Machine Learning and Remote Sensing Based Classification and Vegetation Dynamics Assessment of Inselberg Habitats in Gampaha, Sri Lanka

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Abstract
Inselbergs are isolated rocky outcrops of ecological and geomorphological significance, yet their vegetation dynamics remain understudied in Sri Lanka. This study applied remote sensing and machine learning techniques to classify inselberg habitats in the Gampaha District and to assess vegetation changes over time. A Support Vector Machine (SVM) classifier was developed using selected topographic and spectral covariates, achieving an overall accuracy of 94.5% and a Kappa coefficient of 70.1%. The Digital Elevation Model (DEM), Ferrous Mineral Ratio (FMR), and Sentinel-2 Band 8 (NIR) were identified as the most influential predictors of inselberg presence. Vegetation change was evaluated using NDVI-based change detection between 2001 and 2024, and results indicate notable vegetation reduction in several inselberg habitats. Quarry expansion emerged as the dominant anthropogenic driver of degradation, while inselbergs associated with Buddhist monasteries exhibited comparatively higher vegetation retention. The study highlights the value of geospatial modelling for inselberg habitat assessment and provides insights that can guide targeted conservation planning in rapidly urbanizing landscapes.

Keywords: Inselberg Conservation, Machine Learning, Remote Sensing, Support Vector Machines, Vegetation Dynamics

1. Introduction

Inselbergs serve as unique habitats, often supporting distinct vegetation and specialized wildlife due to their isolated nature and variation in moisture retention. However, inselbergs are increasingly threatened by human activities, such as quarrying and land-use changes, leading to habitat degradation and biodiversity loss. Inselbergs can be defined as rocky outcrops primarily composed of granitic or gneissic formations, shaped over millions of years through weathering and erosion [1] and [2]. These isolated geological features vary significantly in height, from a few meters to towering monolithic structures [3]. They are widely recognised for their ecological importance, often serving as refuges for unique and endemic species due to their stable microclimates and isolation [4]. The biodiversity associated with inselbergs has been a subject of increasing interest, particularly in biogeography and conservation science [5].

Satellite-based Earth observation plays a crucial role in environmental mapping and land cover monitoring, making it an essential tool for conservation efforts [6]. To facilitate this, various classification techniques have been developed, ranging from traditional methods to advanced machine-learning approaches [7]. Artificial Intelligence (AI) encompasses diverse computational techniques that enable machines to replicate human cognitive functions, with machine learning serving as a key subset that focuses on identifying patterns and making data-driven decisions. In Geographic Information Systems (GIS), AI-powered approaches are increasingly being integrated to automate land use analysis. Among these, machine learning algorithms have gained widespread acceptance due to their effectiveness in mapping land cover across extensive geographical regions [7][8][9][10][11] and [12].

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These algorithms also facilitate the incorporation of multiple predictive covariates, improving classification accuracy [13]. Methods like Support Vector Machines (SVM) provide superior classification performance by handling non-linear relationships effectively. Compared to traditional classification approaches, these advanced algorithms enable researchers to analyze diverse environmental covariates with greater precision. Recently Random Forest (RF) and SVM algorithms have been effectively utilized for the identification of inselberg habitats in the region [14].

Despite their ecological and geomorphological significance, inselberg habitats in Sri Lanka remain largely understudied. Sri Lanka is also home to one of the most well-known inselbergs in the world, Sigiriya monolithic rock formation which is also a world heritage with significant cultural values. However, research efforts on inselberg habitats of Sri Lanka have focused mainly on their geological characteristics and cultural aspects [15] and [16], with limited investigations into their ecological status and conservation needs [17] and [18]. Recently there has been some efforts for the identification of spatial distribution of inselbergs in this region [14] and [19]. The Western Province, particularly the Gampaha District, hosts numerous inselbergs, yet many are threatened by quarrying activities and urban expansion [18]. Certain inselbergs associated with Buddhist monasteries have experienced a degree of protection due to religious custodianship, but others continue to be at risk [16].

Given the urgency of habitat degradation, this study aims to apply remote sensing and machine learning Given the accelerating pace of habitat degradation, there is an urgent need to develop reliable approaches for mapping and monitoring inselberg ecosystems. This study applies remote sensing and machine learning techniques to classify inselberg habitats and quantify the anthropogenic pressures that influence their vegetation dynamics. By leveraging geospatial analysis and predictive modelling, the research aims to support conservation initiatives and provide a basis for sustainable management of these ecologically significant landforms. To address this gap, the present study employs a Support Vector Machine (SVM) based remote sensing approach to: (i) classify inselberg habitats using spectral and topographic covariates, (ii) assess long-term vegetation change within inselberg landscapes, and (iii) evaluate the influence of key anthropogenic drivers specifically quarry expansion and temple-associated land use on vegetation degradation. The study is focused in the Gampaha District of Sri Lanka, where inselbergs are increasingly threatened by quarrying activities, while in certain locations cultural custodianship linked to Buddhist monasteries has contributed to reduced disturbance. By integrating habitat classification, vegetation change assessment, and anthropogenic impact analysis within a geospatial modelling framework, this study offers an evidence-based approach to identifying vulnerable inselberg environments. The findings are expected to deepen understanding of human–environment interactions in inselberg ecosystems and to guide targeted conservation planning in landscapes undergoing rapid transformation.

2. Methodology

2.1 Study Area

The study was conducted in Gampaha District, Western Province, Sri Lanka, covering diverse topographic conditions (Figure 1).

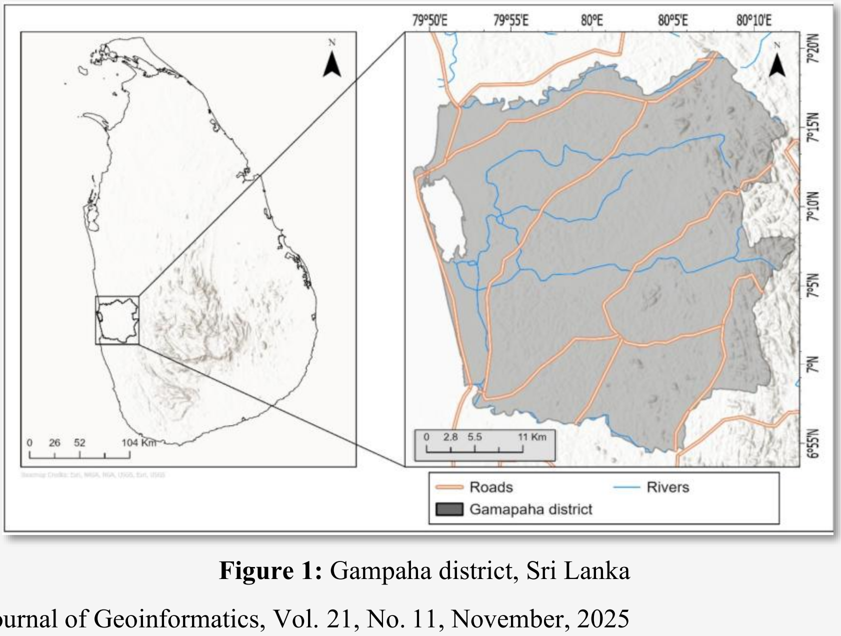

Figure 1: Gampaha district, Sri Lanka

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Gampaha district spans for an extent of 1,387 square kilometres and it is also the second most human populated district of the country with a population of 2,443,000 with an estimated 1,800/km^2 population density [20] and [21]. The district resides in the coastal plain of the island with an altitude ranging from sea level to a maximum of 450 m a.s.l [20]. Due to the high population density and anthropogenic activities, the remaining natural forest cover of the area is limited to 1.2% of the total area [22]. Inselbergs in this region are found mainly in the northeastern and eastern parts, often associated with temple sites or threatened by quarrying activities. Figure 2 illustrates the overall workflow during our work.

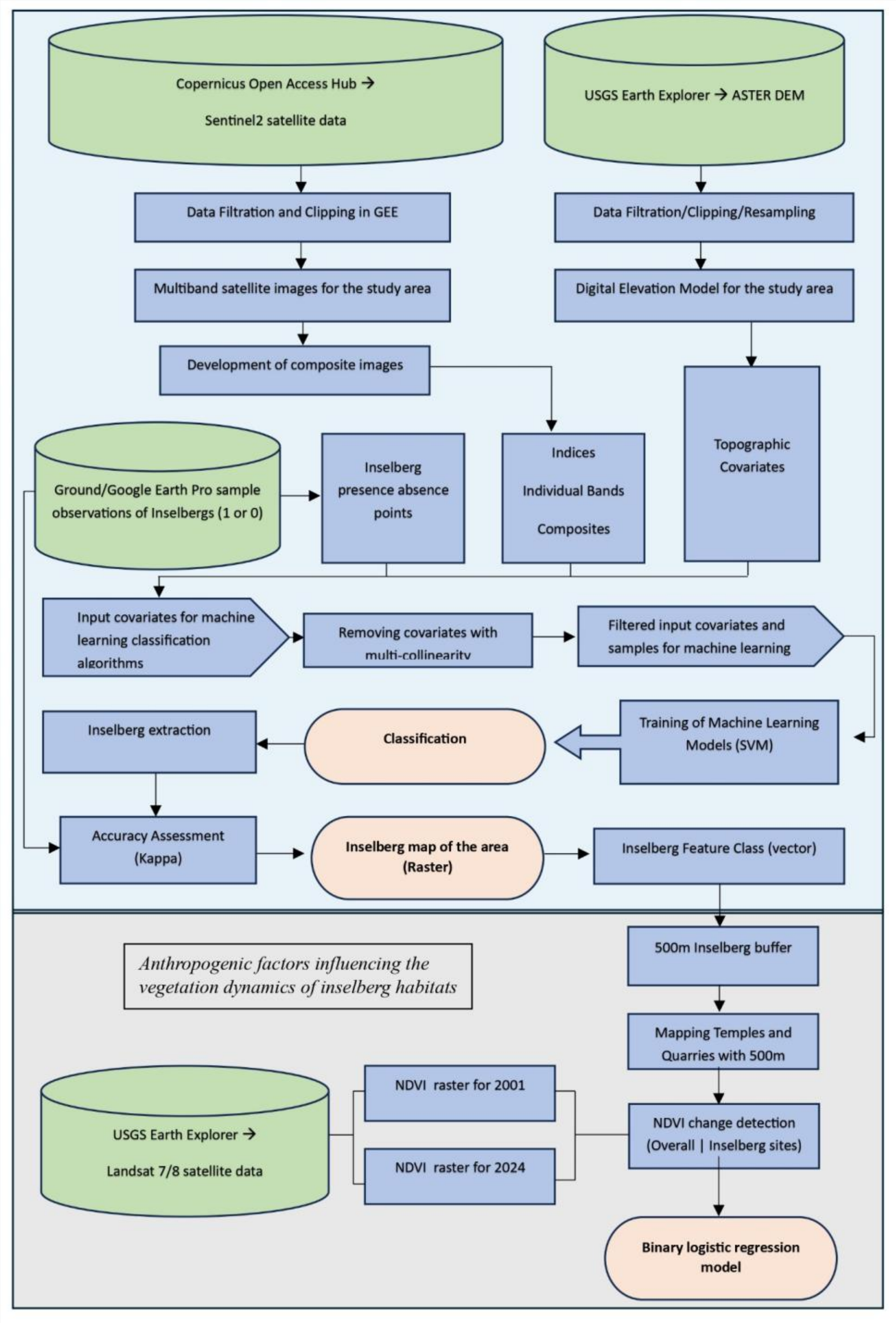

Figure 2: Vegetation dynamics assessment of inselberg habitats study workflow

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2.2 Data Acquisition and Preprocessing

2.2.1 Satellite data for classification

Sentinel-2A imagery was used for model development for the identification and mapping of inselberg habitats. Google Earth Engine (GEE) was used to filter atmospherically corrected Surface Reflectance (SR) Sentinel 2A satellite images from Copernicus Data Space Ecosystem (formerly Open Access Hub) (https://browser.dataspace.copernicus.eu/). We used the "*maskS2clouds*" function in GEE for Cloud and cirrus correction. The "*mosaic*" function was used to combine multiple Sentinel 2A images from the time period 1st January 2020 to 31st December 2024 into a single image. Obtaining this five-year mosaic image reduces any bias caused by inconsistencies in the model when the imagery changes. The generated multiband composite included the spectral bands B2, B3, B4, B7, B8, B11 and B12. Further processing and analysis were conducted in Arc GIS Pro 3.2 (ESRI, Redlands) to generate 14 spectral covariates (Table 1).

Table 1: Spectral covariates considered for modelling

Index	Description	Equation	Relevance to inselberg presence & identification
Normalized Difference Vegetation Index (NDVI)	NDVI is a widely used vegetation index in remote sensing and satellite imagery analysis. [23] and [24].	$\frac{NIR - RED}{NIR + RED}$	Inselbergs typically have sparse or patchy vegetation due to shallow soils and high exposure. NDVI helps distinguish rocky outcrops from surrounding forests or dense vegetation.
Soil-Adjusted Vegetation Index (SAVI)	SAVI is a modified version of NDVI. It is designed to minimize the influence of soil brightness on vegetation index values, making it particularly useful in areas with exposed soil surfaces [24] and [25].	$\frac{1.5(NIR - RED)}{NIR + RED + 0.5}$	Inselbergs have high soil exposure and thin soil cover. SAVI minimizes soil brightness and highlights low-biomass vegetation typical of inselberg slopes.
Green Normalized Difference Vegetation Index (GNDVI)	GNDVI is another vegetation index used in remote sensing and satellite imagery analysis to assess the health and density of vegetation.	$\frac{NIR - GREEN}{NIR + GREEN}$	Useful for detecting stress-tolerant vegetation on inselbergs, which often shows lower chlorophyll content compared to surrounding ecosystems.
Normalized Difference Moisture Index (NDMI)	NDMI is sensitive to variations in water content in leaves and can be useful for monitoring drought conditions, assessing vegetation health, and studying hydrological processes [24].	$\frac{(\mathrm{NIR} - \mathrm{SWIR})}{(\mathrm{NIR} + \mathrm{SWIR})}$	Inselberg vegetation is often water limited. NDMI highlights dry, moisture-stressed areas common on exposed rock surfaces.
Modified Normalized Difference Water Index (MNDWI)	MNDWI can enhance open water features while efficiently suppressing and even removing built-up land noise as well as vegetation and soil noise [26].	$\frac{NIR - SWIR}{NIR + SWIR}$	Helps exclude non-inselberg wet areas, tanks and streams, improving separation of rock surfaces from moist lowlands.
Red Edge Normalised Difference Vegetation Index ($NDVI_{705}$)	$NDVI_{705}$ is a slight alteration to the traditional NDVI and is adopted for use with high spectral resolution reflectance data such as data from Sentinel-2. [27]	$\frac{NIR\text{-}RED\ Edge}{NIR\text{+}RED\ Edge}$	Inselberg vegetation is sparse and stress-adapted. Red-edge bands help capture subtle canopy differences on rocky surfaces that standard NDVI might miss.
Clay Minerals Ratio (CMR)	CMR leverages the fact that hydrous minerals such as the clays, alunite absorb radiation in the 2.0–2.3 micron portion of the spectrum. This index mitigates illumination changes due to terrain since it is a ratio [28].	$\frac{SWIR1}{SWIR2}$	Inselbergs often have minimal clay-rich soils. CMR helps distinguish surrounding weathered soils from exposed rock surfaces.
Iron Oxide Ratio (IOR)	The presence of limonitic-bearing phyllosilicates and limonitic iron oxide alteration cause absorption in blue band and reflectance in red band. The nature of the ratio allows this index to mitigate illumination differences caused by terrain shadowing [29] and [30]	$\frac{RED}{BLUE}$	Inselbergs often include oxidized rock surfaces. IOR highlights iron-bearing weathering crusts typical of exposed granitic domes.
Ferrous Minerals Ratio (FMR)	FMR highlights iron-bearing materials. It uses ratio between the SWIR band and the NIR band [29].	$\frac{SWIR}{NIR}$	Inselbergs frequently show ferrous-rich exfoliation surfaces. FMR enhances exposed bedrock signatures, aiding rock-outcrop detection.

2.2.2 Topographic data

The ALOS PALSAR Digital Elevation Model (DEM) with a 12.5m spatial resolution was acquired from the USGS Earth Explorer database (https://earthexplorer.usgs.gov/). The DEM was clipped to the Gampaha district and resampled to a 10m resolution to match Sentinel imagery. Using the resampled DEM, 25 topographic covariates were generated in raster format (Table 2) using the "RSAGA" package in the R programming environment [31] and [32]. All raster layers maintained the same spatial extent and resolution as the DEM.

2.2.3 Ground data and sample points

Inselberg presence and absence were mapped using Google Earth Pro and verified by field observations where accessible. A total of 1,035 georeferenced sample points were prepared (presence = 1, absence = 0) for model development.

2.3 Machine Learning Model Development

The covariate selection process was carried out in three sequential steps to improve model interpretability and minimize redundancy among predictors: (i) Variables with near-zero variance were removed to eliminate uninformative predictors. (ii) To address multicollinearity, pairwise Pearson correlation coefficients were computed for all continuous covariates, and when two variables were highly correlated ($|r| > 0.8$), the variable with weaker relevance to inselbergs was excluded. (iii) Remaining variables were ranked by importance during the preliminary classification model run, and those with negligible importance were discarded. This procedure ensured that redundant and statistically insignificant covariates were removed prior to modelling [1].

A Support Vector Machine (SVM) with a radial basis function (RBF) kernel was implemented using the "e1071" package in R to classify inselberg presence based on selected topographic and spectral covariates raster layers. Raster values were extracted at 1035 georeferenced sample points using the "raster" and "sf" packages in R, and the dataset was partitioned into training (75%) and testing (25%) subsets with "caret" package. Model performance was evaluated with a confusion matrix using "caret", reporting overall accuracy and kappa coefficient [33] exclusively from the independent 25% test subset. Feature selection was performed to retain the most relevant covariates. The trained SVM model was subsequently applied to the full raster stack to produce a spatial classification map of inselberg habitats. Inselberg map for the Gampaha district was generated and covariates that were significantly contributing to the model were further investigated to identify the relationships. For this purpose, the variable importance was obtained based on Model-Based Variable Importance (MBVI) using the R package "caret". MBVI is a proxy measure of variable importance in SVM derived from the absolute magnitude of the model's feature weights (for linear SVMs) or from sensitivity analysis of model predictions (in kernel-based SVMs).

For linear SVMs, importance is based on the absolute value of the coefficients (weights) associated with each feature. The relative importance scores are scaled between 0 and 100.

Table 2: Topographic covariates considered for modelling (continue next page)

Topographic covariate	Description	Relevance to inselberg presence & identification
Aspect	The compass direction (in degrees) that a slope faces, influencing sunlight exposure and microclimate.	Inselbergs often have sun-exposed, desiccated slopes with distinct vegetation stress patterns on N/S faces, making aspect useful for identifying their micro-climatic footprint.
Convergence Index	Quantifies terrain convergence/divergence, identifying zones of potential water accumulation or flow dispersion.	Inselbergs are typically divergent, water-shedding landforms. Low convergence values help distinguish rock domes from valleys and depressions.
Cross Sectional Curvature	Curvature perpendicular to the direction of slope; affects lateral flow and surface water movement.	Inselbergs exhibit strong convex lateral profiles, helping separate them from valley systems.
Curvature Classification	Categorize landscape based on combinations of profile and plan curvature into forms like ridges, valleys, etc.	Inselbergs form ridge-like and convex morphometric classes, making them detectable in curvature-based landform maps.
DEM	A raster dataset representing ground elevation at each pixel; the basis for most terrain derivatives.	Inselbergs are isolated elevation highs above a lowland background, making DEM the *primary* discriminator of inselberg presence.
Downslope Difference	Measures elevation difference between a point and its steepest downslope neighbor; indicates local relief.	Inselbergs show sharp elevation breaks, highlighting steep-sided rock domes relative to surrounding plains.
Downslope Gradient	Slope steepness in the direction of the steepest descent; influences erosion and water runoff.	Inselbergs often have high-gradient flanks, useful for edge delineation.

Table 2: Topographic covariates considered for modelling (continue from previous page)

Topographic covariate	Description	Relevance to inselberg presence & identification
Generalized Surface	A smoothed or simplified terrain surface highlighting broad landform patterns, reducing fine-scale noise.	Helps reveal inselberg macro-shape by filtering out noisy micro-topography.
Hillshade	A grayscale rendering of terrain using simulated lighting; emphasizes landform visibility but not a quantitative layer.	Enhances visual and textural contrast of inselberg slopes and domes, especially during classification and validation.
Longitudinal Curvature	Curvature along the slope direction; influences acceleration/deceleration of surface flow.	Inselberg slopes show consistent convex longitudinal profiles, aiding shape-based recognition.
Mass Balance Index	Estimates net erosion or deposition potential based on upslope contributing area and slope.	Inselbergs are net erosion surfaces with minimal deposition, giving them distinct negative/neutral MBI signatures.
Maximal Curvature	Represents the greatest convexity/concavity at a point on the surface across all directions.	Inselbergs usually have high convex curvature peaks, reflecting exposed rock summits.
Minimal Curvature	Measures the smallest curvature (least bending) at a point, helping identify flat or linear features.	Helps identify flat rock sheets or gently sloping shoulders of inselbergs.
Morphometric Features	Landform elements (e.g., peaks, ridges, valleys) derived from DEMs using combinations of curvature and slope.	Inselbergs correspond to peak/ridge morphometric classes, improving separability from alluvial landforms.
MRRTF	Highlights ridge-like flat surfaces across scales; useful for identifying interfluves or ridge tops.	Enhances inselberg peak and shoulder features, improving ridge-top detection.
MRVBF	Quantifies valley flatness across scales; commonly used for identifying alluvial plains or wetlands.	Useful for masking out floodplains and valley bottoms, indirectly improving inselberg detection.
Plan Curvature	Curvature of terrain in the horizontal plane; affects the divergence/convergence of flow perpendicular to slope.	Inselbergs tend to be plan-convex forms, reinforcing their diverging flow signature.
Profile Curvature	Curvature in the vertical plane; influences speed of water or material flow along the slope.	Inselbergs show convex flow profiles, helping separate them from channelized slopes.
Slope	The steepness or inclination of the terrain surface, usually expressed in degrees or percent.	Inselbergs have steep perimeter slopes and flatter summits, making slope a strong boundary indicator.
Surface Texture	Measures local variation in elevation (roughness); reflects microtopography or fine-scale heterogeneity.	Inselbergs display low-soil, high-rock roughness patterns, differentiating them from vegetated surfaces.
Terrain Ruggedness Index	Quantifies the variation in elevation between a cell and its neighbors; indicates terrain roughness.	Inselbergs exhibit moderate ruggedness with sharp edges, distinguishing them from both flat plains (low TRI) and dissected hills (high TRI).
Terrain Surface Classification	Categorizes terrain into types (e.g., flat, sloped, concave, convex) using multiple morphometric criteria.	Inselbergs align with peak, mesa, and dome classes, improving categorical landform mapping.
Terrain Surface Convexity	Measures the bulging or dipping of the terrain; positive values for convex (ridges), negative for concave (valleys).	Inselbergs are strongly convex landforms, making convexity a direct geomorphic indicator.
Topographic Position Index	Compares elevation of a point to the mean of its surroundings to classify as valley, slope, ridge, etc.	Inselbergs have very high TPI values (prominent local highs), making TPI one of the best inselberg predictors.
Vector Ruggedness Measure	Captures terrain ruggedness by analyzing variability in 3D orientation of slope vectors; useful in habitat modeling.	Inselbergs show distinct 3D surface orientation stability, separating them from chaotic rugged terrain.

2.4 Change Detection

Landsat 7 (2001) and Landsat 8 (2024) images from the United States Geological Survey online database (https://earthexplorer.usgs.gov/) were utilized to assess vegetation changes. Images were filtered for the month of February of each considered year to reduce extreme weather conditions such as heavy rain or drought which would affect the analysis. The images were pre-processed in GEE, including filtering, cloud masking, and applying quality assurance corrections. CIRES-corrected and cloud-masked Landsat images, specifically Landsat 7 (2001-February) and Landsat 8 (2024-February) (OLI_TIRS sensor/path_141/row_56) were used to generate multiband composites. The composite images incorporated spectral bands 1–7 for Landsat 7 and bands 1–8 for Landsat 8.

Normalized Difference Vegetation indices (NDVI) [25] were computed from Landsat images for 2001 and 2024 to assess vegetation changes.

The "Change Detection" tool in ArcGIS Pro was used for comparing the NDVI rasters from 2001 and 2024. The NDVI values from 2001 were subtracted from those of 2024 to identify changes over the 23-year period. The resulting change detection raster was reclassified to highlight significant changes. A threshold of >0.1 decrease in NDVI was used to identify significant vegetation loss. Selection of this threshold was based on past literature on similar work [34][35] and [36]. This cut-off was chosen based on (i) established practice in moderate-resolution change detection where NDVI change ≈ 0.1 is commonly used to flag meaningful vegetation change, (ii) inspection of the NDVI change histogram for the study area showing an elbow near -0.10, and (iii) visual checks over representative inselberg sites where -0.10 best separated stable surfaces from clearly degraded patches. Pixels not meeting NDVI change ≤ -0.10 were considered stable/unchanged for the purposes of decline mapping. These changes were considered at sites identified as inselberg habitats. Areas with a decrease greater than 0.1 in NDVI were marked as 1, indicating substantial vegetation loss or change, while all other areas were marked as 0. A binary raster was generated based on NDVI change.

2.5 Anthropogenic Factors Influencing the Vegetation Dynamics of Inselberg Habitats

Due to the proximity to the capital district of Colombo, inselberg habitats in Gampaha district are threatened by increasing anthropogenic interventions. We identified two main factors that are associated with the inselberg habitats: Presence of temples (monasteries) and mining quarries. While the former is related to the tradition and culture with a level of sustainability, the later destroys entire inselberg habitats along with associated environmental values. All the temples and quarries within a 500 m buffer from the inselberg site polygons were identified, mapped and considered for the analysis. A binary logistic regression model was used to examine the impact of mining quarries and Buddhist monasteries on vegetation change. This method has been used in past work for similar purposes in determining the factors that affect vegetation change [37] and [38]. NDVI reduction (>0.1) was set as the dependent variable, with temple and quarry presence as independent variables. The logistic regression equation (Equation 1) is as follows:

$$e^{g(Y)} = e^{\beta 0 + \beta 1(Temples) + \beta 2(Quarries)}$$

Equation 1

Where:

$g(Y)$ is the logit link function of the probability of vegetation loss

P is the probability of observing a significant (>0.10) NDVI change.

β_0 is the intercept.

β_1 and β_2 are the coefficients for the presence of temples and quarries, respectively.

The logistic regression model was fitted using R's *glm()* function with a binomial family link function. The following hypotheses were tested based on the developed model;

Null Hypothesis (H_0): The presence of Buddhist monasteries and mining quarries does not significantly influence vegetation change (NDVI reduction).

H_0: $\beta_{Temples} = 0$ (No effect of temples on NDVI)
H_0: $\beta_{Quarries} = 0$ (No effect of quarries on NDVI)

Alternative Hypothesis (H_1): The presence of Buddhist monasteries and mining quarries is associated with increased vegetation loss, while the presence of Buddhist monasteries is associated with reduced vegetation loss.

H_1: $\beta_{Temples} \neq 0$ (NDVI is affected by temples)
H_1: $\beta_{Quarries} \neq 0$ (NDVI is affected by quarries)

To calculate the probabilities of NDVI change for different combinations of Temples and Quarry presence, logistic regression equation (Equation 2) was used:

$$P = \frac{e^{g(Y)}}{1 + e^{g(Y)}}$$

Equation 2

The predicted probabilities (P) for different values of the independent variables were calculated using the predict () function in R with the type = "response" argument, which returns the logistic probability. The resulting probabilities were then visualized using the ggplot2 package to illustrate the effects of temple proximity and quarry proximity on vegetation decline.

3. Results and Discussion

3.1 Covariate Selection and Multicollinearity Analysis

The initial set of 39 environmental and spectral covariates was examined for redundancy and inter-correlation prior to modelling.

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The pairwise correlation matrix (Figure 3) revealed several positive correlations (red clusters) among vegetation indices derived from similar spectral bands, such as NDVI, SAVI, GNDVI, and RENDVI, as well as between moisture- and water-related indices (NDMI, MNDWI). Positive correlations were also evident among the shortwave-infrared bands (Bands 11 and 12) and the mineral-related ratios (CMR, FMR, IOR). In the topographic domain, terrain derivatives representing similar slope or curvature attributes (e.g., slope, terrain ruggedness index, and curvature measures) showed moderate to high inter-correlations. To minimize multicollinearity, variables with Pearson correlation coefficients exceeding |r| > 0.8 were reviewed, and one variable from each correlated pair was removed based on interpretability and contribution to classification. Following this filtering, 28 covariates (Table 3) were retained for Support Vector Machine (SVM) modelling. Eleven highly correlated or redundant variables were excluded (Table 3). The final variable set exhibited acceptable inter-correlation levels (|r| < 0.8) and represented a balanced integration of spectral and geomorphometric information suitable for inselberg habitat classification.

3.2 Inselberg Classification and Covariate Importance

The SVM classifier successfully distinguished inselberg habitats from surrounding landscapes, achieving an overall accuracy of 94.5% and a Kappa coefficient of 70.1% (Table 4). The confusion matrix indicated strong agreement between predicted and reference classes, confirming the suitability of the selected covariates for inselberg mapping. These accuracy levels align with performance ranges reported for SVM-based landform and habitat classification in remote sensing studies [39]. A total of 264 inselberg sites were identified across the district, predominantly in the northeastern and eastern interior, with very few occurring in coastal or low-lying areas (Figure 4). The mapped extent of inselberg habitats totalled approximately 3.4 km². Variable importance analysis revealed that the Digital Elevation Model (DEM), Ferrous Mineral Ratio (FMR), and Sentinel-2 Band 8 (NIR) were the most influential predictors of inselberg presence. DEM provided elevation-based geomorphological discrimination, while FMR and NIR highlighted exposed rock and shallow-soil vegetation characteristics typical of inselbergs. Additionally, Terrain Surface Convexity (TSC) and Soil Adjusted Vegetation Index (SAVI) were identified as important covariates for the model. Secondary predictors contributed marginally and served mainly to refine class boundaries (Figure 5)

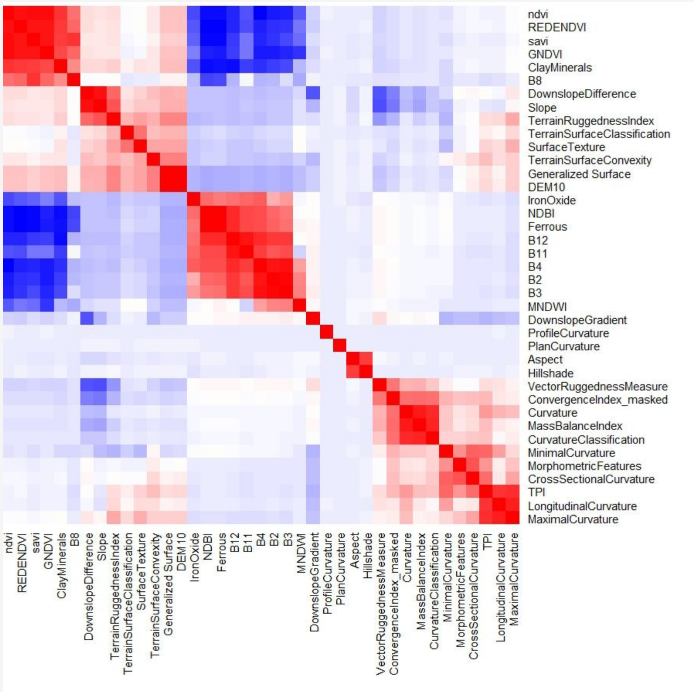

Figure 3: Pairwise correlation matrix of all candidate covariates:
Red tones indicate strong positive correlations, blue tones indicate negative correlations

Table 3: Covariate selection summary showing variables retained and excluded during multicollinearity analysis

Category	Covariates Retained	Covariates Excluded
Spectral Indices	FMR, CMR, MNDWI, GNDVI, NDVI, SAVI, IOR, RENDVI	NDMI
Spectral Bands	Sentinel-2 Bands: Band 2 (Blue), Band 3 (Green), Band 4 (Red), Band 8 (NIR)	Band 11 (SWIR-1), Band 12 (SWIR-2)
Topographic Covariates	DEM, Terrain Surface Convexity, Downslope Difference, Slope, Terrain Ruggedness Index, Maximal Curvature, Minimal Curvature, Longitudinal Curvature, Cross-Sectional Curvature, Profile Curvature, Plan Curvature, Surface Texture, Topographic Position Index (TPI), Vector Ruggedness Index (VRM), Mass Balance Index, Convergence Index	Aspect, Hillshade, Generalized Surface, Curvature Classification, Morphometric Features, MRRTF (Multi-Resolution Ridge Top Flatness), MRVBF (Multi-Resolution Valley Bottom Flatness), Terrain Surface Classification

Table 4: Confusion matrix and accuracy assessment of the classification model

Actual / Predicted	Predicted Presence	Predicted Absence	Row Total	Producer's Accuracy (%)
Actual Presence	56	10	66	84.80%
Actual Absence	21	172	193	89.10%
Column Total	77	182	259	
User's Accuracy (%)	72.70	94.50		
			Overall Accuracy	**88.0%**
			Kappa Coefficient (κ)	**70.1%**

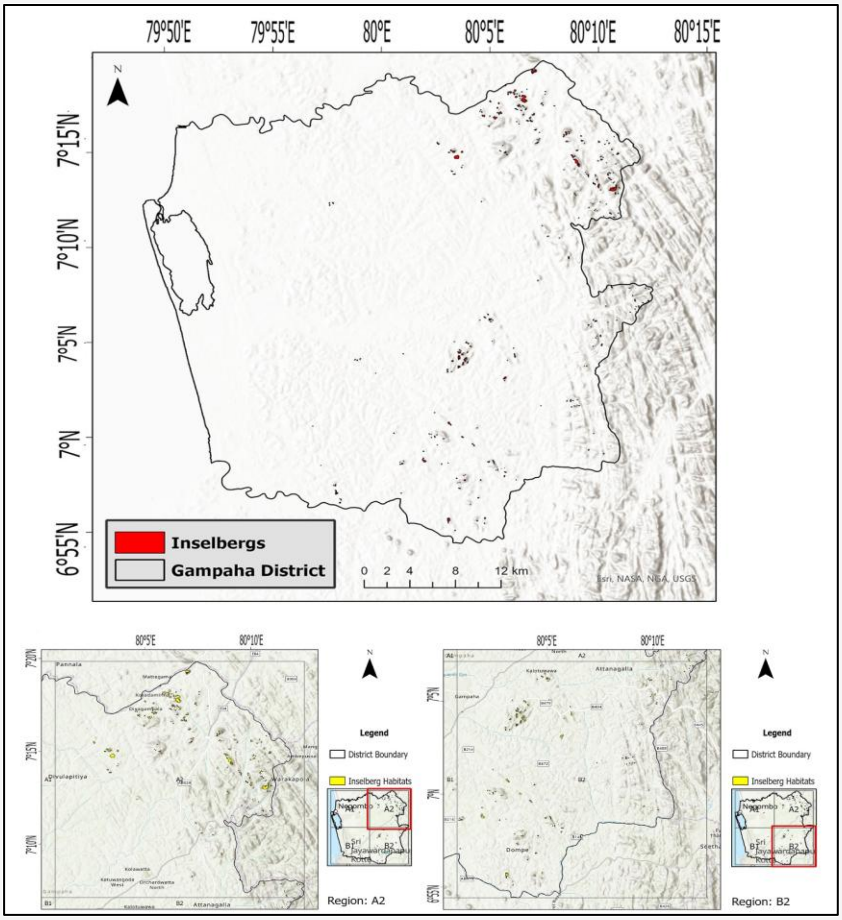

Figure 4: Inselberg habitat map of Gampaha district Sri Lanka

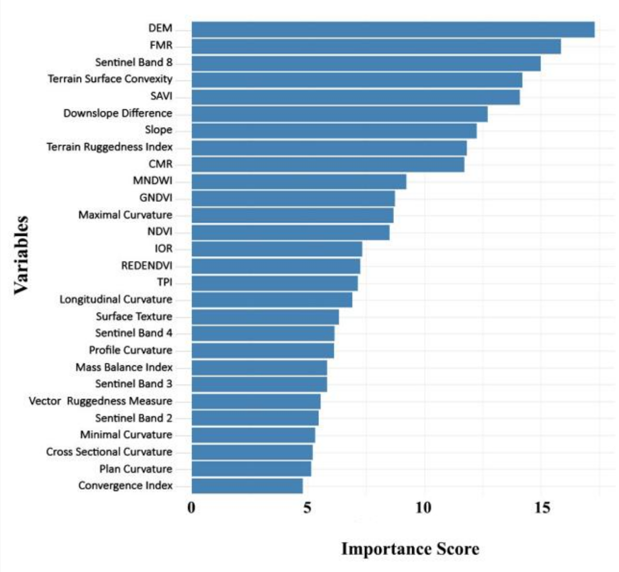

Figure 5: Covariate importance scores in the SVM model prediction

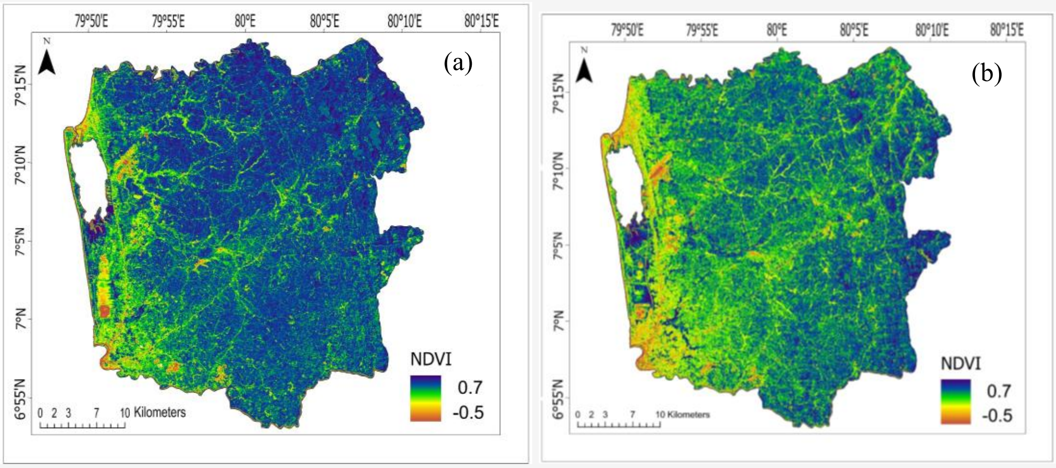

Figure 6: NDVI (a) 2001 and (b) 2024

3.2 Vegetation Dynamics Based on NDVI Change

Figure 6 displays the continuous NDVI surfaces (stretched symmetrically for visual contrast), whereas Figure 7 shows only those pixels meeting the decline threshold ($\Delta\text{NDVI} \leq -0.10$). Consequently, declines appear as scattered patches in Figure 7 rather than covering the entire district. Differences in color ramp and dynamic range between a continuous map (Figure 6) and a binary threshold map (Figure 7) also contribute to the distinct visual impression. The NDVI ranged from -0.46 to 0.51 in 2001 (Figure 6(a)) and -0.07 to 0.66 in 2024 (Figure 6(b)). NDVI change detection revealed significant vegetation loss in inselberg habitats over the past two decades (Figure 7). While these NDVI changes reflected various land cover types, they also represent inselberg habitats, which are typically associated with vegetation and biodiversity [18]. Even bare rock formations showed NDVI variations due to surface reflectance changes, making NDVI a valuable tool for detecting habitat alterations. Moreover, even in the absence of any vegetation, the NDVI index provides corresponding scores for the changes of surface reflectance. Therefore, NDVI change raster was used as a tool to identify changes in the inselberg habitats. Further investigation into specific regions of the Gampaha district revealed that when considering the level of NDVI change more urbanized areas have undergone a greater amount of change losing the amount of vegetation over the past two decades. The visual observation of the maps indicated that certain inselberg habitats were relatively preserved while some others had been altered.

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The preserved inselberg habitats included areas such as "Pilikuththuwa", "Maligathenna" and some other temple-associated habitats. Most of the degraded inselberg habitats showed evidence of mining quarries and construction projects such as highway developments within their vicinity.

3.3 Influence of Anthropogenic Activities

The analysis provided insights into factors contributing to vegetation loss over time. Past literature suggests that most inselberg habitats in Gampaha district as well as other areas of the country are threatened by the establishment of mining quarries [18]. Furthermore, the presence of temples and other religious places may have an influence on the conservation of these inselbergs due to the low level of human interventions because of religious custodianships [15][16] and [18]. When the presence of these two factors (Figure 8) was tested alone with the factor of changed/unchanged NDVI, it was identified that out of the 264 sites that represent inselberg habitats, 77 have been altered during the period from 2001-2024. Mining quarries were present within the inselberg habitats or inside the 500 m buffer range at 92 sites. Temples were present within or adjacent to 74 inselberg sites.

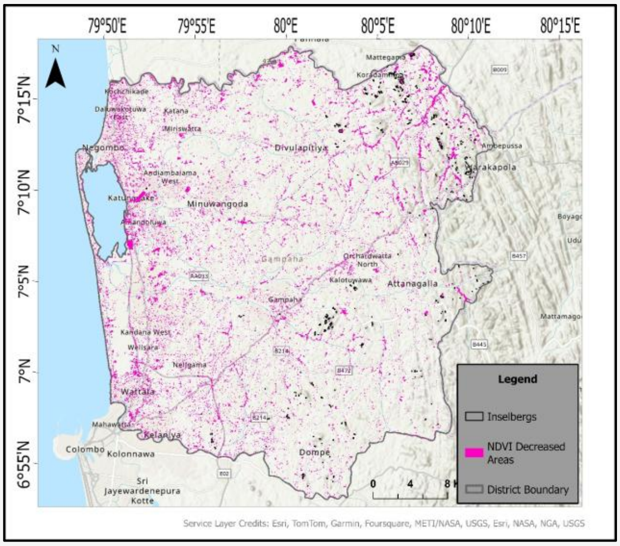

Figure 7: NDVI decrease (>0.10) in Gampaha district from 2001-2024 with the topographic base map

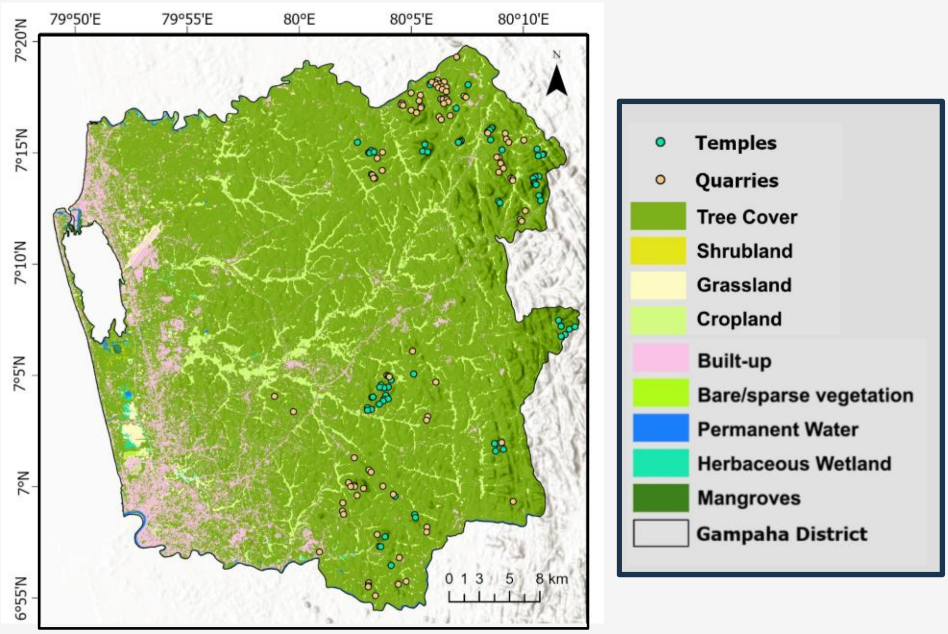

Figure 8: Landcover map of Gampaha district and distribution of inselberg associated temples and quarries

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Table 4 summarises the logistic regression results for the two predictors: *Temple proximity* and *Quarry proximity*. The model coefficients represent the change in the log-odds of vegetation decline for a one-unit change in each predictor. A positive coefficient indicates an increased likelihood of vegetation decline, whereas a negative coefficient indicates a reduced likelihood. The standard error (SE) reflects the uncertainty around each coefficient estimate; smaller SE values indicate greater confidence in the estimate. The z-value and p-value together test whether each predictor has a statistically significant effect on the response, with $p < 0.05$ indicating meaningful contribution to the model.

The null deviance represents the model fit when no predictors are included (intercept-only model), whereas the residual deviance represents the deviance after the selected predictors are added. The large reduction from 318.72 (null deviance) to 141.83 (residual deviance) indicates a substantial improvement in model fit once *Temple* and *Quarry* variables were included. The logistic regression showed that quarry presence significantly increased the probability of vegetation loss (coefficient = 4.317, $p < 0.001$), whereas temple presence significantly reduced the likelihood of vegetation loss (coefficient = −2.007, p = 0.005) (Table 5). Converting these effects to odds ratios, quarry proximity increased the odds of vegetation decline by $e^{4.317} \approx 75$ times, while temple proximity reduced the odds by $e^{-2.007} \approx 0.13$, corresponding to an approximate 87% decrease in the likelihood of vegetation loss. These results highlight that quarry activity poses a substantial threat to inselberg vegetation, whereas temple-associated locations tend to experience reduced disturbance pressure (Figure 9 and 10).

Table 5: Binary logistic regression model results

Parameter	coefficient	Standard error	Z value	*P* value
Intercept	-2.895	0.4232	-6.839	0.000
Temples	-2.007	0.7286	-2.755	0.005
Quarry	4.317	0.4925	8.767	0.000
Null deviance	318.72 on 263 degrees of freedom			
Residual deviance	141.83 on 261 degrees of freedom			

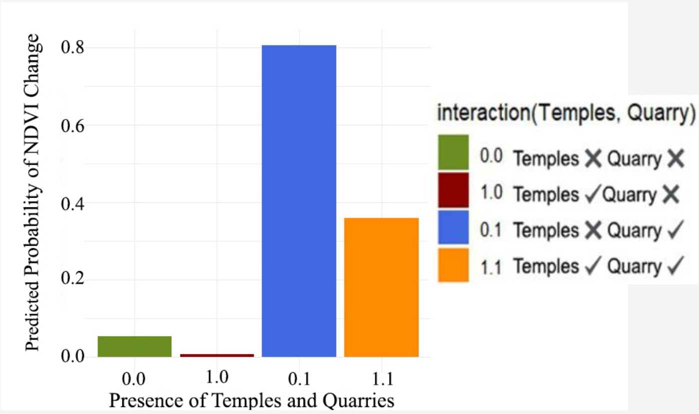

Figure 9: Predicted probability of NDVI change in the presence of temples and quarries

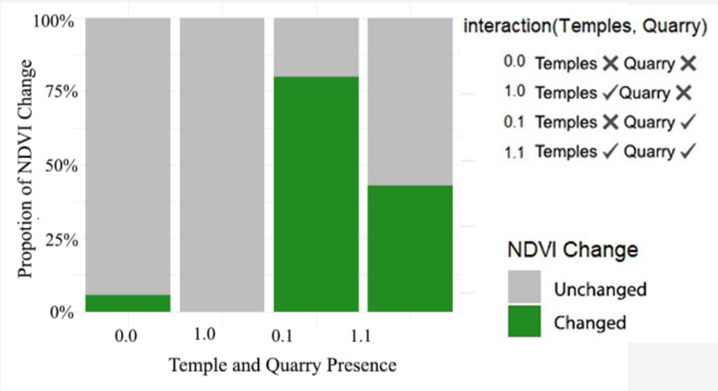

Figure 10: Portion of NDVI change by temples and quarries presence

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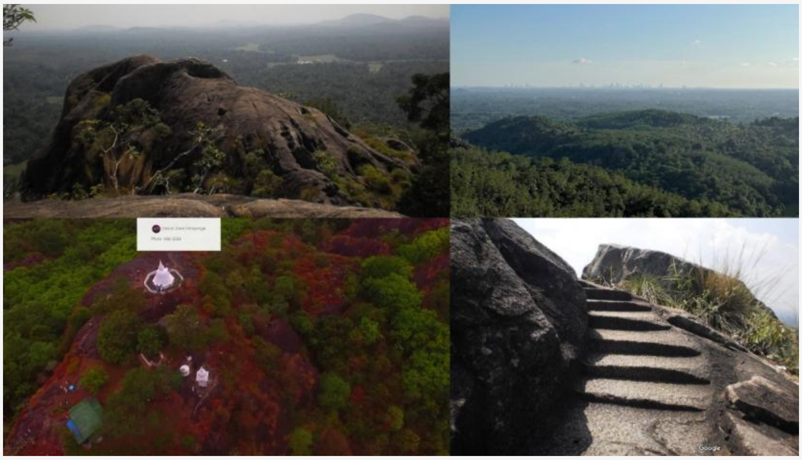

Figure 11: Maligathenna Temple and associated inselberg habitat which is relatively protected with high recreational value

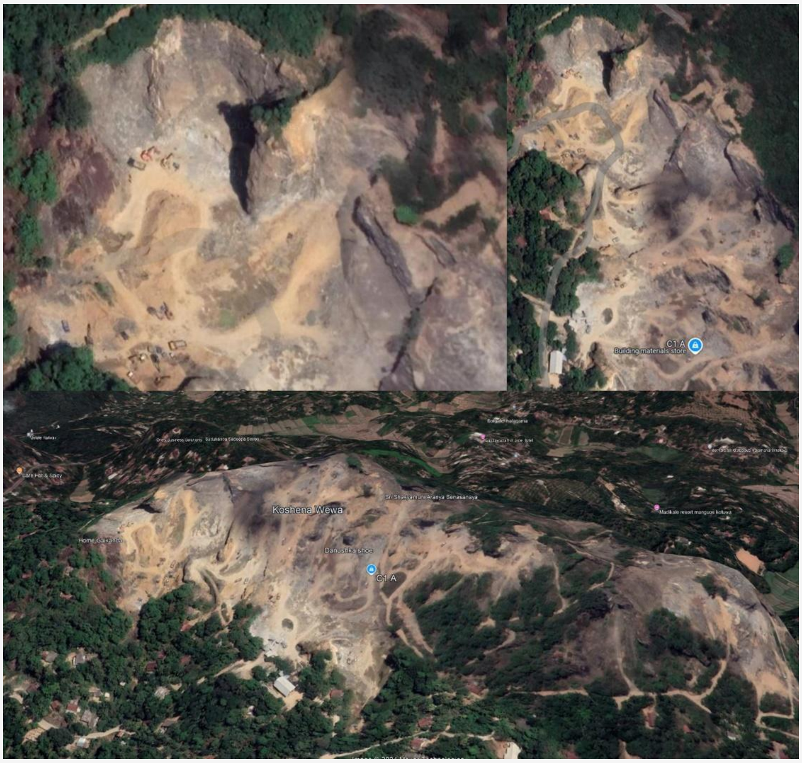

Figure 12: Alteration and degradation of inselberg habitats in the southern region of Gampaha district

The results indicate that mining quarries pose a significant threat to these ecosystems, whereas historical temples have minimal impact and generate a shielding effect from other adverse anthropogenic interventions (Figure 11 and 12). However, any form of new development should be discouraged to prevent further degradation. Figure 11 illustrates the Maligathenna Temple and its surrounding inselberg habitat, which remains relatively intact and protected due to its cultural and religious significance. The area retains high recreational and scenic value, with minimal anthropogenic disturbances, highlighting the potential role of community-managed sites in conservation. Figure 12 shows extensive alteration and degradation of inselberg habitats in the southern region of Gampaha district, primarily resulting from large-scale granite quarrying. The images reveal severe habitat loss and landscape transformation, where extraction activities have stripped away vegetation and exposed bare rock surfaces, posing significant threats to biodiversity and ecosystem stability in these unique habitats. While this study demonstrates the applicability of Support Vector Machines (SVM) for inselberg classification, certain limitations must be acknowledged. First, the analysis was confined to the Gampaha District, and thus the model's generalizability to other regions with differing geomorphological and ecological contexts remains to be tested. Second, the availability and resolution of input data, particularly spectral bands and derived indices, may influence classification accuracy; higher-resolution datasets (e.g. LiDAR) could potentially improve detection of smaller or more fragmented inselbergs. Lastly, the absence of temporal ground-truth data limited the validation of NDVI-based vegetation change assessments over the two-decade period. Addressing these limitations in future work could refine model robustness and enhance its utility for conservation planning at broader scales.

Inselbergs are recognized globally as biodiversity hotspots and micro-refugia due to their unique topography and isolated nature [40]. Similar to findings from Brazilian inselberg systems where quarrying has caused irreversible habitat degradation [41] and [42], our study highlights significant anthropogenic impacts in Sri Lanka's Gampaha District, particularly from granite mining activities [18] and [19]. The observed vegetation loss aligns with NDVI-based assessments elsewhere [37][38] and [43], reinforcing the utility of remote sensing for long-term habitat monitoring. Especially, the findings of [37] presents similar observations at active quarrying sites in România where NDVI reductions have been observed. Notably, the relatively intact inselberg habitats surrounding Buddhist monasteries underscore the role of cultural landscapes in conservation, a pattern also reported in sacred groves across South Asia [44] and [45] and also by the work of [18] on inselberg habitats in Sri Lanka.

This suggests that leveraging community and religious stewardship could be an effective conservation strategy for these fragmented and threatened habitats. Furthermore, the identification of DEM and spectral indices (e.g., SAVI, NIR) as key predictors resonates with studies emphasizing the role of microclimatic and geomorphological variables in shaping inselberg vegetation patterns [40][42][46] and [47]. These findings collectively advocate for integrating geospatial tools with local conservation initiatives to safeguard Sri Lanka's inselberg ecosystems from expanding quarrying pressures.

4. Conclusion

This study demonstrates the effectiveness of integrating remote sensing and Support Vector Machine (SVM) modelling to map inselberg habitats and evaluate vegetation dynamics in the Gampaha District of Sri Lanka. The five most important factors in inselberg extraction are DEM, FMR, NIR band, TSC and SAVI. SVM classification successfully identified 264 inselberg sites with strong classification accuracy. These findings confirm that geomorphologically driven topographic features and rock-associated spectral responses are reliable indicators for extracting inselbergs from surrounding lowland terrain.

Vegetation change analysis revealed localized declines across several inselberg habitats over the past two decades, with quarry expansion identified as a major anthropogenic driver. In contrast, temple-associated inselbergs exhibited greater vegetation retention, illustrating the stabilizing influence of cultural custodianship. The results emphasize the dual role of human activity both destructive and protective in shaping vegetation outcomes on isolated rocky ecosystems. The study provides a replicable geospatial workflow for inselberg habitat assessment and highlights the value of coupling remote sensing with anthropogenic driver analysis to guide conservation planning. Policy recommendations include strengthening environmental regulations for quarrying activities, enhancing conservation efforts through community-based initiatives and Buddhist monastery stewardship, and implementing nature-based solutions such as sustainable tourism with recreational activities in suitable inselberg habitats. Additionally, expanding the application of machine learning models for broader habitat mapping in Sri Lanka is suggested. By adopting geospatial technology and data-driven conservation planning, the long-term sustainability of inselberg habitats can be ensured.

5. Limitations

This study was limited to a single district, and the generalizability of the model to other geological or ecological settings in Sri Lanka has not yet been assessed. Ground verification was restricted to accessible locations, and future work would benefit from expanded field sampling and plot-level vegetation measurements. Additionally, the spatial resolution of freely available satellite datasets may limit the detection of small or fragmented inselbergs. Finally, only two anthropogenic factors were evaluated; incorporating additional socio-economic variables could further improve explanatory power.

6. Recommendations

Future studies should expand this framework to other districts to develop a national-scale inselberg inventory. Incorporating higher-resolution datasets, including UAV imagery or LiDAR, is recommended to enhance object delineation and vegetation characterization. From a management perspective, regulating quarry expansion near inselberg clusters, strengthening buffer-zone enforcement, and formally integrating temple custodianship into community-based conservation programs are encouraged. Establishing periodic remote sensing-based monitoring would support early detection of habitat degradation and inform long-term conservation strategies.

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References

[1] da Silveira, V. A., Veloso, G. V., de Paula, H. B., dos Santos, A. R., Schaefer, C. E. G. R., Fernandes-Filho, E. I. and Francelino, M. R., (2022). Modeling and Mapping of Inselberg Habitats for Environmental Conservation in the Atlantic Forest and Caatinga Domains, Brazil. *Environmental Advances*, Vol. 8. https://doi.org /10.1016/j.envadv.2022.100209.

[2] Burke, A., (2003). Inselbergs in a Changing World - Global trends. *Diversity and Distributions*, Vol. 9(5), 375–383. https://doi. org/10.1046/j.1472-4642.2003.00035.x.

[3] Coor, R., Warren, R. and Goudie, A., (1993). *Desert Morphology*. UCL Press, London.

[4] Porembski, S. and Barthlott, W., (2000). Granitic and Gneissic Outcrops (Inselbergs) as Centers of Diversity for Desiccation-tolerant Vascular Plants. *Plant Ecology*, Vol. 151, 19–28.

[5] Barthlott, W., and Porembski, S. (2000). Why Study Inselbergs? In S. Porembski & W. Barthlott (Eds.), *Inselbergs*. Springer, Berlin.

[6] Thammaboribal, P., and Tripathi, N. (2024). Predicting Land Use and Land Cover Changes in Pathumthani, Thailand: A Comprehensive Analysis from 2013 to 2023 Using Landsat Satellite Imagery and CA-ANN Algorithm, with Projections for 2028 and 2038. *International Journal of Geoinformatics*, Vol. 20(5), 13–27. https://doi.org/10.52939/ijg.v20 i5.3225.

[7] Huang, F., Cao, Z., Guo, J., Jiang, S. H., Li, S. and Guo, Z., (2020). Comparisons of Heuristic, General Statistical and Machine Learning Models for Landslide Susceptibility Prediction and Mapping. *CATENA*, Vol. 191. https://doi. org/10.1016/j.catena.2020.104580.

[8] Maxwell, A. E., Warner, T. A. and Fang, F., (2018). Implementation of Machine-Learning Classification in Remote Sensing: An Applied Review. *International Journal of Remote Sensing*, Vol. 39(9), 2784–2817. https://doi.org /10.1080/01431161.2018.1433343.

[9] Shivaprakash, K. N., Swami, N., Mysorekar, S., Arora, R., Gangadharan, A., Vohra, K. and Kiesecker, J., M., (2022). Potential for Artificial Intelligence (AI) and Machine Learning (ML) Applications in Biodiversity Conservation, Managing Forests, and Related Services in India. *Sustainability*, Vol. 14(12). https://doi.org/10.3390/su14127154.

[10] Aji, A., Husna, V., and Purnama, S. (2024). Multi-Temporal Data for Land Use Change Analysis Using a Machine Learning Approach (Google Earth Engine). *International Journal of Geoinformatics*, Vol. 20(4), 19–28. https://doi. org/10.52939/ijg.v20i4.3145.

[11] Bhatt, P., Maclean, A., Dickinson, Y. and Kumar, C., (2022). Fine-Scale Mapping of Natural Ecological Communities Using Machine Learning Approaches. *Remote Sensing*, Vol. 14(3). https://doi.org/10.3390/rs1 4030563.

[12] Herath, H. M. B. S., (2025). A Review of Integrating Geospatial Technologies and Artificial Intelligence for Habitat Connectivity Assessment in Fragmented Landscapes. *Vidyodaya Journal of Humanities and Social Sciences*, Vol 10(02). 60–70. https://doi.org/ 10.31357/fhss/vjhss.v10i02.05.

[13] Souza, C. M. P. de, Thomazini, A., Schaefer, C. E. G. R., Veloso, G. V., Moreira, G. M. and Fernandes Filho, E. I., (2018). Multivariate Analysis and Machine Learning in Properties of Ultisols (Argissolos) of Brazilian Amazon. *Revista Brasileira de Ciência do Solo*, Vol. 42. https://doi.org/10.1590/18069657rbcs2017041 9.

[14] Jayasekara, D. and Herath, H., (2024). Application of AI-based Modelling and Remote Sensing to Assess Inselberg Habitats in Gampaha District, Sri Lanka. In *Asian Conference on Remote Sensing (ACRS 2024)*. ACRS Colombo. 1–26.

[15] Katupotha, J. and Ravibhanu, A., (2020). Geotourism and Geoheritage Potentials: Vistas and Unique Opportunities of Sri Lanka. *WILDLANKA*, Vol. 8(2), 50–099.

[16] Katupotha, J. and Kodituwakku, K., (2015). Utility of Inselbergs and Boulders as Rock-Shelter Monasteries: A Geoarchaeological Study of Sigiriya and its Environs. *Journal of Social Sciences and Humanities*, Vol. 1(4), 354–360.

[17] Katupotha, J., (2015). Diversity of Vegetation Types of the Pidurangala Granitic Inselberg with Ancient Forest Monastery, Near Sigiriya, Sri Lanka: A Preliminary Study. *Research Publication to Commemorate 125 Years of Service by the Department of Archaeology*. Department of Archaeology, State Ministry of Cultural Affairs, Sri Lanka. 157-167.

[18] Katupotha, J. and Gamage, S., (2023). Inselbergs in Sri Lanka: their Ecology and Biodiversity Value. In *WILDLANKA International Symposium – 2023*. https://doi.org/10.13140/RG.2.2.30080.61440.

[19] Katupotha, J., Ratnayake, N. P., Batapola, N. M. and Katupotha, J., (2024). Spatial Distribution of Inselbergs and Their Relationship to Geomorphological and Geological Controls in Gampaha District, Sri Lanka. *Article in Journal of the Geological Society of Sri Lanka*, Vol. 24(2), 43–54. https://doi.org/10.4038/cjas.

[20] Fernando, G. M. T. S., (2018). Identification of Urban Heat Islands & Its Relationship with Vegetation Cover: A Case Study of Colombo & Gampaha Districts in Sri Lanka. *Journal of Tropical Forestry and Environment*, Vol 8(2), 82–100. https://doi.org/10.31357/jtfe.v8i2.3765.

[21] Withanage, G. P., Viswakula, S. D., Nilmini Silva Gunawardena, Y. I. and Hapugoda, M. D., (2018). A Forecasting Model for Dengue Incidence in the District of Gampaha, Sri Lanka. *Parasites and Vectors*, Vol 11(1), 1-10. https://doi.org/10.1186/s13071-018-2828-2.

[22] Premakantha, K. T., Chandani, R. P. D. S., Kingsly, S. A. D., Dias, H. U. and Kekulandara, N. S. B., (2021). Forest Cover Assessment in Sri Lanka Using High Resolution Satellite Images. *The Sri Lanka Forester*, Vol. 40, 1–16.

[23] Ali, Z., Jaelani, L., and Sumargana, L. (2024). Detection of Corn Phenological Stages with Landsat Satellite Imagery: A Case Study in Ngawi Regency, Indonesia. *International Journal of Geoinformatics*, Vol. 20(9), 1–15. https://doi.org/10.52939/ijg.v20i9.3535.

[24] Pantazi, X. E., Moshou, D. and Bochtis, D., (2020). Utilization of Multisensors and Data Fusion in Precision Agriculture. *Intelligent Data Mining and Fusion Systems in Agriculture*. 103–173. Elsevier. https://doi.org/10.1016/B978-0-12-814391-9.00003-0.

[25] Liang, P., Qin, C., Zhu, A., Hou, Z., Fan, N. and Wang, Y., (2020). A Case-based Method of Selecting Covariates for Digital Soil Mapping. *Journal of Integrative Agriculture*, Vol 19(8), 2127–2136. https://doi.org/10.1016/S2095-3119(19)62857-1.

[26] Xu, H., (2006). Modification of Normalised Difference Water Index (NDWI) to Enhance Open Water Features in Remotely Sensed Imagery. *International Journal of Remote Sensing*, Vol. 27(14), 3025–3033. https://doi.org/10.1080/01431160600589179.

[27] Evangelides, C. and Nobajas, A., (2020). Red-Edge Normalised Difference Vegetation Index (NDVI705) from Sentinel-2 Imagery to Assess Post-fire Regeneration. *Remote Sensing Applications: Society and Environment*, Vol 17. https://doi.org/10.1016/j.rsase.2019.100283.

[28] Zhou, X., Liu, D., Bu, H., Deng, L., Liu, H., Yuan, P., Du, P. and Song, H., (2018). XRD-based Quantitative Analysis of Clay Minerals Using Reference Intensity Ratios, Mineral Intensity Factors, Rietveld, and Full Pattern Summation Methods: A Critical Review. *Solid Earth Sciences*, Vol 3(1), 16–29. https://doi.org/10.1016/j.sesci.2017.12.002.

[29] Abay, H. H., Legesse, D., Venkata Suryabhagavan, K. and Atnafu, B., (2024). Mapping of ferric (Fe3+) and ferrous (Fe2+) Iron Oxides Distribution Using ASTER and Landsat 8 OLI data, in Negash Lateritic Iron Deposit, Northern Ethiopia. *Geology, Ecology, and Landscapes*, Vol. 8(3), 223–240. https://doi.org/10.1080/24749508.2022.2130556.

[30] Segal, D., (1982). Theoretical Basis for Differentiation of Ferric-iron Bearing Minerals, Using Landsat MSS data. Proceedings of Symposium for Remote Sensing of Environment. In *2nd Thematic Conference on Remote Sensing for Exploratory Geology*. Fort Worth, Texas. 951.

[31] Brenning, A., Bangs, D. and Becker, M., (2023). RSAGA: SAGA Geoprocessing and Terrain Analysis. R package version 1.4.1. [Online]. Available: https://github.com/r-spatial/rsaga. [Accessed: May. 2, 2025].

[32] R Core Team. (2024). R: A language and Environment for Statistical Computing. Vienna, Austria: R Foundation for Statistical Computing. [Online]. Available: https://www.R-project.org/. [Accessed: May. 2, 2025].

[33] Shi, D., and Yang, X., (2016). An Assessment of Algorithmic Parameters Affecting Image Classification Accuracy by Random Forests. *Photogrammetric Engineering & Remote Sensing*, Vol. 82(6), 407–417. https://doi.org/10.14358/PERS.82.6.407.

[34] Singh, A., (1989). Digital Change Detection Techniques Using Remotely-sensed Data. *International Journal of Remote Sensing*, Vol 10(6), 989–1003. https://doi.org/10.1080/01431168908903939.

[35] Jin, S. and Sader, S. A., (2005). MODIS Time-series Imagery for Forest Disturbance Detection and Quantification of Patch Size Effects. *Remote Sensing of Environment*, Vol 99(4), 462–470. https://doi.org/10.1016/j.rse.2005.09.017.

[36] Demissie, F., Yeshitila, K., Kindu, M. and Schneider, T., (2017). Land Use/Land Cover Changes and their Causes in Libokemkem District of South Gonder, Ethiopia. *Remote Sensing Applications: Society and Environment*, Vol. 8, 224–230. https://doi.org/10.1016/j.rsase.2017.10.001.

[37] Topliceanu, T. S., Geanina, F., Vizireanu, M. G. and Telea, A. E., (2025). Assessment of Renaturation in Active and Inactive Quarries Using Remote Sensing Data. *Annals of the Academy of Romanian Scientists Series on Biological Sciences*, Vol 14(1), 30–46. https://doi.org/10.56082/annalsarscibio.2025.1.30.

[38] Worachairungreung, M., Kulpanich, N., Yodsuk, P., Kaewnet, T., Sae-ngow, P., Ngansakul, P., Thanakunwutthirot, K. and Hemwan, P., (2024). Using a Logistic Regression Model to Examine the Variables Influencing Changes in Northern Thailand's Forest Cover and Comparing Machine Learning Algorithms. *Forests*, Vol. 15(6). https://doi.org/10.3390/f15060981.

[39] Praticò, S., Solano, F., Di Fazio, S. and Modica, G., (2021). Machine Learning Classification of Mediterranean Forest Habitats in Google Earth Engine Based on Seasonal Sentinel-2 Time-Series and Input Image Composition Optimisation. *Remote Sensing*, Vol. 13(4). https://doi.org/10.3390/rs13040586.

[40] Porembski, S. and Barthlott, W., (2000). *Granitic and Gneissic Outcrops (Inselbergs) as Centers of Diversity for Desiccation-tolerant Vascular Plants*. *Plant Ecology*, Vol. 151, 19-28.

[41] Gondim Lambert Moreira, F. A., Carvalho, F. and de Paula, L., (2025). Non-native Plant Species on Inselbergs of Brazilian Tropical Forests: Checklist and Insights for Biodiversity Management and Conservation. *ARPHA Preprints*. https://doi.org/10.3897/arphapreprints.e156814.

[42] Porembski, S., (2007). Tropical Inselbergs: Habitat Types, Adaptive Strategies and Diversity Patterns. *Brazilian Journal of Botany*, Vol 30(4), 579–586.

[43] Aristizábal-Botero, Á., Páez-Pérez, D., Realpe, E. and Vanschoenwinkel, B., (2021). Mapping Microhabitat Structure and Connectivity on a Tropical Inselberg Using UAV Remote Sensing. *Progress in Physical Geography: Earth and Environment*, Vol. 45(3), 427–445. https://doi.org/10.1177/0309133320964327.

[44] Zannini, P., Frascaroli, F., Nascimbene, J., Persico, A., Halley, J. M., Stara, K., Midolo, G. and Chiarucci, A., (2021). Sacred Natural Sites and Biodiversity Conservation: A Systematic Review. *Biodiversity and Conservation*, Vol. 30(13), 3747–3762. https://doi.org/10.1007/s10531-021-02296-3.

[45] Bhagwat, S. A. and Rutte, C., (2006). Sacred Groves: Potential for Biodiversity Management. *Frontiers in Ecology and the Environment*, Vol. 4(10), 519–524. https://doi.org/https://doi.org/10.1890/1540-9295(2006)4[519:SGPFBM]2.0.CO;2

[46] Couto, D. R., Francisco, T. M., De Paula, L. F. A., Paula, R. R. and Nascimento, M. T., (2025). Woody Vegetation on Tropical Inselbergs: Floristic-structural Characterization and Aboveground Carbon Storage. *Journal of Mountain Science*, Vol 22(5), 1517–1534. https://doi.org/10.1007/s11629-024-8961-9.

[47] Vanschoenwinkel, B., de Paula, L. F. A., Snoeks, J. M., Van der Stocken, T., Buschke, F. T., Porembski, S. and Silveira, F. A. O., (2025). The Ecological and Evolutionary Dynamics of Inselbergs. *Biological Reviews*, Vol. 100(2), 481–507. https://doi.org/10.1111/brv.13150.

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