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RESEARCH

Spatial-statistical modeling of deforestation from an ecogeomorphic approach in typical Hyrcanian forests, Northern Iran

F. Pourfarrashzadeh · A. Madadi · M. Gharachorlu · S. Asghari Sareskanrood

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Abstract Deforestation is a significant environmental concern of the present century. This issue has received serious attention from global and regional communities due to its relationship with various environmental issues such as climate change, erosion, water quality, and biodiversity. Concerns about deforestation in arid and semi-arid countries, such as Iran, are quite tangible since it confronted with a shortage of forest resources on the one hand and acute issues caused by flood and erosion hazards on the other hand. The Talesh forests in the north of Iran, which are a manifestation of the ancient Hyrcanian forests with huge ecological reserves, is exposed to forest loss due to the expansion of human activities such as agriculture, wood harvesting, livestock grazing, and mining, despite the implementation of watershed management plans and forest conservation. The conservation and restoration of these forest ecosystems necessitate knowledge of the location and rate of deforestation, as well as its driving factors, through a systemic and interdisciplinary approach that has not yet been taken into account. By using an ecogeomorphic approach to model the deforestation event, we attempted to investigate the link between the ecological process of deforestation and geomorphological processes by combining the spatial terrain analysis with the statistical logistic regression. Given the approach in deforestation modeling, we were able to explain the effects of both physical and anthropogenic factors on deforestation only by incorporating physical variables (geomorphology), which can easily be derived from available digital elevation models (DEMs). First, we succeeded in mapping deforestation points in 12 catchments over 32 years using Landsat images acquired in 1991 and 2022 through change detection technique. The results of the assessment of negative changes in forest cover from 1991 to 2022 showed that about 90 km^2 (4.5% of the total area of catchments) has been deforested. The percentage of deforestation area varied from 7.7% in Haviq catchment to 1.8% in Dinachal catchment. We used the spatial logistic regression model to explain the relationship between geomorphological variables and deforestation probability, since the model is the most efficient predictive model to gather a group of independent variables of different natures without the need for their normal distribution. Geomorphologically independent variables included altitude, slope, topographic position index (TPI), northness, eastness, plan curvature, profile curvature, length of

F. Pourfarrashzadeh · A. Madadi (✉) · M. Gharachorlu · S. A. Sareskanrood
Department of Physical Geography, University of Mohaghegh Ardabili, Ardabil, Iran
e-mail: a_madadi@uma.ac.ir

F. Pourfarrashzadeh
e-mail: pourfarrash@uma.ac.ir

M. Gharachorlu
e-mail: gharachourlou@uma.ac.ir

S. A. Sareskanrood
e-mail: s.asghari@uma.ac.ir

slope (LS) factor, slope length, topographic wetness index (TWI), contributing area, distance to stream, and terrain ruggedness index. The results of logistic regression analysis by revealing the direction of multivariate relationships showed that the probability of forest loss is higher in such places: low altitude and valleys, low slopes, divergent flow points, convex surface, downstream section, flat areas with homogeneous, and dry zones with low moisture. In addition, determining the intensity of the relationships between the independent variables and the dependent variable through regression test showed that the variables of slope, altitude, and ruggedness index with coefficients of β equal to -2.82, -2.1, and 1.92, respectively, are among the most important variables explaining deforestation. In contrast, the variables of eastness, northness, distance from the river, and slope length with coefficients of β equal to -0.000017, -0.000031, and -0.000124, respectively, were identified as the insignificant variables in explaining the deforestation and were excluded from the final prediction model. Furthermore, the results of evaluating the efficiency of the logistic regression model through pseudo-R^2 (0.19) and relative operating characteristic (0.75) statistics indicated a good fit and an acceptable agreement between the actual map and the predictive map of deforestation. However, the use of more accurate and high-quality DEMs with different spatial resolutions was recommended for future studies. Regional, urban, and rural policymakers and planners should pay attention to the geomorphic environments that have a high probability of deforestation based on the results of this study. The need for more care and protection is evident in these areas, and any human interference in them must be done consciously and in accordance with environmental sustainability principles.

Keywords Deforestation · Geomorphometry · Modeling · Logistic regression · Talesh

Introduction

Land use and land cover change are significant environmental issues worldwide that cause ecosystem change (Solaimani & Darvish, 2024). In this context, the change and destruction of the natural land cover, including forests and rangelands, can initiate many environmental problems (Shabani et al., 2022). Forests serve as renewable resources within the Earth system, providing enormous ecosystem services, including provisioning, regulating, supporting, and cultural services for humans since ancient times (Bera et al., 2022). Deterioration and loss of forest cover is one of the serious environmental challenges of the present century. Historically, since the 1960s, anthropogenic pressure on forest resources has increased due to various demands such as mining, urban development, and farming, leading to widespread deforestation (Ramachandran et al., 2018). Between 2000 and 2020, the global tree cover decreased by -101 million hectares (-2.4%). The loss of global humid forest was 76.3 million hectares between 2002 and 2023, which represents 16% of the total tree cover loss during the same period. Total area of humid primary forest decreased globally by 7.4% in this period (www.globalforestwatch.org). There have been worrying reports of flood hydrological changes due to deforestation in various watersheds (Sriwongsitanon & Taesombat, 2011). In this regard, researchers have pointed out the deforestation impact on increased streamflow and flooding (e.g., Alvarenga et al., 2016; Dias et al., 2015; Ewane & Lee, 2020; Salazar et al., 2015). Deforestation is the main factor contributing to land degradation (Malede et al., 2023), leading to climate change (Bax et al., 2016; Plata-Rocha et al., 2021), reduction of biodiversity and ecosystem services (Lohani et al., 2020), deterioration of water quality, and soil erosion (Plata-Rocha et al., 2021). Given these consequences, monitoring and predicting negative changes in forest cover (deforestation) is crucial for the sustainability of water and soil resources at the catchment scale. This issue is particularly important for countries in arid and semi-arid regions like Iran, where maintaining healthy and sustainable water and soil resources is a challenge. Iran is poor in forest cover, and it ranks last among the countries in terms of forest cover due to its location in the dry belt of the world (Velayati & Kadivar, 2010). Deforestation and forest degradation due to human encroachments are a significant environmental concern in the Hyrcanian forests of Northern Iran (Pir Bavaghar, 2015). Like many developing countries where agriculture is the main cause of deforestation (Malede et al., 2023), this factor has also changed the forest landscape in the Hyrcanian forests of the Talesh watershed located in the west of the Caspian Sea.

The Talesh region, located in Gilan Province, NW of Iran, is a unique region in the west of the Caspian Sea characterized by a predominantly mountainous and forest-covered landscape. The plains stretch in a narrow and continuous strip at the point where the Caspian Sea meets, where most of the region's population resides. The Talesh forest, despite its limited size, is a precious collection of tree species. Several of these species have exterminated in Europe during the Quaternary glaciation. Therefore, the preservation of this valuable world heritage is of great importance (Ranjbar, 2006). The Talesh region has experienced a decline in natural vegetation cover in recent years due to agricultural activities and deforestation (Shahzeidi, 2023). As the urban lands located in the Talesh plain advance toward the suburban villages and agricultural areas, the farmers also migrate toward the foothills and forest areas. Consequently clearing of natural land cover and deforestation are becoming more frequent. The consequences of these actions include erosion, flooding, and the deterioration of the ecological conditions in the region. Notable examples of these issues can be observed in the catchments of Navarood (Fatolahzadeh & Sarvati, 2012), Shafarood (Nikooy et al., 2010), and Lisar (Panahandeh, 2018).

Protecting, conserving, and restoring forests requires a comprehensive understanding of the interactions between environmental factors and the spatiotemporal dynamics of forests. Detecting temporal and spatial variations of deforestation and its drivers requires the development of spatial-statistical methods that are a combination of remote sensing (RS), geographic information system (GIS), and multivariate statistical analysis (Plata-Rocha et al., 2021; Pujiono et al., 2019; Saha et al., 2020). The useful output information from the spatial-statistical models can be a reference for the decision-making of managers and planners, because managers and planners need to obtain a spatial view of the situation of the deforestation event and the factors affecting it (Pir Bavaghar, 2015). Two issues can address research challenges in the spatial-statistical modeling of deforestation. The primary focus is on the factors that contribute to deforestation. Although a combination of various human and physical factors is involved in deforestation, most of the literature has focused on anthropogenic drivers (Bax et al., 2016; Lohani et al., 2020). Kumar et al. (2014) considered three variables, including distance from the forest edge, distance from the road, and settlement, as explanatory variables of forest cover variation in Usri watershed. Pujiono et al. (2019) focused on the impact of cultural and organizational factors on deforestation. Plata-Rocha et al. (2021) used socio-economic variables (agricultural expansion, infrastructure extension, timber extraction, mining operations) in the modeling of deforestation. However, they notice the link between causal factors of deforestation, such as agricultural development, and deforestation factors, such as elevation and slope. Bera et al. (2022) gave more weight to anthropogenic factors (settlement density, agriculture density, etc.) than to physical factors (elevation, slope, etc.) in deforestation modeling. Studies on the temporal and spatial changes of Hyrcanian forests in Northern Iran have also mainly focused on human factors affecting deforestation (e.g., Salman Mahini et al., 2009; Pir Bavaghar, 2015; Shirvani et al., 2017; Shirvani, 2020). Now, two questions emerge in this context: (1) Aren't these human activities established and developed on the physical basis? (2) Isn't the initial growth and development of plants reliant on the natural conditions and land features? The approach of the current study to deforestation is determined by the responses to these questions, which distinguishes it from earlier studies. We utilize the discipline of geomorphology and its association with ecology, known as "Ecogeomorphology" in this context. Ecogeomorphology integrates ecology with hydrology and geomorphology, geomorphology and hydrology with ecology, and hydrology with ecology and geomorphology. The given geomorphological perspective on ecology provides a spatial-based and temporal-based view of ecological processes (here: deforestation) and is able to provide quantitative tools for predicting how landscapes will change over time and space (Renschler et al., 2007). This fact arises from the understanding that landforms and geomorphic factors such as elevation, slope, and terrain concavity or convexity significantly influence microclimate, hydrology, and soil formation conditions, particularly in mountainous and rugged terrains (see Hoersch et al., 2002; Khafaghi & Omar, 2012; Detto et al., 2013), thereby influencing the spatial distribution of vegetation. For instance, the significant impact of slope on plant distribution has been demonstrated. Increasing slope leads to substantial runoff and erosion, and steep slopes may have limited vegetation because of insufficient soil stabilization and the formation of shallow and dry soils.

Nevertheless, in terms of accessibility, the steep slope plays a crucial role in protecting the natural vegetation from human interference, which is essential for forest conservation. Research conducted by Deng et al. (2007) and Cadol and Wine (2017) suggests that vegetation on steep slope is declined less than mild slope and continues to thrive. Engelhardt et al. (2011) mentioned the protection of forests in rough and hilly watersheds. Bebi et al. (2017) found that the expansion of alpine forests from the nineteenth century onwards occurred mainly on steep slopes. It seems that the modeling of the role of geomorphological factors in spatiotemporal variation of forest cover can provide insights into both the natural elements promoting forest growth and the anthropogenic impacts on forest cover changes. The ecogeomorphic view of deforestation suggests that geomorphological forms and processes are not only the basis for spatial variations of vegetation cover, but also the establishment and persistence of dynamic human activities, as a direct driver of deforestation, which are influenced by the geomorphic setting and landforms. In this context, agricultural activity is a clear evidence. Generally, farmers choose flat land and avoid deep slopes and hollows to produce the highest yield (Detto et al., 2013). However, this approach, in contrast to earlier approaches, focuses on physical factors as primary direct drivers of deforestation and will indirectly highlight the human impact on deforestation.

In order to carry out the aforementioned approach, a comprehensive and robust methodology is required to explain the relationship between the geomorphological features of the watershed and the occurrence of deforestation (ecological process). The "terrain analysis" method, which is based on the study of Hoersch et al. (2002), is a pixel-based method in the analysis of habitat and environmental changes and paves the way for discovering the relationship between form-process and forest cover changes. In this method, various geomorphometry parameters that indicate microclimate, relief, hydrology, and pedology conditions are used to explain the spatial variation of vegetation. Most studies in the spatial modeling of deforestation have not used this method, focusing only on topography variables including elevation, slope, and aspect in explanation of the deforestation process. Nevertheless, the application of diverse geomorphometry parameters through "Digital Terrain Analysis" provides an opportunity to uncover the actual and unique capability of geomorphology in modeling the temporal-spatial changes in ecological patterns (deforestation). For instance, convex or concave indices of the Earth's surface, which demonstrate the distribution or accumulation of water, sediment, and nutrients (Gharachorlu et al., 2018), significantly contribute to the stabilization and renewal of forests and can be utilized in modeling the spatial distribution of deforestation.

The second research challenge concerning spatial-statistical modeling of deforestation pertains to the regionalization of the models. While there has been extensive researches on the spatial and temporal analysis of deforestation, most of the researches has been site-specific (Pir Bavaghar, 2015), probably due to the considerable spatial variability of deforestation. Similarly, the factors influencing deforestation may vary from one location to another. Thus, it is reasonable to implement predictive models of deforestation across various regions with distinct physiographic traits and diverse land use and management practices. Such a necessity is clearly apparent in the Talesh region, and no research has been conducted on the temporal and spatial modeling of deforestation in this area yet. Consequently, the current study is a significant advancement in the assessment and prediction of deforestation probability in the Talesh region by employing the ecogeomorphic approach and digital terrain analysis methodology, which will undoubtedly assist future researchers with the obtained findings.

In the context of modeling of forest cover variations and prediction of deforestation, various techniques such as Markov analysis, automated networks, and statistical methods like logistic regression have been established, among which statistical approaches being the most favored and acknowledged. The spatial logistic regression approach has been employed by numerous researchers (Bravo-Peña et al., 2016; Kucsicsa & Dumitrică, 2019; Pir Bavaghar, 2015; Plata-Rocha et al., 2021; Pujiono et al., 2019; Saha et al., 2020) either separately or alongside other models to predict deforestation events. One of the advantages of these models is our capability to combine statistical techniques with remote sensing and GIS methods (Bravo-Peña et al., 2016; Saha et al., 2020) which, on the one hand, disclose the rate and location of deforestation and, on the other hand, allow us to recognize and assess the key factors influencing deforestation (Bravo-Peña et al., 2016). The benefit of logistic regression compared to ordinary regression arises from the binary nature of the dependent variable (occurrence/non-occurrence), which evaluated concerning the group of predictive variables and utilizing a logit function. Another benefit of this method is the incorporation of both discrete and continuous variables in the modeling of environmental phenomena. Additionally, logistic regression, in contrast to ordinary regression, does not require a normal distribution of variables (Bai et al., 2010). Nonetheless, in this approach, experience and knowledge in choosing the appropriate independent variables to develop an effective model is crucial, which can pose a limitation. Kucsicsa and Dumitrică (2019) considered the accessibility to various spatial data and layers as another constraint of this model.

The current research, emphasizing on ecogeomorphic approach, seeks to identify the negative changes in forest cover in connection with geomorphological features within the Talesh catchments. As noted, our investigation will address the ecological setting for the growth and stability of forest cover in accordance with the geomorphic setting, which is disregarded in many studies assessing deforestation. In addition, this study employs 15 geomorphological variables to assess the effectiveness of digital terrain analysis (geomorphometry) in illustrating the form-process relationships and its influence on deforestation occurrence, which had not been discussed yet. Nonetheless, the incomplete and imprecise quality of the digital elevation model (DEM) may pose a constraint in utilizing this method for accurate understanding of the processes influencing deforestation. We will utilize a DEM with a high spatial resolution of 30 m to solve this issue. The application of the logistic regression technique might also face information redundancy because of the addition of extra parameters in estimating deforestation probability. We will try to fix this problem by eliminating the weak independent variables in the ultimate model. The aims of the study are as follows: (1) identification of the rate and spatial distribution of deforestation in Talesh catchments, (2) determination of the form-process relationships in the field of deforestation, and (3) development of a predictive statistical model for deforestation based on geomorphological factors. The results can enable the prioritization of conservation, protection, and restoration practices for forest cover in the catchments and can establish a suitable and encouraging foundation for the sustainable use of these essential natural resources.

Materials and methods

Study area

The Talesh region, covering an area of 3207 km^2, is located in the Northern Iran (Fig. 1). Politically, this area is situated on northern part of Gilan Province and is bordered by Azerbaijan Country to the north, Ardabil Province to the east, and the Caspian Sea to the west. The main population centers of the region are the cities of Astara, Lisar, Hashtpar, and Rezvanshahr, which is situated on the plain and at an elevation of 100 m below sea level. The studied catchments include 12 catchments with a total area of 1992 km^2. Topographically, most of the region lies within the mountain unit that extends from south to north along the Iran-Azerbaijan border. The elevation range of Talesh catchments varies from − 22 to 3238 m, showing notable topographic diversity. The Talesh plain, which includes the eastern section of the region, is characterized by alluvial deposits resulting from the erosion of rivers that flow into the Caspian Sea. This plain is narrow in the north, spanning 2 to 3 km in width, but gradually widens to 6 to 8 km as it extends southward. Distance to the Caspian Sea and the distribution and extent of the mountains are crucial factors influencing the climate of this area. Substantial elevation changes over a short distance create considerable climatic diversity and the vicinity to the Caspian Sea as a moisture source balances the climatic conditions (Sari Saraf et al., 2009). The 500 to 1500 mm isohyet lines, which trend from west to east, indicate the considerable rainfall in this area. These prevailing topoclimatic conditions in the region, through biophysical and biochemical weathering, have established conditions conducive to the development of relatively thick and fertile soils and, as a result, the formation of dense and semi-dense forests. While the mountainous characteristics of the region have led to the predominance of inceptisol soils with minimal evolution, more developed soils such as vertisol and mollisol found in the foothills of the mountains. Brown forest soils with rich humus within the inceptisol category significantly contribute to the stabilization and regeneration of forests. The Talesh forests,

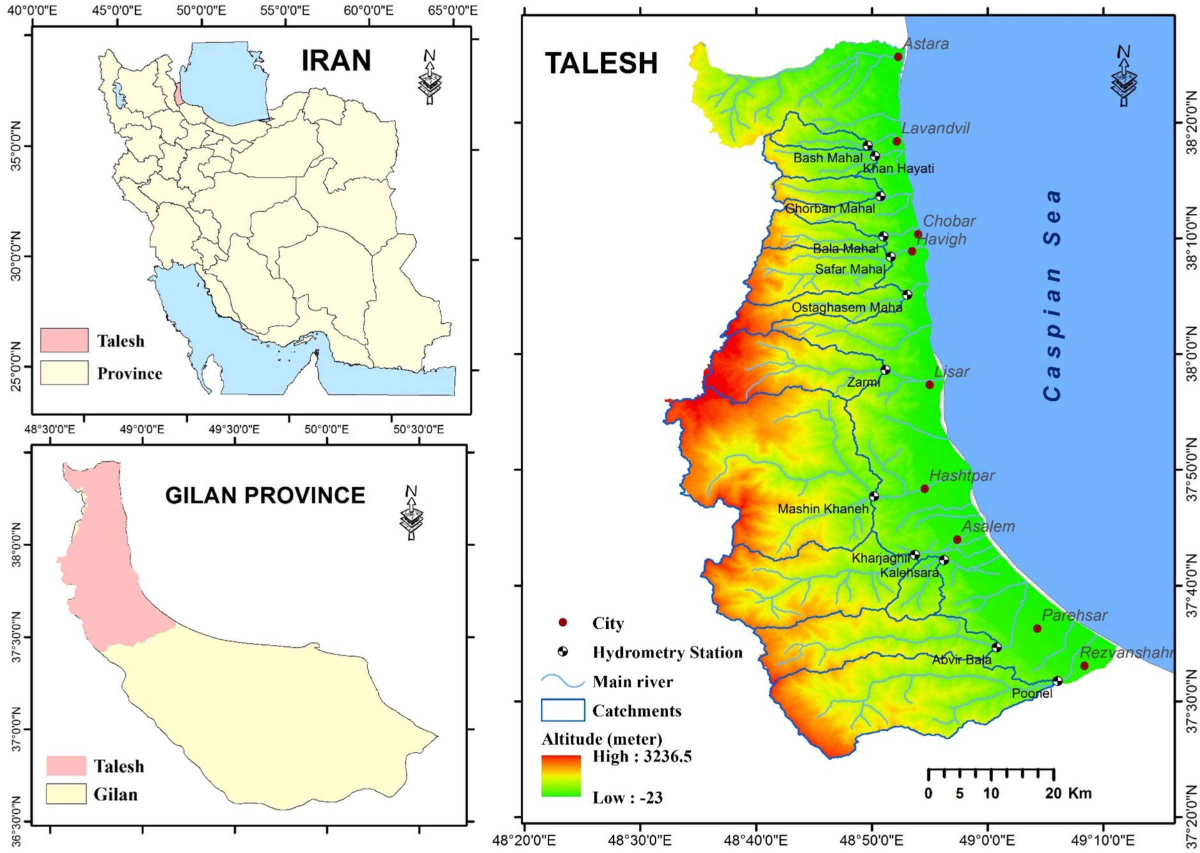

Fig. 1 Location of Talesh catchments

which begin at the boundary of the plain and extend to elevations of 2000–2200 m, are crucial in mitigating rapid runoff and erosion, thereby supporting the environmental balance of the area. These forests are considered as Hyrcanian forests that date back to the Tertiary Era. In 2018, the Hyrcanian forests of Northern Iran were designated as a UNESCO World Heritage site. Concurrently, the Lisar in the Talesh region is recognized as a protected area, thereby limiting human interference (www.hamshahrionline.ir). The Hyrcanian Forest Multipurpose Management Project is one initiative focused on conserving forest resources within the Talesh watershed. This project's execution spanned 6 years, from 2011 to 2018. The objective of this project was to establish a unified strategy for integrated watershed management for Hyrcanian forests, with the goal of advancing multipurpose and community-based forestry, habitat preservation, and ecosystem function maintenance (International counsellor of MikeMooser, 2018).

The structural zone of Talesh, which is part of the Alborz Great Zone, is defined by fractured structures and dense folds. The most significant fault in the area is the Astara fault, which has resulted in the elevation of the Talesh range and the sinking of the Caspian basin. The sinking of the Caspian basin and the rising relative height between the peaks and the coastal foothills have also contributed to increased river erosion. Under these circumstances, the streams have carved deep channels into the slopes that dominate the coastal plain. The presence of numerous fractures and faults in the region has played a crucial role in geomorphic processes and the modification of landforms. Regarding lithology, a mix of metamorphic, igneous, and sedimentary rocks exists in the area, with volcanic and igneous rocks being the most common. Precambrian granite represents the oldest rocks, while the sediments of the marine terraces are the newest lithological unit. The most extensive lithological unit in the region consists of Cretaceous andesitic volcanoes, which account for 39% of the area. The andesitic volcanic rocks from the Eocene period rank second, covering nearly 20% of the area. Rivers, as the primary erosive agents in the region, flow through deep and twisting valleys. The maximum flow of the rivers occurs in late autumn and winter, while the minimum flow takes place in late spring and early summer. The high erosive and flooding capacity of the rivers, driven by topoclimatic and morphotectonic conditions, highlights the vulnerability of the catchments to human interventions and shifts in their ecogeomorphic conditions.

Data used

We utilized multiple databases including Landsat satellite images, Google Earth images, and DEM in various stages of research. The details of the data used are shown in Table 1.

Methodology

The present study is based on spatial-statistical analysis. We utilized three software programs at various stages of the research, specifically Esri ArcGIS Desktop 10.8, SAGA 7.0, and IDRISI 17.0. SAGA 7.0 software facilitated terrain analysis and the extraction of geomorphometry variables on the one side and the classification of satellite images on the other side. ArcGIS Desktop 10.8 was used to derive standard geomorphometry variables like slope and aspect, as well as to create maps and align the projection system of spatial layers. The intersection of forest cover maps to generate the deforestation layer, together with the application of the logistic regression model and the display of model statistics, was executed using IDRISI 17.0 (Selva) software (Fig. 2).

The spatiotemporal modeling and prediction of deforestation probability using geomorphologic variables was conducted in three primary stages as detailed below.

Detection of negative forest cover changes

The ongoing advancement of RS, coupled with convenient and widespread access to satellite datasets like Landsat, has facilitated the identification and monitoring of changes in forest cover across various spatial and temporal scales. Landsat data (TM, ETM, OLI) has been extensively utilized for land cover classification and change detection due to its spatial resolution (30 m), revisit interval (16 days), and wide spatial coverage (185 km) (Gomez et al., 2016). We utilized two Landsat images acquired in years 1991 and 2022 to identify forest cover changes over 32 years. In selecting appropriate satellite images, we tried to ensure the images were free of cloud cover, phonological limitations, and scanline gaps. Additionally, considering the peak vegetation greenness in the region during June and July (Shahzeidi, 2023), the images were selected from these months. Since both images were Landsat Level-2, geometric and radiometric corrections were not required. We utilized "Post-Classification" method to assess the extent and spatial pattern of forest cover changes in the study area. This method is more commonly than alternative change detection methods (see Were et al., 2013; McRoberts, 2014; Scharsich et al., 2017). In this method, two forest/non-forest classes are identified based on two sets of forest/non-forest training data, and then, two classified maps are compared to change detection (McRoberts, 2014). One must consider several important factors in using the post-classification method for change detection: (1) consistency and uniformity between maps (Sexton et al., 2013), which can be achieved by applying the same training data for both classifications (Almutairi & Warner, 2010), and (2) timing of data collection and their seasonality: the data utilized for change detection

Table 1 Characteristics of the data used

Satellite	Sensor	Spatial resolution	Year	Derived variables	Source
Landsat 5	TM	30	1991	Forest cover	https://earthexplorer.usgs.gov
Landsat 8	OLI	30	2022	Forest cover	https://earthexplorer.usgs.gov
Shuttle Radar Topography Mission	SRTM	30	2000	Geomorphometry	https://earthexplorer.usgs.gov

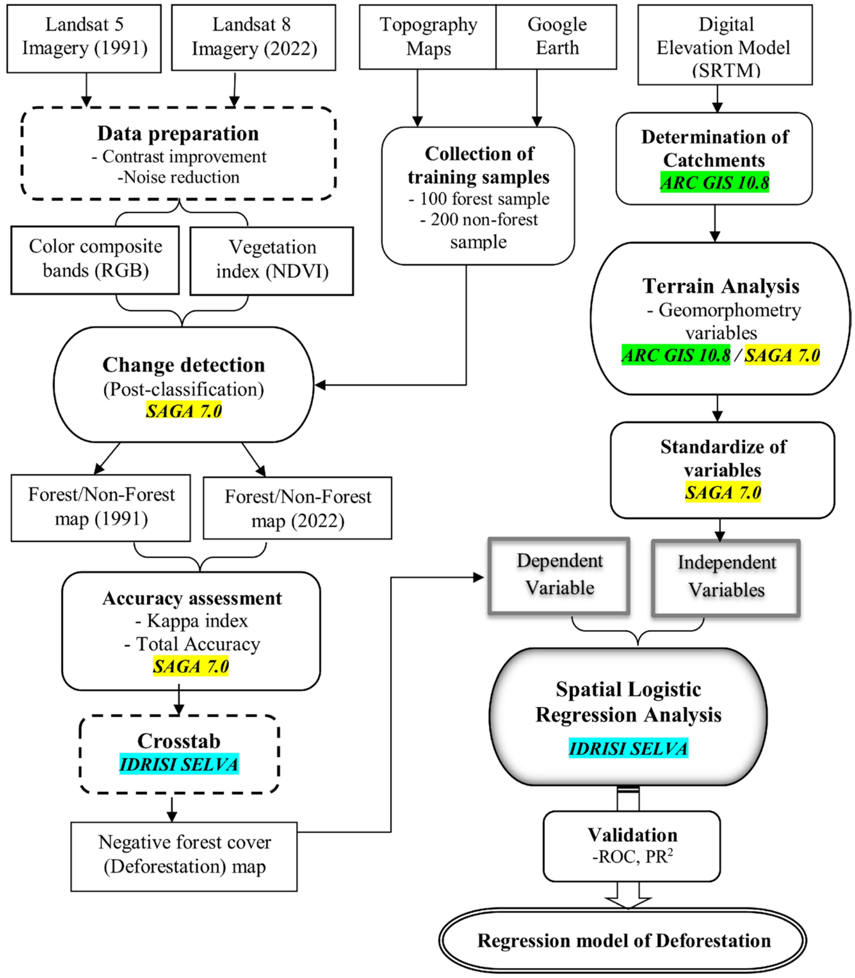

Fig. 2 Flowchart of the methodology used in this study

ought to be collected during similar time frames (season or month) and in seasons that are suitable for the phenomenon detection. This ensures that the spectral reflectance of the phenomena is consistent across both images (Ranjbarnejad et al., 2013). We implemented the post-classification method using SAGA 7.0. Firstly, we prepared a false-color composite (RGB) image using infrared, red, and green bands. Secondly, we calculated normalized difference vegetation index (NDVI) for two images. NDVI is a widely used indicator of vegetation health and can effectively distinguish between forested and non-forested areas. Thirdly, we combined the composite layer with the NDVI layer. This combined image serves as the input for the subsequent classification. We used the maximum likelihood classification (MLC) algorithm to classify the images in two classes: (1) forest and (2) non-forest. In this regard, training samples were carefully prepared using Google Earth images and in accordance with the region's topographic maps and NDVI layer. We also consider field survey in the interpretation of these points. We draw 5 km × 5 km grid to ensure an appropriate distribution of training samples across the study area (Fig. 3). We tried to collect one sample per cell, encompassing both forest and non-forest points. The image classification was fulfilled using 300 training points (100 points for the forest class and 200 points for the non-forest class). During the preparation and selection of training samples, we ensured that the samples were located in the center of continuous forest masses and not within narrow strips of forest cover or along road margins. This helps to minimize the impact of edge effects and ensures the accuracy of the classification.

Since no classification was complete until its accuracy was assessed, half of the training points was used

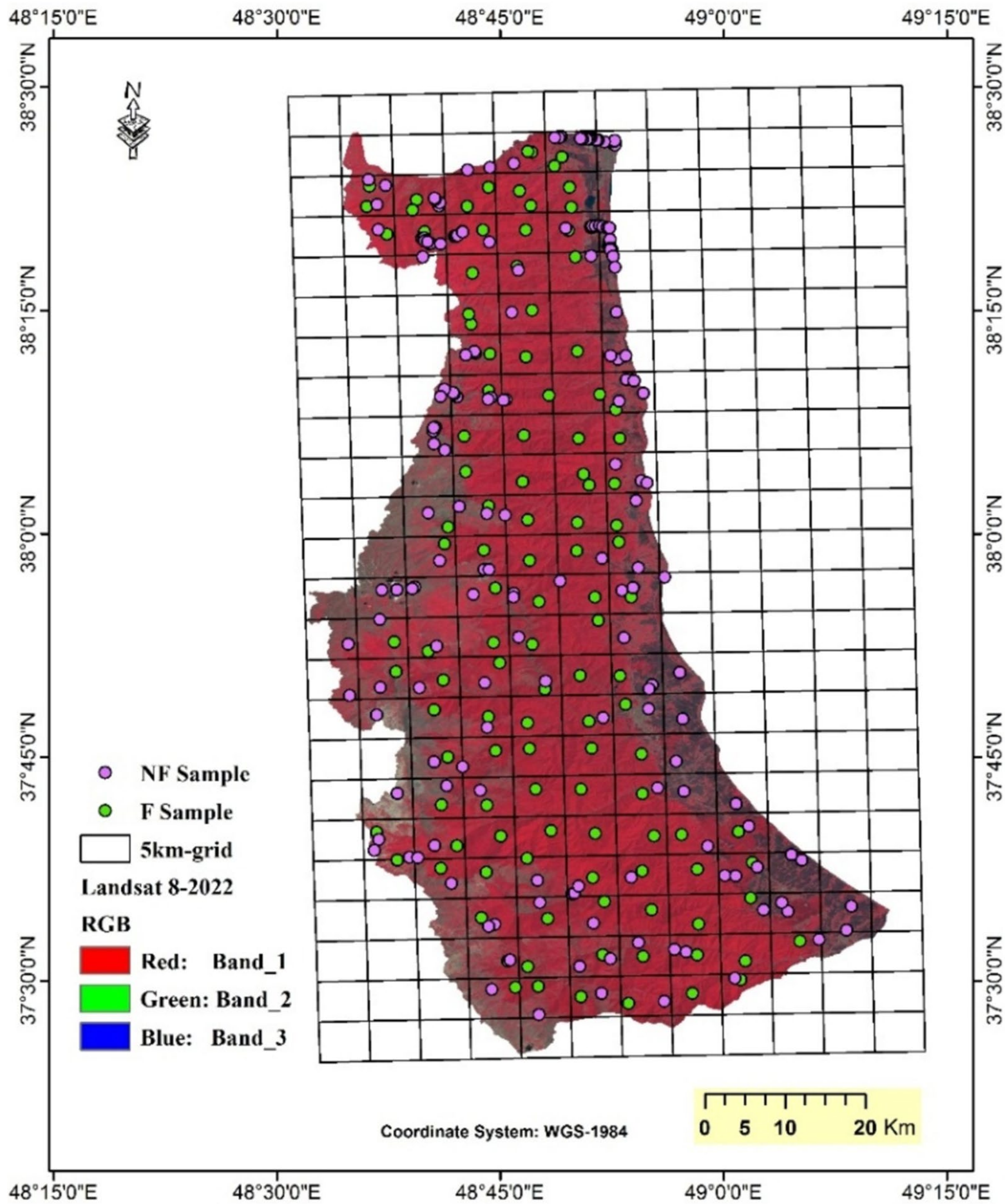

Fig. 3 False color composite (5–4-3) of Landsat 8 image and distribution of training points. F, forest; NF, non-forest

to perform the classification and the other half was used to evaluate its accuracy. The accuracy assessment of the classification is based on the overall accuracy and kappa coefficient metrics. Calculation of the overall accuracy is as follows (Rwanga & Ndambuki, 2017):

The overall classification accuracy = number of correct points / total number of points (1).

Certainly, the high values of the criteria are indicative of high accuracy. The kappa statistic is representative of the discrepancy between the real agreement between reference data and automated classification and the chance agreement between the reference data and the random classification as shown in Eq. (2) (Lillesand & Kiefer, 2004)

$$K = \frac{N\sum_{i=1}^{r} x_{ii} - N\sum_{i=1}^{r}\left(x_i + X_{x+1}\right)}{N^2 - \sum_{i=1}^{r}\left(x_{ii}X_{x+1}\right)} \tag{2}$$

where r is the number of rows and columns in error matrix, N is the total number of observations (pixels), x_{ii} is the observation in row i and column i, x_i+ is the marginal total of row i, and $x+i$ is the marginal total of column i (Rwanga & Ndambuki, 2017). The rate of the accuracy of the classified map based on the kappa coefficient was determined according to Table 2.

After classifying and verifying their accuracy, we calculated and compared the forest cover areas of each catchment to ascertain the rate of deforestation over a 32-year period in the catchments. This procedure was in ArcGIS Desktop 10.8 software. In the following step, we converted the two classification maps to the IDRISI Selva software for comparison. Within this software environment, we used cross-tabulation tools to extract the deforestation layer. Subsequently, in the resulting layer, the deforested areas were assigned a code of 1, while the remaining areas were assigned a code of 0. Thus, the layer of the dependent variable was set as an input into the logistic regression model.

Extraction and preparation of geomorphological variables

We employ RS-GIS methods to assess various terrain characteristics and the morphometry of catchments, as they provide a flexible framework and effective tools for handling and evaluating spatial data (Aparna et al., 2015). We utilized the Esri ArcGIS Desktop 10.8 and SAGA 7.0 software for terrain analysis and preparation of the layers of independent variables. In contrast to earlier studies that have mainly relied on topographic variables in deforestation modeling, we examined a more comprehensive array of terrain variables comprising 15 geomorphometry variables for deforestation modeling (Table 3). These variables represent elevation and slope position, landform, hydrology, and soil formation conditions, affecting the spatial and temporal variations of forests in various aspects. The spatial layers of all these variables were derived from DEM. Given the different scale and range of independent variables, scale matching was required prior to conducting logistic regression analysis. This is accomplished in the SAGA software using the following equation, which adjusts the spatial layers of independent variables to a range of zero to one:

$$X_{\text{normalized}} = \frac{x - \min(x)}{\max(x) - \min(x)} \tag{3}$$

where x is the initial value of the variable, $\min(x)$ is the minimum of the variable, and $\max(x)$ is the maximum of the variable.

Table 2 Rating criteria of kappa statistics (Richards, 2022)

Kappa coefficient	Classification can be regarded as
Below 0.4	Poor
0.41–0.60	Moderate
0.61–0.75	Good
0.76–0.80	Excellent
0.81 and above	Almost perfect

Modeling negative change of forest cover (deforestation)

Spatial regression models are a useful method for establishing the relationship between vegetation maps and maps of environmental variables, all of which combined into a GIS (Bax et al., 2016). "These models address three key research questions: (1) where? – identifying areas affected by change and areas that are most likely to undergo some change in the future; (2) why? – linking potential causal factors with change; and (3) when? – measuring rates of change" (Rutherford et al., 2008). Common parametric models such as binary logistic regression have found extensive application in this field. Logistic regression is a statistical method belonging to generalized linear models that predicts the probability of a phenomenon occurring using independent variables. The key aspect of logistic regression is that the dependent variable is binary, meaning it can only take values of 0 (indicating non-occurrence) or 1 (indicating occurrence). In this study, deforestation and non-deforestation data are considered as the dependent variables. The dependent variable is binary, 0 and 1, which are

Table 3 Geomorphological variables involved in the modeling of deforestation

Variable	Symbol	Description	Reference
Altitude	Alt	–	–
Slope	*S*	The rate of change of elevation in the direction of the steepest descent	Wilson and Gallant (2000)
Topographic position index	TPI	TPI compares the elevation of a cell to the mean elevation of the surrounding cells in a specified area. Positive values represent 10 ridges, and negative TPI values represent valleys while flat areas have a value near 0	Agren et al. (2014)
Northness	*N*	Linear transformation of aspect to 2 sections: north (value = 1) and south (value = −1) as follows:Northness = cos(aspect)	Rodriguez-Moreno and Bullock (2014)
Eastness	*E*	Linear transformation of aspect to 2 sections: east (value = 1) and west (value = − 1) as follows:Eastness = sin(aspect)	Rodriguez-Moreno and Bullock (2014)
Planform curvature	PlC	The curvature along the line of intersection between the surface and the *xy* plane. Plan curvatures are set to positive when the curvature is convex. Negative values indicate concave curvature. This value is undefined when the slope is exactly 0	Jenness (2012)
Profile curvature	PrC	Positive values is indicative of concave surface (when water would decelerate as it flows over this point). Negative values indicate convex surface (where stream flow would accelerate)	Jenness (2012)
Convergence index	CI	This index measures the rate of convergence/divergence of flow in a pixel. Negative and positive values indicate convergence and divergence, respectively	Olaya (2004)
Slope length factor	LS	LS is the length-slope factor that accounts for the effects of topography on erosion. This variable is calculated based on 2 parameters: (1) specific area (A_s) and (2) slope (β) as follows: $L_s = (n+1)\left(\frac{A_s}{22.13}\right)^n\left(\frac{\sin\beta}{0.0896}\right)^m$, where $n = 0.4$ and $m = 1.3$	Moor et al. (1991)
Slope length	SL	Slope length from highlands to lowlands along the flow direction	Hickey (2000)
Topographic wetness index	TWI	This index is calculated based on 2 parameters: specific area (A_s) and slope (β) as follows: $\mathrm{TWI} = \ln(A_s/\tan(\beta))$ TWI is mainly used to characterize the long-time soil moisture status at each point. High values show wetlands, but low values indicate arid lands	Ma et al. (2010)
Contributing area	CA	A matrix where each cell is assigned a value equal to the number of cells that flow into it	Temimi et al. (2010)
Stream density	Str-Dens	A measure of the length of stream channel per unit area of drainage basin	https://esdac.jrc.ec.europa.eu
Distance to stream	Str-Dist	Calculates, for each cell, the Euclidean distance to the closest stream	ArcGIS Tutorial
Terrain ruggedness index	TRI	The sum of elevation variations between 1 pixel and 8 neighbors surrounding it	Riley et al. (1999)

representative of no deforestation and deforestation, respectively (Saha et al., 2020). The independent variables are the geomorphological variables in this study that are introduced into the model to explain the occurrence of deforestation. The logistic regression prediction equation is as follows:

$$\log(P/1+P) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_k x_k \tag{4}$$

where β_i represents the parameter for each variable estimated by the model, and x_i is the factor included in the model ($i = 1, 2, \ldots, k$); finally, P is the probability that a non-deforested pixel will become deforested (Plata-Rocha et al., 2021). The resulting model is evaluated using a percentage of sample points randomly selected from the initial deforestation map using systematic or stratified random sampling methods. Given statistics for evaluation involve "Pseudo R^2" and "Relative Operating Characteristic (ROC)." The pseudo-R^2 index, based on the likelihood ratio principle, tests the goodness of fit in logistic regression and is calculated as follows:

$$\text{Pseudo} - R^2 = 1(\log(\text{likelihood})/\log(\text{L0})) \tag{5}$$

where likelihood is the value of the probability function in the case that the model fits perfectly, and L_0 is the value of the probability function in the case that all the coefficients except the "a" (y-intercept) are zero. Unlike R^2 of ordinary regression, pseudo-R^2 does not represent the ratio of variance explained by the model, but this index shows the degree of correlation between the experimental data and the output of the regression model; hence, its value is generally lower than R^2 (Arekhi et al., 2013). Pseudo-$R^2 = 1$ indicates a perfect fit, whereas pseudo-$R^2 = 0$ indicates no relationship (IDRISI Help). ROC is an excellent statistic for measuring the goodness of fit of logistic regression. The ROC value ranges from 0 to 1, where 1 represents a perfect fit and 0.5 means a random fit. The rates above 0.7 are considered as accurate models, whereas values above 0.9 are considered as highly accurate models (Franklin & Miller, 2010).

We utilized the IDRISI 17.0 (Selva) software to conduct the logistic regression analysis. The deforestation layer, coded as 0 (indicating no deforestation) and 1 (indicating deforestation) in the prior stage, was considered as the dependent variable. The spatial layers of the normalized geomorphological variables were considered as independent variables into the IDRISI environment. Subsequently, we performed a multivariate logistic regression analysis to predict the deforestation probability based on geomorphological variables. During the execution of logistic regression, the layer of the catchment was selected as a mask to carry out spatial modeling within the confines of these catchments. It is noteworthy that field evidence and local data aided us, to some extent, in interpreting the relationship between the independent variables and the dependent variable.

Results and discussion

Detection of negative changes in forest cover (deforestation)

The classification of Landsat images resulted in two maps showing the forest/non-forest areas (Fig. 4). As the classification of satellite imagery was carried out in two well-defined classes (forest and non-forest) and training samples were selected carefully, it was expected that the accuracy of the classification would be acceptable. The results also indicated high classification accuracy for the two images (Table 4).

The map of negative changes in forest cover is shown in Fig. 5, indicating deforestation areas, generated by intersecting the two classification maps. Before dealing with the details of negative changes in forest cover, it is important to note that the studied catchments are located in the mountainous region and are relatively far from the anthropogenic interventions of urban centers situated in the plains in the eastern part of the region. As a result, these catchments can reflect the relationship between physical factors and deforestation. In these areas, human interventions are mainly in the form of agriculture and livestock breeding. Although a comparison of the forest/non-forest classification maps reveals fairly the expansion of deforestation from the plains toward the mountains, the deforestation map shows more clearly this fact. This map shows that deforestation is not only occurring along the main valleys toward the headwaters, but that forest destruction is also traceable in different altitude zones and landforms, indicating a hazardous ecogeomorphic event. The rates of forest loss in the catchments are shown in Table 5. Considering that the catchments were listed from north to south, it is determined that the percentage of deforestation in the northern catchments is relatively higher than

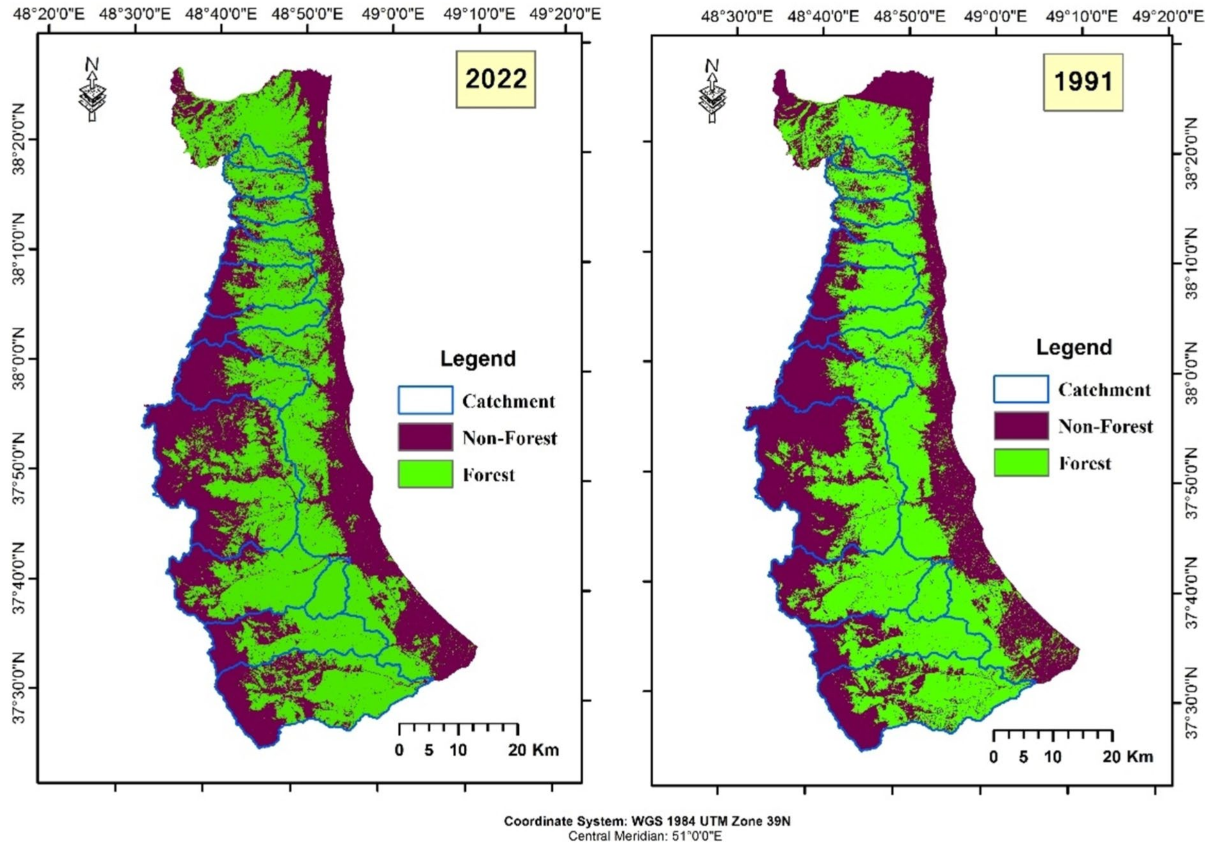

Fig. 4 Classification of Landsat images into two categories: non-forest and forest

Table 4 Results of accuracy assessment of classification of satellite images

	Kappa coefficient	Overall accuracy (%)
Landsat 8–2022	0.94	95.61
Landsat 5–1991	0.91	93.14

that in the southern ones, even though these catchments are smaller. Out of the total area of catchments, which is equal to 1993 km^2, an area of 174 km^2 (8.7%) has been exposed to deforestation during 32 years. The Havigh catchment has the highest percentage of deforestation (7.7%) among the catchments. The spread of deforestation in the main valley of this catchment toward the headwaters is visible, indicating the degradation of the riparian zone. The lowest percentage of deforestation (1.8%) belongs to the Dinachal catchment.

Although riparian forests and shrubs in small and rugged catchments are more abundant than in large and less rugged catchments (Engelhardt et al., 2011), it should also be noted that small catchments are more sensitive to land degradation and soil erosion compared to large catchments and have a faster hydrological response. Important studies by Milliman et al. (1999) in the East Indies and Vanmaercke et al. (2011) in the European catchments refer to this high response of small catchments and their sensitivity to floods and landslides. Such catchments characterized by the narrow valley and bedrock dominance are typically under the control of floods and may exhibit significant channel variations during high flows. As a result, these catchments are highly sensitive to both natural and human disturbances and require preventive land-use management practices such as grazing, roads, and recreation. Compared to small catchments, large catchments have an abundance of grasslands and meadows (Engelhardt et al., 2011) and have a slower

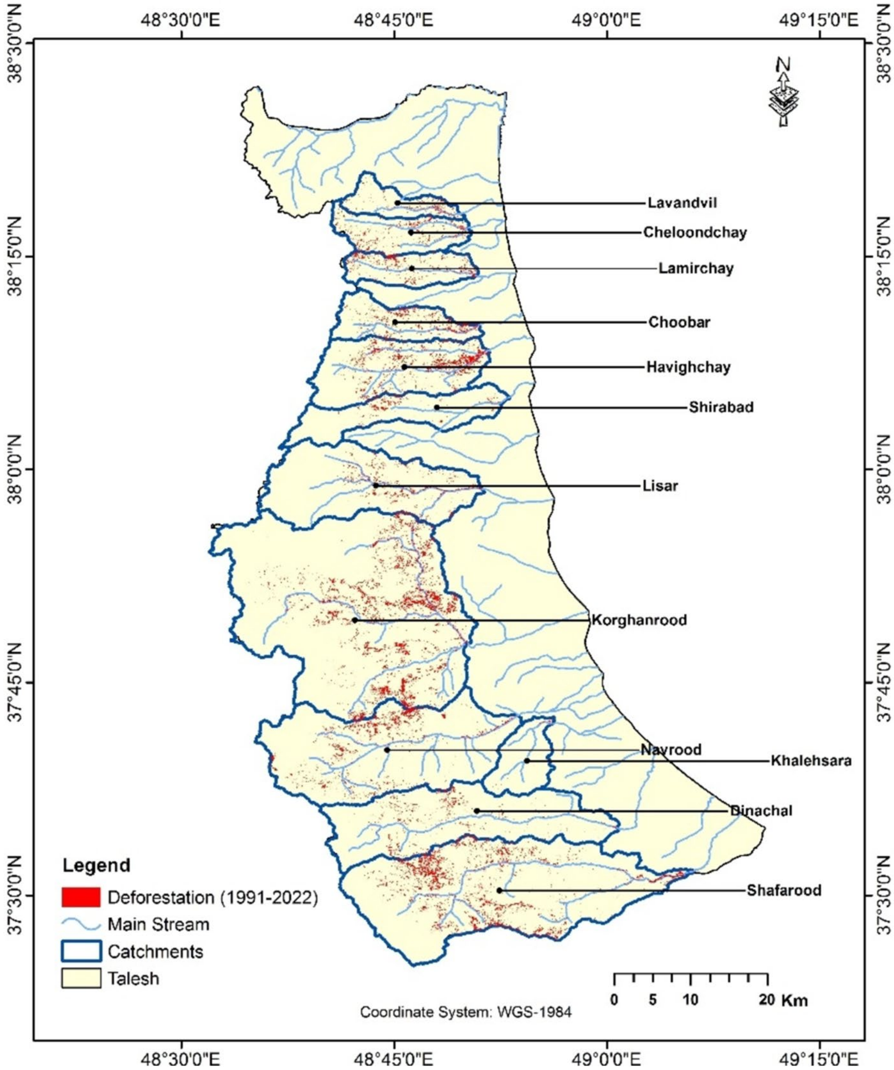

Fig. 5 Map of deforestation over 32 years (1991–2022) in Talesh catchments

hydrogeomorphic response due to the extensive river network and the large distance between the upstream and downstream. However, it is clear that the protective role of forests in protecting water and soil resources is greater than grasslands, and the lower forest cover of large catchments such as Korghanrood and Shafarood has made the risk of floods and erosion in these catchments serious. Furthermore, the issue of the tree line is important in this case. The tree line in the region is located at an altitude of 2000 to 2200 m. As the area of the catchments increases by moving from north to south of the region, the catchment divides recede to the west and cross the tree line. From another view, as the area of the catchments increases, the percentage of bare land or rock outcrops in the upper reaches

Table 5 The rate of deforestation in Talesh catchments over 32 years (1991–2022)

Catchment	Area (km^2)	Deforestation (km^2)	Deforestation (%)
Lavandvil	37.44	1.4	3.7
Cheloond	61.60	3.7	6.0
Lamir	51.59	3.2	6.2
Choobar	61.89	4.5	7.2
Havigh	126.78	9.8	7.7
Shirabad	85.76	2.6	3.0
Lisar	174.86	5.3	3.1
Korghanrood	528.08	27.2	5.1
Navrood	264.83	8.7	3.3
Khalehsara	49.22	1.2	2.4
Dinachal	202.27	3.7	1.8
Shafarood	348.59	18.6	5.3

of the catchments increases. Therefore, it is clear that maintaining environmental balance in all catchments is essential and depends on the conservation and restoration of forests.

Relationship between geomorphologic variables and deforestation (logistic regression model)

The spatial logistic regression analysis produced a spatial predictive model for the likelihood of deforestation based on geomorphological factors, highlighting the direction and strength of the relationships between the dependent and independent variables. We can grasp these from the β coefficients of the independent variables (Table 6). The highest β coefficients are linked to the variables of slope, altitude, and ruggedness index, respectively. In contrast, the lowest β coefficients are attributed to the variables of eastness, northness, distance to river, and slope length factor, respectively. Additionally, the resulting statistics indicate that some variables have different standard deviation values in comparison to others. These independent variables include eastness, northness, distance to river, slope length factor, and stream density. It appears that the variance inflation factor in these variables has obscured their impact on the dependent variable. Consequently, these variables may be excluded from the final model.

The primary predictive model of deforestation is as follows:

$$\begin{aligned}\text{Logit (deforestation)} = & -1.1803 - 2.097567 \times \text{Alt} - 0.292042 \times \text{TPI} \\ & - 2.819719 \times \text{S} - 0.000031 \times \text{N} - 0.000017 \\ & \times \text{E} + 0.000312 \times \text{LS} + 0.118545 \times \text{SL} - 1.921002 \\ & \times \text{TRI} + 0.744707 \times \text{PlC} - 0.170077 \times \text{PrC} \\ & - 0.272819 \times \text{CI} - 0.510281 \times \text{CA} + 0.000751 \times \text{Str} \\ & - \text{Dens} - 0.000124 \times \text{Str} - \text{Dist} - 1.262366 \times \text{TWI}\end{aligned} \tag{6}$$

By removing the variables that have had a negligible effect on deforestation, the final equation for estimating deforestation is according to the following equation:

$$\begin{aligned}\text{Logit (deforestation)} = & -1.1803 - 2.097567 \times \text{Alt} - 0.292042 \times \text{TPI} \\ & - 2.819719 \times \text{S} + 0.118545 \times \text{SL} - 1.921002 \\ & \times \text{TRI} + 0.744707 \times \text{PlC} - 0.170077 \times \text{PrC} \\ & - 0.272819 \times \text{CI} - 0.510281 \times \text{CA} - 1.262366 \times \text{TWI}\end{aligned} \tag{7}$$

Table 6 Results of the spatial logistic regression model

Variables	β	Mean	SD
Intercept	−1.1803		
Altitude	−2.097567	0.425755	0.207935
Slope	−2.819719	0.352952	0.149924
Topographic position index	−0.292042	0.517694	0.066098
Northness	−0.000031	2.198835	164.169762
Eastness	−0.000017	4.834466	438.585629
Planform curvature	0.744707	0.428578	0.012491
Profile curvature	0.170077	0.519295	0.073199
Convergence index	0.272819	0.500006	0.069497
Slope length factor	0.000312	0.098057	6.719884
Slope length	0.118545	0.047187	0.066390
Topographic wetness index	1.262366	0.244014	0.110255
Contributing area	0.510281	0.003470	0.018297
Stream density	0.000751	2.969180	406.873646
Distance to stream	−0.000124	1.662839	477.545318
Terrain ruggedness index	1.921002	0.161414	0.076821

The first geomorphological variable considered in explaining the spatiotemporal changes in vegetation cover is altitude. As elevation increases to a certain extent, precipitation usually increases, and if the maximum elevation of the region does not reach the snow line, favorable topoclimatic circumstances are generally provided for the growth and development of forests. Altitude is one of the most important factors in estimating the probability of deforestation (Pujiono et al., 2019). As expected, a strong relationship is observed between altitude (Alt) and the probability of deforestation in the Talesh catchments. The negative relationship between the two variables of altitude and topographic position index (TPI) and the occurrence of deforestation indicates that deforestation has occurred at lower altitudes and in valleys (Fig. 6). Receiving increased moisture and minimizing evaporation at high altitudes create beneficial ecological conditions for plant growth. Consequently, the amounts of greenness and plant density are higher in highland areas (Cadol & Wine, 2017; Deng et al., 2007; Mokarram & Sathyamoorthy, 2016). Furthermore, the decrease in forest cover in these areas can be significantly restored. Nonetheless, the geomorphic constraints of high altitudes and adverse topoclimatic conditions for human activities

Fig. 6 Deforestation and anthropogenic disturbances in low altitudes of Choobar catchment

play a significant role in limiting deforestation in these areas. Most researchers have also mentioned the accessibility factor when examining the relationship between altitude and deforestation. As observed by Pujiono et al. (2019), the high probability of deforestation at lower altitudes is associated with agricultural expansion in these regions. Additionally, the main valleys provide a permanent water reserve for livestock breeding and these landforms accelerate the adjacency of roads to the dense forest (Vanacker et al., 2003). Therefore, it is clear that anthropogenic interventions and deterioration of natural resources have been more concentrated in river valleys. However, the inverse relationship between altitude and forest loss was widely mentioned by researchers (e.g., Arekhi et al., 2013; Kumar et al., 2014; Bax et al., 2016; Pujiono et al., 2019; Plata-Rocha et al., 2021; Saha et al., 2020). In this regard, there are a few studies that have found a direct relationship between these two variables (see Kucsicsa & Dumitrică, 2019).

Furthermore, this relationship indicates that the riparian zone and coastal buffers of the Talesh

Fig. 7 Forest deterioration in the riparian zone of Korghanrood catchment

catchments are under threat of degradation (Fig. 7). "This transitional zone (ecotone) plays a prominent role in the equilibrium of the entire catchment and acts as a regulator of flowing and transportation of water, sediment, and nutrients between the river and the adjacent uplands" (Patten, 1998). This zone is particularly sensitive to flooding in mountainous catchments. In addition, assuming the significance of the flood forest as a complete part of the food chain and the high scarcity of the remaining flood forest, the conservation of this forest should be a main conservation strategy (Lohani et al., 2020). It appears that this problem has been overlooked in the Talesh forests.

The second geomorphic factor that many researchers employed to explain the deforestation is the slope. The slope influences the ecological conditions for plant growth and expansion by affecting soil moisture, wind, snow, the intensity and frequency of processes, radiation, temperature, and land use (Hoersch et al., 2002). Field studies show a significant negative correlation between water residence time and the slope. Consequently, soil moisture in steep terrains is lower, and soil thickness is reduced (Pelletier & Rasmussen, 2009). These shallow soils may lack the capability to support dense forest cover. The prevalence of soil erosion and mass movements on steep slopes is also one of the geomorphic constraints that complicate the establishment and stabilization of plant communities. Nevertheless, due to the prevalence of steep lands at high altitudes, the level of greenness and plant density in these steep areas is typically greater than that in flat regions (Cadol & Wine, 2017; Deng et al., 2007). Furthermore from anthropogenic viewpoint, the inaccessibility of steep slopes and their unsuitable conditions for the establishment and continuation of human activities, especially agriculture, can be a cause of tree greenness and preservation of forests against deforestation. The inverse relationship between deforestation and slope in Talesh catchments refers to this issue and the refuge of forests in steep lands. Most of the researchers, referring to the accessibility factor, demonstrated this inverse relationship (e.g., Arekhi et al., 2013; Kumar et al., 2014; Pir Bavaghar, 2015; Pujiono et al., 2019; Plata-Rocha et al., 2021; Saha et al., 2020). However, some researchers have achieved different results about the relationship between slope and deforestation. Gonzalez-Gonzalez et al. (2021) in their analysis of the spatiotemporal changes of deforestation in Colombia stated that low slope acts as a preventive factor to deforestation, whereas high slope acts as an attractor factor to deforestation. He stated that the reason of this direct relationship is establishment of the agricultural lands in gentle slopes, where they prevented from floods on steep slopes. Bravo-Peña et al. (2016) also attributed the direct relationship between slope and deforestation to the advancement of agricultural lands toward steep slopes.

In addition to topographic factors such as altitude and slope, some variables indicate the land roughness. Among these, two factors can be mentioned: slope length (SL) and terrain ruggedness index (TRI). SL is a geomorphological variable that is measured along the maximum slope, and its high values are observed in large and main valleys. The slope length variable reflects the altitudinal changes along the longitudinal extent of the catchment. The positive relationship between slope length and deforestation indicates that deforestation has occurred in the downstream areas and main valleys (Fig. 8). In contrast, forests in the upstream and first-order tributaries have been less affected by deforestation. Although the volume of floods and sediments increases in the downstream part of the catchment, and this factor may be effective in the destruction of forests due to the removal of plants or the burial of neonate shrubs and seeds under sediments, this fact is less observed in the Talesh catchments. Goebel et al. (2012) believe that the occurrence of floods leads to the generation and conservation of habitats for various plant species due to increasing erosion and sediment transport. So, it can be said that the same factor of easy access and the special attractions of the downstream coastal areas have led to the tendency and concentration of human activities (agriculture, tourism, etc.) in these areas which, in turn, have caused forest destruction. Meanwhile, the expansion of the river channel and the formation of a floodplain downstream have led to the extended use of water resources and suitable soil in this section of the catchment, resulting in deforestation there. In addition to the SL factor, which is, to some extent, a reflection of hydrogeomorphic processes across the catchments, the TRI is a reflection of the morphodynamic conditions of the slopes and morphogenetic strength. This index is also a rate of topographic heterogeneity (Riley et al., 1999) so the high values of this index indicate low homogeneity of landforms in a specific area. The negative

Fig. 8 Forest clearing in downstream of Navrood catchment

relationship between TRI and deforestation indicates that uneven and topographically heterogeneous areas have not been exposed to deforestation. Although the adaptation and balance of vegetation cover is greater in homogeneous environments, the ecological diversity of heterogeneous environments is high. A review of the literature also indicates that researchers have acknowledged and emphasized the effects of the heterogeneity of geomorphological conditions on the abundance and diversity of vegetation cover (see Hoersch et al., 2002; Stallins, 2006; Reinhardt et al., 2010; Bailey et al., 2017). In addition, high values of the TRI indicate vigorous elevation gradients that provide an unfavorable environment for human activities and limit the uniform spread of human works. Therefore, it appears that the ruggedness factor has been beneficial for the preservation and conservation of forest cover in the Talesh catchments.

After examining the relationship between deforestation and the factors signifying slope position and the extent of morphogenesis, it is now necessary to explore the relationship between deforestation and the factors that represent landform. Land curvature variables are useful measures for interpreting the significant water and sediment transport processes in a landscape. Plan curvature (PlC) represents the degree of divergence or convergence perpendicular to the flow direction, while profile curvature (PrC) represents convexity or concavity along the flow direction. The impact of these variables on spatial and temporal changes in vegetation cover (forest) occurs due to control of transport and deposition processes, as well as linear and point accumulation of materials such as water and sediment. The availability of the necessary moisture for soil-forming biophysical and biochemical processes in concave and depressed areas makes them fertile and productive, and concave areas have characteristics that make them more conducive to plant growth and net primary production (Gessler et al., 2000). The direct relationship between the PlC and the forest cover loss in the Talesh catchments indicates this matter. This relationship shows that deforestation has occurred on the convex surfaces of the slopes. This fact attributed to the dispersion and movement of sediments and water and the limitation of soil formation and development on convex surfaces, which constrains the stability and regeneration of forests. From an anthropogenic perspective, it appears that the existence of limited, relatively flat surfaces at the top of anticlines makes access to these areas easy, especially for livestock breeders, leading to deforestation. Furthermore, the avoidance of humans from the shade and humidity of depressions and hollows can also be a reason for the lower probability of deforestation in these areas. The reverse relationship between the second curvature variable (PrC) could be in the completion of the former relations (PlC vs. deforestation), indicating loss of forest cover on convex surfaces on the slope. In other words, areas with accelerated flow have been exposed to deforestation. In contrast, depressions and hollows along the slope with decelerated flow have been less exposed to deforestation.

In addition to land curvature variables, which are both indicators of landform and process, there is another variable called the convergence index (CI) that is not sensitive to absolute elevation changes and emphasizes more on the hydrogeomorphic process. This index indicates the convergence/divergence of flow, and its high values are observed on ridges and its low values are observed in river valleys. The resulting inverse relationship between this variable and the dependent variable indicates that the probability of deforestation is higher in the areas with flow convergence and valleys than in other parts of the catchment. Lohani et al. (2020) also found that deforestation is more prevalent in floodplains than upland areas. From an anthropogenic viewpoint, this fact refers to the attractiveness and accessibility of floodplains, which was explained earlier. From a natural viewpoint, the occurrence of geomorphological disturbances such as landslides and floods can also be involved in this matter. Geomorphological processes such as floods and landslides are important factors in ecological disturbances (Rice et al., 2012). This is particularly important in large catchments such as Korghanrood and Shafarood, which have extensive floodplains (Fig. 9). Typically, the distributions of riparian tree species were limited to riverine corridors where floodplains are preserved from wearing floods (Shaw & Cooper, 2008). However, the expansion of human activities, such as agriculture and gardening, construction of roads, dams, and villas, is evident in the Talesh region from the plains (east) toward the mountains and across the catchments (west), resulting in deforestation. Given the fact that areas near the streams have greener vegetation (Cadol & Wine, 2017), this issue can be a serious risk to river ecosystems.

Although the morphological and roughness variables described refer to the hydrologic conditions of the catchments, some variables are more indicative of the hydrological characteristics across the catchments. The variables of contributing area (CA) and topographic wetness index (TWI) are among them. CA indicates the potential of flow accumulation at a specific location. This location can be any point in the catchment that gathers upstream water flow. Therefore, this parameter has been used in spatial modeling of soil moisture (Temimi et al., 2010). The inverse relationship between this variable and deforestation indicates that areas with high flow accumulation

Fig. 9 Land cover change (forest loss) in the floodplain of Korghanrood catchment

are less affected by deforestation. Conversely, areas with unfavorable hydrological conditions and scarce water have experienced more deforestation. Obviously, the growth and development of forests is more in areas with moist and nutrient-absorbing soils and forest regrowth is easier due to the ecological support of forest plants in these areas. This fact can be more clearly and completely traced in the relationship between the last geomorphological variable, the TWI, and deforestation. The involvement of slope and specific contributing area parameters in the calculation of the TWI makes this variable a composite variable that reflects both roughness and hydrological circumstances. The inverse relationship of this variable with the probability of deforestation in the studied catchments shows that forest loss is higher in areas with good drainage and low humidity than in areas with high surface and subsurface moisture. In other words, steep areas that are prone to rapid runoff and lack of moisture accumulation are more likely to experience deforestation. Such areas repel moisture and nutrients and hinder the growth and stabilization of forest growth. Conversely, areas that are representative of wetlands, where flow accumulation and sedimentation occur, naturally have more nutrients due to biogeochemical processes for the development and stabilization of forests. From anthropogenic viewpoint, this geomorphic factor is effective in attracting human communities due to the need for water resources, and the higher fertility of wet soils compared to dry soils can be a stimulus for agricultural activities, which ultimately leads to deforestation.

One of the important goals of spatial-statistical modeling of deforestation is to identify the most significant factors contributing to deforestation. The findings from logistic regression modeling indicate that the variables of slope, altitude, and ruggedness are among the most influential factors in the occurrence of deforestation, respectively. Earlier researchers have primarily focused on altitude and slope variables when modeling the deforestation probability. Although past studies have utilized these topographic factors alongside human factors to model deforestation and comparing these studies with the current research is not thorough concerning the significance of independent variables, this can still serve as a reference for future investigations. For example, Plata-Rocha et al. (2021) found that biophysical and accessibility factors significantly influence land cover change and deforestation in the state of Mexico. Although human factors were included in the model, they found that slope and elevation are the primary elements in deforestation, as these factors enhance or restrict the growth of agriculture and urban areas. Gonzalez-Gonzalez et al. (2021), while utilizing the slope and water body as ecological and geomorphological variables in modeling deforestation, emphasized the human factor and indicated that the significance of each variable in deforestation is related to the accessing cost to land and forest resources. Unlike previous studies that emphasized human accessibility over biophysical and ecogeomorphic characteristics in spatial logistic regression models, we assert that the physical factors should be regarded as more important than human factors. We demonstrated that physical factors, while creating advantages and limitations for the expansion and development of forest cover, also influence the accessibility and human intervention aspects. In other terms, the beneficial opportunities provided by a geomorphic environment and its elements for the protection, stability, and regrowth of trees can be regarded as constraints on human activities and the expansion of human settlements. Grasping this interaction and complex relationship of natural and human factors concerning deforestation can be achieved through a systematic approach of geomorphology.

If we aim to condense the findings of regression analysis related to the connection between geomorphological variables and deforestation, we can state that the effect of form and process (geomorphology) on deforestation is distinctly demonstrated in the association between geomorphometry variables and the deforestation probability. At the same time, the anthropogenic effects on environmental change through deforestation are inherent within these interactions. The findings suggest that hydrology, geomorphology, and ecology of fluvial systems cannot be fully understood in isolation from one another (Cadol & Wine, 2017). Although the identification of these multi-directional and interwoven relationships is intricate, the ecogeomorphic approach to understanding how geomorphic components and elements affect the changes in vegetation cover offers a foundation to enhance our understanding of the interaction between geomorphological and ecological processes. In this context, we have examined hydrogeomorphic processes, which have been overlooked in spatial modeling of deforestation, by incorporating variables such as topographic wetness index, contributing area, and convergence index into deforestation modeling. The significance of this matter is referable by the findings of the current study. The findings indicate that the multi-directional relationship among hydrology, geomorphology, and ecology can be more thoroughly examined in certain geomorphic settings. A notable illustration of this matter is the ongoing deforestation in the main large valleys of Talesh, along with the alteration and transformation of forest cover in the floodplain and riparian zone. The available evidence also indicates that the deforestation of these regions in recent years has resulted in substantial harm to human habitats and infrastructure due to increasing the frequency of floods. Although the removal of riparian trees is occasionally linked to coastal erosion, the human influence on this phenomenon outweighs the purely natural causes. In this context, Bera et al. (2022) stated that "In high altitude zones, deforestation mainly occurs due to physical factors such as weathering, mass wasting, aeolian process, landslide, etc. whereas, in low altitude zones, deforestation mainly happens due to anthropogenic factors." In any case, we again highlight the physical foundation of river environments and landform characteristics as a framework for the initiation and growth of human activities and we support the occurrence of deforestation in the principal valleys and floodplains by noting that these areas possess favorable geomorphic conditions for the extension of human activities. However, we assert that the ecogeomorphic sensitivity of the floodplain and riparian zones is greater than that of other sections of the catchment. The preservation of these environments is a priority due to their significant ecological role in regulating and managing the water and sediment flow in small and mountainous catchments such as the northern catchments of Talesh.

Accuracy assessment of the logistic regression model

After assessing the quality and quantity of the independent variables' effects on the dependent variable, we analyze the validity and performance of the logistic regression model. This analysis was done based on the pseudo-R^2 (PR^2) and ROC statistics (Table 7). The PR^2 value of the regression is 0.19, indicating a satisfactory fit of the regression line. Pir Bavaghar (2015) noted that if the values of this statistic lie between 0.2 and 0.4, the model fit is good. However, because of the high variability of experimental data and their pixel nature, values lower than 0.2 are inevitable. Arekhi et al. (2013) also reported P$R^2 < 0.2$. Kumar et al. (2014) attained only a value of 0.29 in one of the four predictive models. Bravo-Peña et al. (2016) likewise recorded a value of 0.26. The variations in the statistics may arise from different factors, local characteristics, or input information, having discussed below.

Table 7 Evaluation statistics of the logistic regression model

$-2\log(L_0)$	827,230.3545
$-2\log(\text{likelihood})$	808,031.0847
Pseudo-R-squared	0.19
ROC	0.75
Chi-square	19,199.2697

The ROC statistic is more important than the PR^2 statistic and refers to the agreement between the actual deforestation map and the map obtained from the deforestation prediction model. This statistics, which "signifies the predictive capability of the models for future probability of deforestation" (Saha et al., 2020), is affected by the quality and quantity of the input data. The ROC value in the Talesh catchments was 0.75, which indicates that the predictive regression model is good. This statistic was also 0.76 in the model of Arekhi et al. (2013). However, Kumar et al. (2014), Pir Bavaghar (2015), Bravo-Peña et al. (2016), Pujiono et al. (2019), and Saha et al. (2020) attained higher rates. The ROC values obtained by these researchers were 0.87, 0.81, 0.88, 0.86, and 0.87, respectively. These differences in the evaluation values of predictive models can be due to various reasons that may occur in all spatial-statistical analyses. The sampling method, both in preparing forest cover maps and in the selection of deforestation samples, is one of the factors that affect the ultimate outcome of the model. In this study, an attempt was made to correctly apply the principles of sampling in both stages with a good distribution. However, the spatial distribution of deforestation samples is not within the control of the researcher. The existence of forest loss areas in a scattered and point-like manner may make it somewhat difficult to explain the spatial distribution of deforestation. Therefore, although the binary nature of the dependent variable (event/no event) is considered as one of the advantages of the logistic regression method, the high dispersion of deforestation data can induce problems in modeling. The reference data for generating maps of independent variables and the spatial resolution of digital elevation models are another crucial element in modeling changes in forest cover. Kucsicsa and Dumitrică (2019) emphasized the significance of the precision of the input data and the scale difference of the spatial layers in the execution of the logistic regression model, viewing it as one of the possible constraints of the model. Nonetheless, it must be acknowledged that the incorporation of both discrete and continuous variables (regardless of the scale difference of the variables) in the logistic regression model is an advantage (Bai et al., 2010). In this research, contrary to earlier studies, since all independent variables were derived from the digital elevation model at the same spatial scale, the aforementioned issue in mapping cannot compromise the reliability of the modeling. Nevertheless, the existence of unnecessary and erroneous data in certain areas, along with the difficulties in transforming raw elevation data, is a common issue in terrain analysis. It appears that this issue arose in this study. The primary concern was the presence of stripping in the digital elevation model, observable in many of the raster layers of independent variables. This flaw could influence the variable values across the wide pixel space, and potentially erroneous and incorrect values may diminish the accuracy and predictability of regression models. In this context, although the variables of aspect and distance to river have been among the most frequently utilized variables in deforestation modeling, they omitted from the final model in this study because of their high variance. This does not imply that these variables are less significant in explanation of the spatiotemporal variation of forest cover. It seems that some issues arose in the output layers concerning the distribution of the values during the scale matching process, which require further investigation.

Another important issue in the logistic regression model is the selection of appropriate independent variables to perform regression analysis that can create a constraint. In this context, access to different spatial data and layers can be a limitation of these models (Kucsicsa & Dumitrică, 2019). In this study, we emphasized on geomorphological variables in explaining the deforestation event. However, some researchers have mentioned other environmental variables such as climate (Lohani et al., 2020; Plata-Rocha et al., 2021), forest density (Saha et al., 2020), and forest biomass (Plata-Rocha et al., 2021), which can improve the efficiency of regression models.

Conclusion

The current study aimed to introduce an interdisciplinary ecogeomorphology approach to the challenge of deforestation and its physical drivers. The findings of the study indicated that this innovative approach on deforestation, historically utilized as advanced interdisciplinary knowledge for managing and conserving river ecosystems, can provide a spatially and temporally based understanding of ecological processes (deforestation), allowing us to offer a quantitative tool for forecasting how landscapes will change in the future over time and space (Renschler et al., 2007). In this context, we successfully introduced a predictive model of deforestation probability based on geomorphological factors in the Talesh catchments, by integrating comprehensive terrain analysis and geomorphometry tools with statistical techniques and logistic regression. The spatial prediction model can serve as a resource for watershed planners and managers to address environmental challenges and consider suitable conservation initiatives and forest restoration, acknowledging the pioneering nature of this study in the region. Furthermore, the change detection of forest cover in relation to geomorphological variables can aid in creating future forest cover scenarios, as one benefit of employing geomorphometry variables in modeling of land cover change is their stability, which decreases uncertainty in predicting land cover changes.

For planning and management purposes, the spatial logistic regression model indicates the locations where deforestation is expected more to take place. These points in Talesh catchments are low altitudes and valleys, low slopes, flow divergence points, convex land surfaces, downstream, homogeneous flat areas, and low humidity areas. We can say that the "ecogeomorphic sensitivity" of these environments to deforestation is greater than that of other environments. Determining this sensitivity is complete once we understand which geomorphological variables significantly affect the incidence of deforestation. The results revealed that slope, elevation, and ruggedness index are significant contributors to deforestation, a finding that aligns with prior studies focused on modeling deforestation probability. The distinctive aspect of this research lies in its emphasis on elucidating the impacts of both physical and anthropogenic factors on deforestation by solely integrating physical variables (geomorphology) within the spatial logistic regression model. This approach led us to the conclusion that anthropogenic influences on forest cover change are inherently linked to the interactions between geomorphological features and ecological processes related to deforestation. Unlike earlier studies, our research prioritized the physical context in the modeling of deforestation occurrence. Nonetheless, we recognized that landform characteristics susceptible to deforestation implicitly indicate the accessibility factor and the positioning of human activities.

This research pointed out the significance and necessity of employing the ecogeomorphology approach alongside terrain analysis methods as effective tools for geomorphologists in assessing and predicting changes in forest cover for subsequent studies. In order to promote this interdisciplinary understanding, it is essential to possess a thorough understanding of the strengths and weaknesses of spatial-statistical models. The quantity and quality of input data and information for spatial logistic regression model significantly influence the model's results. Consequently, it is advisable to utilize more precise and high-quality digital elevation models (DEMs) in future investigations to enhance the predictive accuracy of these models. Furthermore, improved results may be attained by resampling DEMs and increasing resolution through some techniques such as moving window analysis and the application of majority filters, which can mitigate environmental heterogeneity, presenting new perspective for future research. Another critical aspect to consider in spatial modeling is the selection and number of independent variables. While this study demonstrated that it is possible to overcome the challenges of accessing various spatial data and layers through terrain analysis and digital elevation models, the limitations may persist if future research incorporates anthropogenic variables, such as timber extraction and wood fuel usage, in deforestation modeling. Ultimately, integrating anthropogenic factors into deforestation modeling and developing hybrid models for future researches in the Talesh region are regarded as a scientific perspective.

Finally, the findings of this research can provide essential guidance for prioritizing initiatives related to forest management and the conservation of natural resources within the Talesh catchments. In this regard, regions that are susceptible to deforestation require increased attention and support, and any human activities in these areas should be accompanied with environmental awareness and in line with sustainability of natural resources. Specifically, it is crucial that policymakers as well as regional, urban, and rural planners focus more on the protection and restoration of the areas most affected by deforestation in the floodplain and riparian zones.

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Declarations

Competing interests The authors declare no competing interests.

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