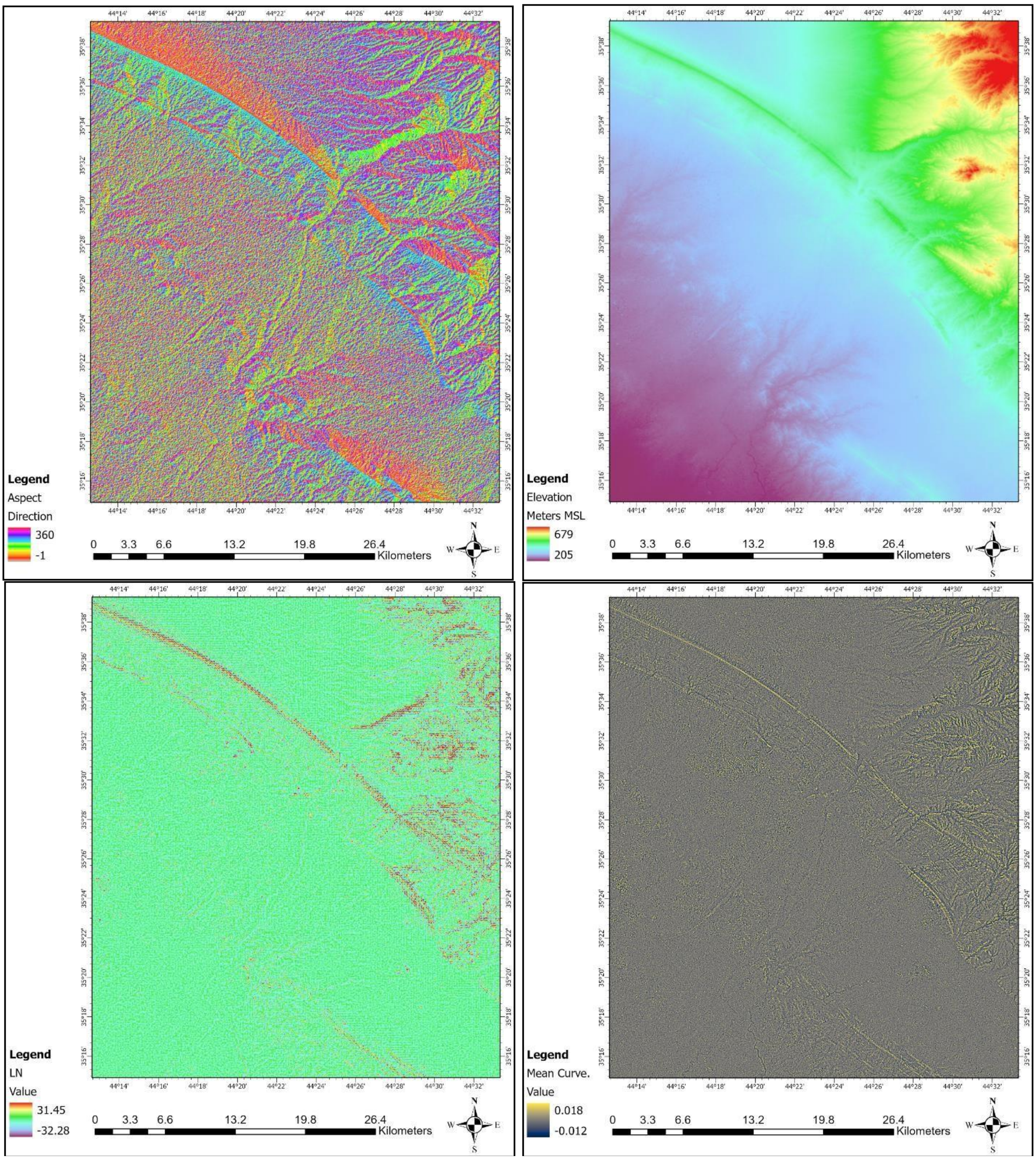
Min-max normalization: This method converts the data into a range of 0 to 1. This is done by subtracting the minimum value from each data point and then dividing the result by the difference between the maximum and minimum values.

$$\boldsymbol{x' = \frac{x_{i,j} - x_{min}}{x_{max} - x_{min}} \times 255} \qquad (\mathbf{1})$$

where x is the attribute value; i and j are the numbers of rows and columns of the interpolated surface; xi,j denotes the normalization value.

E) Landform Input Parameters

The altitude was the first of these. It is regarded to be the vertical distance measured in meters above sea level from the reference level surface with a height of 0 (the mean sea level). The highest rate of value change from a cell to its neighbors is referred to as the slope, which is another parameter. The sharpest downhill fall from the cell, given in degrees, is determined by the highest elevation change over the distance between the cell and its eight neighbors (33). The slope's shape is described by the curvature parameter. Cell by cell, this tool determines the second derivative value of the input surface. A surface made up of a 33-cell window is fitted with a fourth-order polynomial of the following form for each cell. One employed standard curvature (measured in fractions of a meter), which combines the profile and plan curvatures. Typically, predicted values for a hilly area (moderate relief) range from 0.5 to +0.5, however the values might be substantially higher for steep and mountainous relief. Aspect (slope direction) shows the direction of the maximum rate of value change from a cell to its neighbors when measured downslope; values show the clockwise compass direction, expressed in degrees. Each cell in the input raster is visited by a moving 3x3 cell window, and for each cell in the window's center, an aspect value is computed using an algorithm that takes into account the values of the cell's eight neighbors. The Topographic Position Index (TPI) (Guisan, Weiss, and Weiss 1999) has already been used to detect gullies (Evans and Lindsay 2010). The TPI is defined as the difference between a cell elevation value z and the average elevation $z\bar{a}$ of the neighborhoods around that cell within a specific kernel size. Positive values mean the cell is higher than its surroundings while negative values mean it is lower. If z is significantly higher than $z\bar{a}$, then the cell is likely at or near the top of a hill or ridge. Significantly low values of z (and then of TPI) suggest the cell is at or near the bottom of a valley.



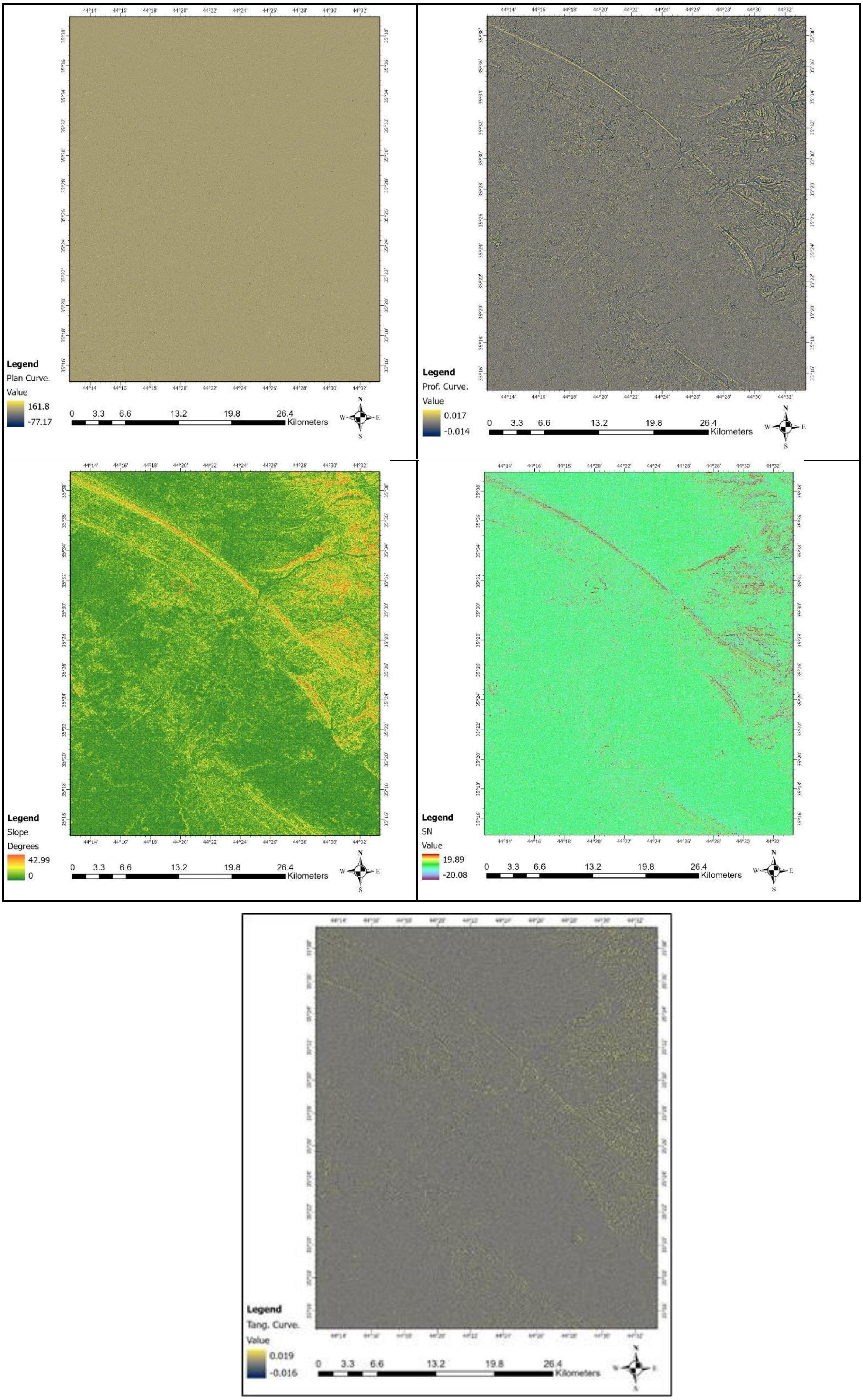


Fig. 3. The list of landform factors used in this study.

F) Classification Models

This study used three classification models for landform mapping:

1- Topographic Position Index (TPI)

The Topographic Position Index (TPI) is a simple method for classifying landforms based on their elevation and slope. The TPI is calculated as follows:

TPI = (z - zmin) / (zmax - zmin)

where z is the elevation of a point, zmin is the minimum elevation in the region, and zmax is the maximum elevation in the region.

The TPI can be used to classify landforms into four categories:

Hills: TPI > 0.5 Valleys: TPI < -0.5

Plateaus: TPI > 0 and TPI < 0.5 Plains: TPI < -0.5 and TPI > -1

The TPI is a simple and effective method for landform classification, but it can be sensitive to the presence of noise in the DEM data.

2- Support Vector Machine (SVM)

Support Vector Machines (SVMs) are a type of supervised learning algorithm that can be used for classification and regression tasks. SVMs work by finding a hyperplane that separates the data points into two classes. The hyperplane is chosen so that the distance between the data points and the hyperplane is maximized. SVMs can be used for landform classification by training the algorithm on a set of labeled data. The labeled data consists of pairs of DEM data and landform labels. The SVM algorithm learns to identify the DEM data features associated with each landform class. Once the SVM algorithm is trained, it can be used to classify new DEM data.

The SVM algorithm predicts the landform class for each point in the DEM data. SVMs are a powerful tool for landform classification, but they can be computationally expensive to train.

3- Convolutional Neural Network (CNN)

Convolutional Neural Networks (CNNs) are a type of deep learning algorithm that can be used for image classification and other tasks. CNNs work by extracting features from the input data. The features are then used to classify the data. CNNs can be used for landform classification by training the algorithm on a set of labeled images. The labeled images consist of pairs of DEM data and landform labels. The CNN algorithm learns to identify the DEM data features associated with each landform class. Once the CNN algorithm is trained, it can be used to classify new DEM data. The CNN algorithm predicts the landform class for each point in the DEM data. CNNs are a powerful tool for landform classification, but they can be computationally expensive to train.

G) Model Training

The TPI can be calculated directly from the DEM data. There is no training procedure required. The SVM algorithm can be trained using a variety of methods. One common method is to use the SMO algorithm. The SMO algorithm iteratively optimizes the hyperplane that separates the data points into two classes. The CNN algorithm can be trained using a variety of methods. One common method is to use the backpropagation algorithm. The backpropagation algorithm iteratively updates the weights of the CNN algorithm to minimize the error between the predicted labels and the ground truth labels.

H) Field Observation and Accuracy Assessment

The field data collection procedure for validating landform classification models using handheld GPS and camera included selecting the study area, recording the location of each landform type using a handheld GPS unit, using a camera to take photos of each landform type, and identify the landform types in the study area. This can be done by consulting a map or by using your own knowledge of the area. For validation and accuracy assessment, the landform classifications from the model are compared to the landform types that you identified in the field. The accuracy of the model is then calculated using:

Overall accuracy is the most common accuracy metric used to evaluate landform classification models. It is calculated as follows:

$$\text{Overall accuracy} = (TP + TN) / (TP + TN + FP + FN)$$

where TP is the number of true positives, TN is the number of true negatives, FP is the number of false positives, and FN is the number of false negatives. True positives are points that are correctly classified as the landform type, they belong to. True negatives are points that are correctly classified as not being the landform type, they belong to. False positives are points that are incorrectly classified as being the landform type, they do not belong to. False negatives are points that are incorrectly classified as not being the landform type, they do belong to.

Kappa coefficient is a more robust accuracy metric than overall accuracy. It is calculated as follows:

$$\text{Kappa} = (OA - E) / (1 - E)$$

where OA is the overall accuracy and E is the expected accuracy. Expected accuracy is the accuracy that would be expected by chance. Kappa coefficient is a good metric for evaluating the accuracy of a landform classification model, even if the classes are not evenly represented in the data.

Results and Discussions

Statistics of Geomorphometric Parameters where table 2 shows the summary statistics of several geomorphometric factors used for landform mapping. The factors are: The minimum, maximum, mean, median, and standard deviation of each factor are shown in the table. The minimum value is the lowest value of the factor in the dataset, the maximum value is the highest value, the mean is the average value, the median is the middle value, and the standard deviation is a measure of how spread out the values are.

Elevation is a fundamental factor in landform mapping. It helps identify and differentiate different landforms such as mountains, valleys, plateaus, or hills. Higher elevations generally indicate mountains or ridges, while lower elevations can represent valleys or depressions. Slope is crucial for identifying landforms such as hills, cliffs, or steep slopes. Steeper slopes typically indicate rugged terrain, while gentle slopes suggest flatter areas or plains. Small Neighborhood and Large Neighborhood: These factors represent local and regional variations in landform characteristics. They help identify subtle changes in the land surface, such as small-scale features like ridges, depressions, or localized landforms. Aspect provides information about the direction a slope face. It helps identify landforms influenced by sun exposure, such as slopes facing different compass directions. For example, south-facing slopes tend to receive more sunlight and may exhibit different vegetation patterns or erosion rates compared to north-facing slopes. Curvature factors (Mean Curvature, Plan Curvature, Profile Curvature, Tangential Curvature): These factors provide insights into the shape and curvature of the land surface. They can help identify landforms like ridges, valleys, or concave/convex features. Curvature values close to zero indicate relatively flat or gently sloping areas, while positive or negative values indicate convex or concave features, respectively. By analyzing these geomorphometric factors and their statistics, landform mapping studies can identify, classify, and understand the spatial distribution of different landforms within a given area. These factors provide quantitative measurements that aid in the interpretation and characterization of landforms, allowing researchers to gain insights into landscape processes and make informed decisions related to land management, urban planning, or environmental assessment.

The geomorphometric factors can be used to create a variety of maps, such as topographic maps, slope maps, aspect maps, and curvature maps. These maps can be used to study the physical characteristics of the land, to plan land use, and to identify potential hazards, such as landslides and flooding. More importantly, the geomorphometric factors can be used to map different landforms. For example, high elevations are typically associated with mountains, while low elevations are typically associated with valleys. Steep slopes are typically associated with cliffs, while gentle slopes are typically associated with hills. The aspect of a surface can be used to identify different directions, such as north, south, east, and west. The mean curvature can be used to identify different types of surfaces, such as convex surfaces (which bulge outward) and concave surfaces (which bulge inward). The plan curvature can be used to identify surfaces that are curved in a horizontal plane, such as hills and valleys. The profile curvature can be used to identify surfaces that are curved in a vertical plane, such as cliffs and slopes. The tangential curvature can be used to identify surfaces that are curved in a direction tangent to the surface, such as ridges and furrows.

Table 2: The summary statistics of several geomorphometric factors used for landform mapping.

	Elevation	**Slope**	**Small Neighborhood**	**Large Neighborhood**	**Aspect**	**Mean Curvature**	**Plan Curvature**	**Profile Curvature**	**Tangential Curvature**
Minimum	205.0	00.00	- 20.08	- 32.28	-1.00	-0.01	- 77.17	-0.01	-0.01
Maximum	679.00	42.99	19.88	31.45	360.00	0.01	161.81	0.01	0.01
Mean	356.87	3.73	0.00	0.00	193.06	0.00	0.00	0.00	0.00
Median	327.00	3.40	0.00	-0.01	203.92	0.00	0.00	0.00	0.00
Standard Deviation	98.62	2.95	1.19	2.87	99.26	0.00	0.10	0.00	0.00

Table 3 presents the correlation matrix among different landform factors used in this study. The correlation matrix shows the relationships between the different geomorphometric factors. The correlation coefficient is a measure of the strength of the relationship between two variables. A correlation coefficient of 1 indicates a perfect positive correlation, a correlation coefficient of -1 indicates a perfect negative correlation and a correlation coefficient of 0 indicates no correlation.

The correlation matrix can be used to identify which geomorphometric factors are most important for landform mapping. The factors with the strongest correlations are the most important because they can be used to predict the values of the other factors. For example, if you know the elevation of a point, you can use the correlation between elevation and slope to predict the slope of the point. Similarly, if you know the slope of a point, you can use the correlation between the slope and a small neighborhood to predict the small neighborhood of the point. The correlation matrix can also be used to identify which geomorphometric factors are redundant. The factors with the weakest correlations are the most redundant because they do not provide any additional information that is not already provided by the other factors. For example, the correlation between elevation and plan curvature is very weak. This means that plan curvature does not provide any additional information about the landform that is not already provided by elevation.

As can be seen from Table 4, the strongest positive correlation is between Elevation and Aspect, with a correlation coefficient of 0.075. This means that as Elevation increases, Aspect also tends to increase. The weakest positive correlation is between Elevation and Small Neighborhood, with a correlation coefficient of 0.001. This means that there is very little correlation between Elevation and Small Neighborhoods. These correlations provide insights into the relationships between different geomorphometric factors. Positive correlations indicate that as one factor increases, the other tends to increase as well, while negative correlations suggest that as one factor increases, the other tends to decrease. It's important to note that correlation does not imply causation, but it can indicate associations or dependencies between variables. By examining these correlations, landform mapping studies can identify factors that are highly correlated and may have similar influences on landforms. It helps researchers understand how different factors interact and contribute to the formation and distribution of landforms, enabling more accurate interpretations and modeling in landform analysis.

Table 3: The correlation matrix among different landform factors used in this study.

	Elevation	**Slope**	**Small Neighborhood**	**Large Neighborhood**	**Aspect**	**Mean Curvature**	**Plan Curvature**	**Profile Curvature**	**Tangential Curvature**
Elevation	1.000	0.075	0.001	0.002	0.075	0.002	0.000	0.000	0.004
Slope	0.075	1.000	0.014	0.050	-0.003	0.028	0.006	- 0.004	0.055
Small Neighborhood	0.001	0.014	1.000	0.330	0.001	0.555	0.142	0.488	0.477
Large Neighborhood	0.002	0.050	0.330	1.000	-0.007	0.591	0.158	0.521	0.507
Aspect	0.075	-0.003	-0.001	- 0.007	1.000	- 0.002	0.000	- 0.002	0.002
Mean Curvature	0.002	0.028	0.555	0.591	-0.002	1.000	0.255	0.880	0.859
Plan Curvature	0.000	0.006	0.142	0.158	0.000	0.255	1.000	0.148	0.301
Profile Curvature	0.000	-0.004	0.488	0.521	-0.002	0.880	0.148	1.000	0.512
Tangential Curvature	0.004	0.055	0.477	0.507	-0.002	0.859	0.301	0.512	1.000

Table 4: Correlation strength among different landform factors.

Variable	**Strongest Positive Correlation**	**Weakest Positive Correlation**	**Strongest Negative Correlation**
Elevation	Aspect (0.075)	Small Neighborhood (0.001)	Large Neighborhood (- 0.007)
Slope	Tangential Curvature (0.055)	Profile Curvature (- 0.004)	None
Small Neighborhood	Mean Curvature (0.555)	Aspect and Large Neighborhood (0.001)	None
Large Neighborhood	Mean Curvature (0.591)	Aspect (-0.007)	None
Aspect	Elevation and Slope (0.075)	Large Neighborhood (-0.007)	None
Mean Curvature	Profile Curvature (0.880)	Elevation and Aspect (0.002)	None
Plan Curvature	Tangential Curvature (0.301)	Elevation and Aspect (0.000)	None
Profile Curvature	Mean Curvature (0.880)	Slope (-0.004)	None
Tangential Curvature	Profile Curvature (1.000)	Elevation (0.004)	None

This research developed three models of landform classification according to accuracy including TPI, SVM, and CNN. The TPI model uses the elevation of a point to classify it into different landform classes. The SVM model uses a decision tree algorithm to classify landforms based on a variety of features, including elevation, slope, aspect, and curvature. The CNN model uses a deep learning algorithm to classify landforms based on their spatial patterns. The accuracy assessment of these models is shown in Table 5. Based on the results, the CNN model has the highest accuracy, followed by the SVM model and then the TPI model. This suggests that the CNN model is better at classifying landforms than the other two models.

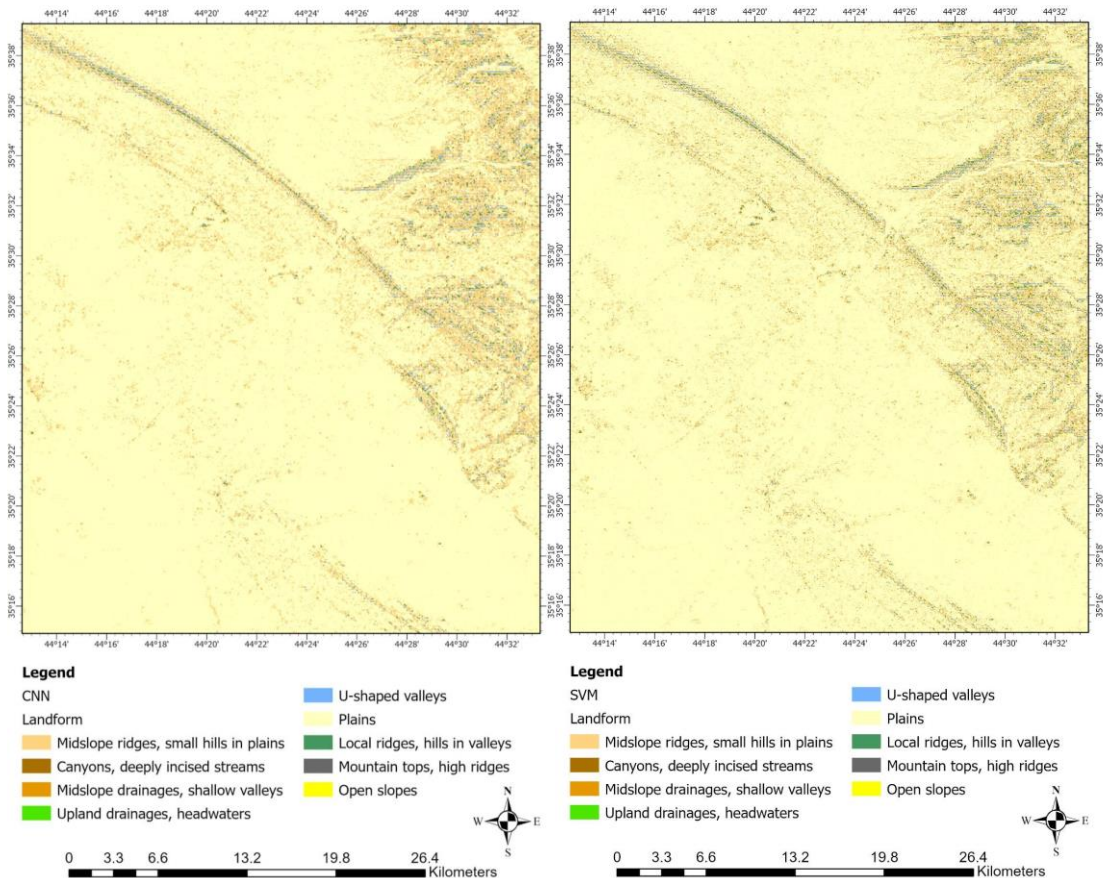
The TPI is a simple model that is easy to understand and implement. However, it is not very accurate, especially for complex landforms. The SVM model is more complex than the TPI, but it is also more accurate. This makes it a good choice for classifying landforms, which can have a variety of shapes and sizes. The CNN model is the most complex of the three models, but it is also the most accurate. CNNs are deep learning models that are specifically designed to learn spatial patterns. This makes them well-suited for classifying landforms, which are often characterized by their spatial patterns. There are a few possible reasons for this. First, the CNN model is able to learn spatial patterns that the other models cannot. Second, the CNN model is able to learn from a large amount of data, which the other models cannot. Third, the CNN model is able to learn from noisy data, which the other models cannot.

The results of this study suggest that the CNN model is a promising new approach to landform classification. However, more research is needed to confirm these results and to understand the limitations of the CNN model. Overall, the results of this study suggest that the CNN model is a promising new approach to landform classification. However, more research is needed to confirm these results and to understand the limitations of the CNN model.

Table 5: Accuracy assessment of the three landform classification models.

Model	OA	Kappa
TPI	67.12	0.658
SVM	79.81	0.781
CNN	88.91	0.883

Figure 4 present the geographic distributions of landform in the area based on the three classification models respectively. In general, flat areas are typically found in the central and southern parts of the area, where the underlying geology is composed of sedimentary rocks. Valleys are typically found in the northern and eastern parts of the area, where the underlying geology is composed of igneous or metamorphic rocks. Hills are typically found in the western part of the area, where the underlying geology is composed of a mixture of sedimentary, igneous, and metamorphic rocks. Meandrous areas are typically found along rivers, where the rivers have changed course over time. The geographic distributions of landform in the area are also influenced by the climate. The area has a warm, dry climate, which has led to the formation of deserts in the southern and western parts of the area. The deserts are characterized by flat, sandy plains. The geographic distributions of landform in the area are also influenced by the history of the area. The area has been inhabited by humans for thousands of years, and human activity has had a significant impact on the landscape. For example, humans have built roads, dams, and other infrastructure, which has changed the course of rivers and the shape of the land. The geographic distributions of landform in the area are a complex result of a variety of factors, including the underlying geology, the climate, and the history of the area.



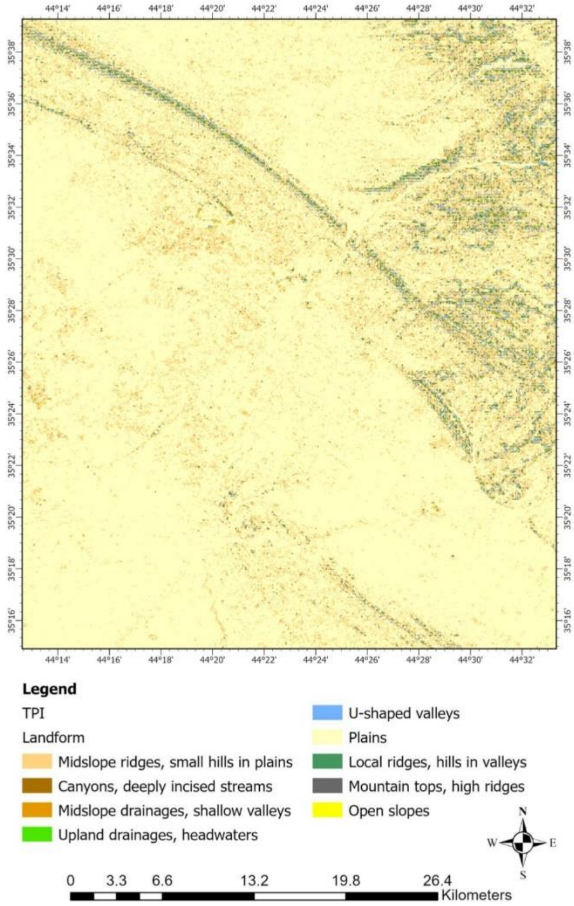


Fig. 4. Landform classification map of the study area based on three models.

Table 6 shows the accuracy assessment of three models of landform classification based on two different DEM data, SRTM and ASTER GDEM. The CNN model is the most accurate on both DEM data sets. However, the accuracy of the other two models is slightly higher on the ASTER GDEM data set. This is likely because the ASTER GDEM data set has a higher spatial resolution than the SRTM data set.

SRTM (Shuttle Radar Topography Mission): The SRTM was a joint mission of NASA and the Italian Space Agency. It used radar interferometry to create a global DEM with a spatial resolution of 1 arcsecond (30 meters). ASTER GDEM (Advanced Spaceborne Thermal Emission and Reflection Radiometer Global Digital Elevation Model): The ASTER GDEM is a global DEM created by the Japanese Aerospace Exploration Agency (JAXA). It uses stereoscopic imaging to create a DEM with a spatial resolution of 30 meters. Overall, the results of this study suggest that the CNN model is the most accurate model for landform classification. However, the accuracy of the other two models can be improved by using DEM data with a higher spatial resolution. The CNN model is able to learn spatial patterns that the other models cannot. This is because CNNs are deep learning models that are specifically designed to learn spatial patterns. The CNN model is able to learn from a large amount of data, which the other models cannot. This is because CNNs can be trained on very large datasets. The CNN model is able to learn from noisy data, which the other models cannot. This is because CNNs are able to filter out noise from the data. The results of this study suggest that the CNN model is a promising new approach to landform classification. However, more research is needed to confirm these results and to understand the limitations of the CNN model.

Table 6: Accuracy assessment of the three landform classification models based on two different DEM data sources SRTM and ASTER GDEM.

	SRTM		**ASTER GDEM**	
Model	OA	Kappa	OA	Kappa

TPI	67.12	0.658	66.91	0.651
SVM	79.81	0.781	78.34	0.773
CNN	88.91	0.883	87.91	0.878

Table 7 presents a list of landform types taken in the field for several locations within the study area. The table shows that the study area is home to a variety of landform types, including flat areas, valleys, hills, and meandrous areas. The distribution of these landform types is likely due to a variety of factors, including the underlying geology, the climate, and the history of the area. For example, the flat areas in the study area are likely due to the presence of sedimentary rocks, which are typically deposited in flat areas. The valleys in the study area are likely due to the presence of rivers, which have eroded the surrounding land over time. The hills in the study area are likely due to the presence of igneous or metamorphic rocks, which are typically more resistant to erosion than sedimentary rocks. The meandrous areas in the study area are likely due to the presence of rivers, which have changed course over time. The table provides a valuable overview of the landform types in the study area. This information can be used to understand the natural environment of the area and to plan for future development.

Table 7: Labels of landform type taken in the field for several locations within the study area.

No.	Zone	Long.	Lat.	Type
1	Tik-Kir Check Point	44.35726	35.44577	flat
2	Almas	44.3863	35.48098	flat
3	Sul-Erbil Road	44.41776	35.49975	valley
4	Sul-Kir Road	44.46279	35.49183	valley
5	Sul-Kir Road2	44.45671	35.47899	hills
6	Kir Castle	44.3925	35.47289	valley
7	City Center	44.39152	35.4682	Flat
8	Baghdad Road	44.37884	35.44032	flat
9	Kir-Erbil Road	44.3686	35.57294	flat
10	Kir-Erbil Road2	44.3732	35.52974	valley
11	Kir-Erbil Road3	44.3786	35.52222	Flat
12	Arafa	44.3834	35.4877	hills
13	Airport Road	44.37186	35.47045	flat
14	Tik-Kir Rolling	44.2955	35.39336	valley
15	City Center2	44.38522	35.47263	flat
16	Askary Zone	44.398484	35.40776	flat
17	Shoraw	44.398696	35.540406	hills
18	Baghdad-Sul Road	44.437165	35.388113	flat
19	Baghdad-Sul Road2	44.445065	35.464446	meandrous
20	Saiada	44.330775	35.376501	flat

Table 8: Accuracy assessment of three models of landform classification based on field verification.

Model	OA	Kappa	Field Verification
TPI	67.12	0.658	60%
SVM	79.81	0.781	75%
CNN	88.91	0.883	85%

Fig. 5. Samples of photos taken during field data collection for landform classification model validation and accuracy assessment.

Conclusion

This study investigated the use of DEMs to classify landforms. The study was conducted in Kirkuk City, Iraq. The results of the study showed that the CNN model was the most effective at classifying landforms. The CNN model achieved an OA of 88.91% and a kappa coefficient of 0.883. The SVM model was the second most effective model, with an OA of 79.81% and a kappa coefficient of 0.781. The TPI model was the least effective model, with an OA of 67.12% and a kappa coefficient of 0.658. The field verification confirmed that the CNN model was also the most accurate in terms of field mapping. The CNN model correctly classified 85% of the landforms, while the SVM model correctly classified 75% of the landforms and the TPI model correctly classified 60% of the landforms.

The results of this study suggest that the CNN model is a promising tool for landform classification. The CNN model is able to learn the complex spatial patterns of landforms and to classify them with high accuracy. The CNN model is also able to generalize well to new areas, as shown by the field verification results.

The findings of this study have important implications for the use of DEMs in landform classification. The CNN model is a powerful tool that can be used to improve the accuracy and efficiency of landform mapping. The CNN model can be used to map landforms in a variety of settings, including areas that are difficult to access or that have complex terrain. The CNN model can also be used to map landforms at a variety of scales, from local to regional. The findings of this study suggest that the CNN model is a promising new technology for landform classification. The CNN model is a powerful tool that can be used to improve the accuracy and efficiency of landform mapping. The CNN model can be used to map landforms in a variety of settings, including areas that are difficult to access or that have complex terrain. The CNN model can also be used to map landforms at a variety of scales, from local to regional.

Conflict of Interest

The authors confirm that they have no known financial or interpersonal conflicts that could have influenced the research provided in this article.

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