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Spatial Patterns and Multiple Linear Regression Model for Forest Settlement and Vegetation using Remote Sensing and Geospatial Techniques. A Case Study in Sirumalai Hill

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Abstract

Accessing localized information in densely forested areas poses significant challenges. This study utilizes Sentinel-2 imagery with 10m NDVI data to derive a detailed vegetation map, complemented by high-resolution Google Earth feature identification for cross-verification. The primary aim is to map the forest landscape comprehensively and analyze the spatial patterns of settlements and forest-agriculture interactions within the forest, using publicly available data sources. The study specifically examines areas with slopes exceeding 23.8 degrees, which are unsuitable for settlements due to the heightened risk of landslides. By correlating NDVI data with slope calculations through a multiple linear regression model, the study identifies significant statistical relationships, with an R^2 *value of 0.2 and a P-value of 0.006. Results indicate that the forest's spatial structure supports two distinct settlement patterns: linear settlements on slopes ranging from 0 to 8.6 degrees and scattered settlements on slopes between 16.22 and 23.79 degrees. These findings highlight the critical influence of slope on settlement distribution. This research provides valuable insights into the living environments of forest residents and underscores the importance of sustainable forest ecosystem management.*

Keywords: Remote Sensing; Recoding; Unsupervised classification; NDVI; LCLU; DEM; Sirumalai; Settlement pattern 2

1 Introduction

Due to rapid developmental activities and the need to expand land for construction[(1)], remote sensing (RS) is an excellent tool for forest monitoring, as it allows for the easy monitoring of inaccessible areas using NDVI calculations[(2,3)]. The study area of Sirumalai hill, located in the southernmost Eastern Ghats in India, is characterized by dense semi-evergreen forests[(4)] and saw the emergence of numerous hill stations after the 1820s[(5)].

Agricultural yield is the primary economic source for farmers and agricultural laborers who require roads to access harvesting sites[(6)]. Delineation of road lines, footpaths, and other infrastructure can be effectively carried out using Google Earth. Forests not only meet human needs and ensure survival but also drive local economic development[7]. Agricultural vegetation and natural forest canopy can be easily differentiated using Sentinel-2 imagery[8] and Google Earth. Sentinel-2 is capable of mapping complex landscapes, including agriculture, settlement patterns, roads, and water bodies in the Sirumalai forest, though it cannot interpret individual tree species. However, these two data sources are highly valuable for distinguishing natural vegetation from manmade cultivation and settlement patterns across the study area[8].

Satellite sensors, equipped with multispectral instruments comprising 13 bands, are designed to support vegetation, land cover, and environmental monitoring. The spectral mixing of satellite imagery varies, as neighboring pixels do not have the same spectral reflectance curve, which can improve classification performance. Digital Elevation Models (DEMs) form the basis for slope analysis and can be further analyzed through Geographic Information System (GIS) techniques[9–13]. Forest land cover and human occupation are accurately identified using medium-resolution imagery and high-resolution Google Earth data. Medium-spatial-resolution multispectral sensors are particularly useful for estimating vegetation coverage[14].

Settlement patterns in forested areas tend to be scattered due to factors like hillslopes, vegetation cover, and valleys, as well as the integration of residential activities with the surrounding environment[15]. Forest structural dimensions are organized by geographical scale, landscape, patches, and other topological categories[16,17].

Polluted waste, such as the direct deposition of animal feces, can affect water quality[18], alongside human-induced pollution driven by increasing and varied needs. Effective forest management plans are necessary to maintain timber resources and landscape management.

2 Study area

The study area of Sirumalai hill is located in middle of Dindigul and Madurai district in Tamil Nadu and it's aerial extension between 77°54'51.828"E 10°17'48.753"N and 78°12'6.132"E 10°6'49.578"N.

The study area is located 25 km from Dindigul town and 85 km from Madurai City. Approximately 85 plant species have been identified in this region[19]. The area is notable for its common vegetable and fruit plantations and the presence of a fast-growing timber tree, Pimenta officinalis Lindle, belonging to the Myrtaceae family, within the coffee estate. The indigenous Sirumalai hill tribes belong to the "Paliyar Tribe"[20].

The hill is well-connected to both Dindigul and Madurai, falling under the jurisdiction of these two districts. Transportation to the hill is facilitated by a roadway featuring 20 hairpin bends, with regular bus and taxi services available from both cities. Figure 1 presents a location map of the study area, derived from Survey of India (SoI) toposheets, which delineates the reserved forest boundary, the areal extent of the forest, roads, benchmarks, pillars, and marked trees and poles that define internal boundaries. Figure 2 offers an aerial view of Sirumalai hill using Sentinel-2 imagery, highlighting the topographic features and reserved forest boundary.

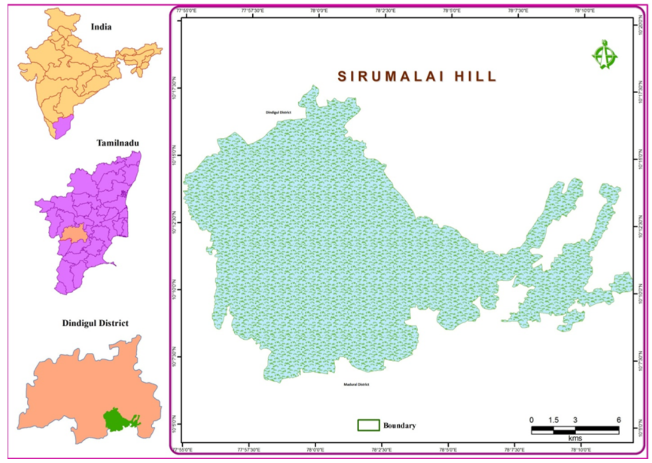

Fig. 1. Location map of study area reserved forest boundary (Source: Survey of India (SoI) Toposheet 1:50,000 scale)

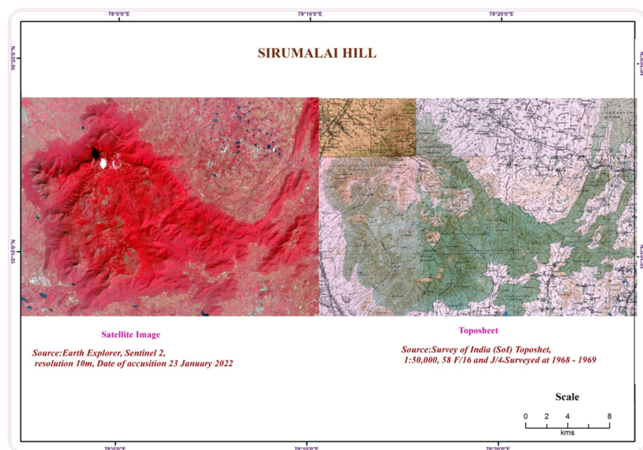

Fig. 2. Sirumalai hill forest cover view through satellite image and toposheet

2.1 Acquisition of RS data and method

Multispectral optical imagery from Sentinel-2, featuring 13 bands with spatial resolution as detailed in Table 1, was utilized in this study. Specifically, Band 2 (blue), Band 3 (green), Band 4 (red), and Band 8 (Near Infrared) were selected for Land Cover and Land Use (LCLU) and Normalized Difference Vegetation Index (NDVI) calculations. The imagery, acquired on January 23, 2022, was sourced from the USGS Earth Explorer.

Table 1. Radiometric and Spatial Resolutions of Sentinel-2

S.No	Band No	Sentinel-2 Band	Radiometric Resolution of wave-length (μm)	Spatial Resolution (m)
1	Band 1	Coastal aerosol	0.443	60
2	**Band 2**	**Blue**	**0.490**	**10**
3	**Band 3**	**Green**	**0.560**	**10**
4	**Band 4**	**Red**	**0.665**	**10**
5	Band 5	Vegetation Red Edge	0.705	20
6	Band 6	Vegetation Red Edge	0.740	20
7	Band 7	Vegetation Red Edge	0.783	20
8	**Band 8**	**NIR**	**0.842**	**10**
9	Band 8A	Vegetation Red Edge	0.865	20
10	Band 9	Water vapor	0.945	60
11	Band 10	SWIR – Cirrus	1.375	60
12	Band 11	SWIR	1.610	20
13	Band 12	SWIR	2.190	20

Source: Earth Resources Observation and Science (EROS) Center, USGS EROS Archive - Sentinel-2

For LCLU analysis, we applied unsupervised classification techniques in digital image processing (DIP), following methodologies established by Karuppaiah et al. (2021) [21], Tamilenthi et al. (2011) [12,13], and Jensen (1989) [22]. These methods have been instrumental in studying various land cover features and resource applications, as documented by Navalgund et al. (1996) [23].

Additionally, Shuttle Radar Topographic Mission (SRTM) data was employed to create slope and Digital Elevation Model maps (Figure 3). The topographic map, at a 1:50,000 scale, illustrated primary geographic features, including contours.

2.2 Remote Sensing for Forest Landscape Mapping

High-resolution images, while offering exceptional detail, come with higher costs and limited photographic coverage. In contrast, multispectral medium resolution images, which are freely available, are more suitable for larger landscapes despite their limited temporal acquisition and potential cloud cover interference. Satellite imagery, therefore, proves highly effective for viewing expansive areas.

Sirumalai hill is strategically connected to the districts of Dindigul and Madurai, with transportation primarily via a roadway featuring 20 hairpin bends. Regular buses and taxis operate from both cities. Figure 1 illustrates the study area's location map, derived from Survey of India (SoI) toposheets, detailing the reserved forest boundary, forest spread, roads, benchmarks, pillars, painted standing trees, and poles marking internal boundaries. Figure 2 presents an aerial view of Sirumalai hill using Sentinel-2 imagery, highlighting the topographic expression of the reserved forest boundary.

2.3 Sentinel-2 Image Processing for Land Cover and Land Use (LCLU)

Sentinel-2 satellite imagery, collected at processing level 1C for January 2022, contains pixel values in surface reflectance. This imagery necessitated atmospheric corrections and digital image processing techniques to accurately extract features from each pixel. This processing is crucial for deriving meaningful data about land cover and land use, ensuring precise analysis and interpretation of the forest landscape.

Table 2. Land Cover and Land Use area calculation based on pixel density

S.No	Class Name	Area in sqkm	%
1	Dense Forest	230.66	79.31
2	Forest Open and Shrub	58.28	20.04
3	Settlement	0.6	0.21
4	Forest Agriculture	1.3	0.45
	Total	290.85	100

The use of unsupervised classification techniques, particularly through the recording method, proved essential for accurately reclassifying mixed pixels. This approach allowed for a thorough examination of the study area, revealing that 79.31% is densely forested, while the remaining portion is comprised of various other features.

Within the forest area, open spaces are devoid of trees or plantations primarily due to timber extraction and landslide-prone slopes [24–26]. Additionally, some regions have experienced vegetation removal. Open forest areas, now dominated by shrubs and tall grasses, cover 58.25 sq km, accounting for 20.04% of the total study area. Approximately 1.3 sq km (0.45%) has been converted to agricultural land. Furthermore, 0.6 sq km (0.21%) of forested land has been transformed into human settlements. However, the potential for rapid settlement expansion is limited due to varying sub-soil surface roughness and other factors such as slope and geology.

2.4 Forest settlement pattern

In the forested area, open spaces without any trees or plantations are evident due to timber collection and landslides on sloped regions [24–26].

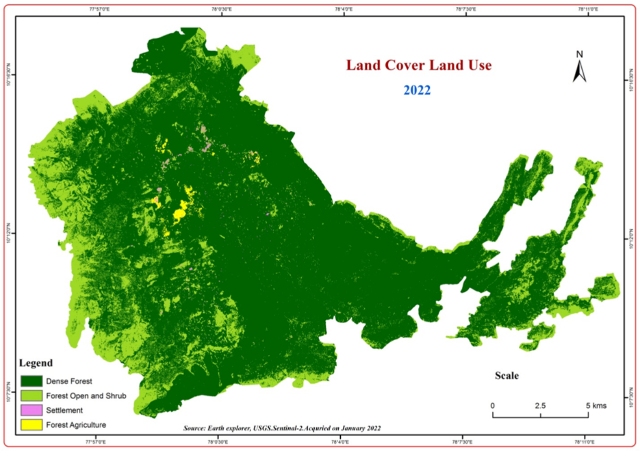

Fig. 3. Land cover feature land-use activities mapped by the source data of Sentinal-2 image with the help of remote sensing techniques of digital image processing

Additionally, some areas have been cleared of vegetation. Within these open forests, shrubs and tall grasses have grown, covering an area of 58.25 sq km, which constitutes 20.04% of the total study area. Moreover, approximately 1.3 sq km (0.45%) of the forest has been converted into agricultural land. Human settlements have expanded into 0.6 sq km (0.21%) of forested land. However, the potential for rapid settlement growth is limited due to the variable sub-soil surface roughness, influenced by factors such as slope and geology.

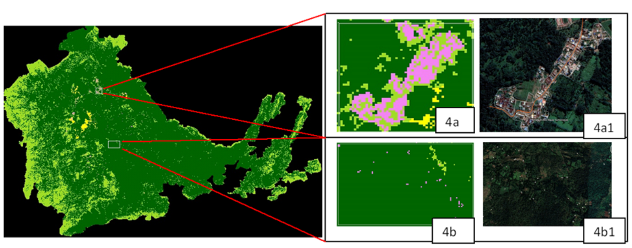

Fig. 4. LCLU map from Sentinel 2 and its enlarged portion of linear settlement pattern 4a. (sentinel 2 classified image), 4a1. (Google Earth), scattered settlement pattern 4b. (sentinel 2 classified image), 4b1. (Google Earth). 4a and 4a1 are settlement constructed in the slope range of 0° to 8°

According to the Census of India 2011, Sirumalai village has a total population of 5,041 (Indian Village Directory). The housing structures in the village are diverse, with 60% comprising huts and asbestos-roofed dwellings, while the remaining are tiled-roof and a few congregate houses. The huts and asbestos-roofed residences are predominantly scattered due to the challenging hill slopes, whereas the tiled and congregate houses follow a linear pattern.

The study identified two primary settlement patterns: linear and scattered, as depicted in Figure 4. The linear settlements consist of approximately 500 houses, which are situated along the roadsides at the top of the hill in flat regions with slopes ranging from 0 to 8 degrees. In contrast, the scattered settlements are found in the densely forested middle areas, highlighting the influence of the topography on settlement distribution.

2.5 Google Earth Data

Google Earth provides high-resolution satellite imagery that is invaluable for verifying data obtained from low-accuracy optical remote sensing. For this study, land use features were extracted from Google Earth Pro in vector file format (.kml), which was instrumental in identifying settlement patterns and distinguishing between forest, open, and agricultural lands. The classified images of the study area were cross verified with coordinates on Google Earth to examine settlement patterns and other features accurately.

2.6 Slope

Slope is a critical factor influencing settlement growth, especially in hilly regions. In the study area, the slope degree ranges from 0° to 68.94°. Table 3 categorizes the land cover and land use types according to their slope ranges. Notably, the slope range of 0° to 8.65° covers an area of 71 sq km, which is generally suitable for settlement growth. However, in the study area, only 0.6 sq km within this slope range is classified as settlement by Sentinel-2 data. The remaining 70.4 sq km in this slope range is predominantly covered by vegetation.

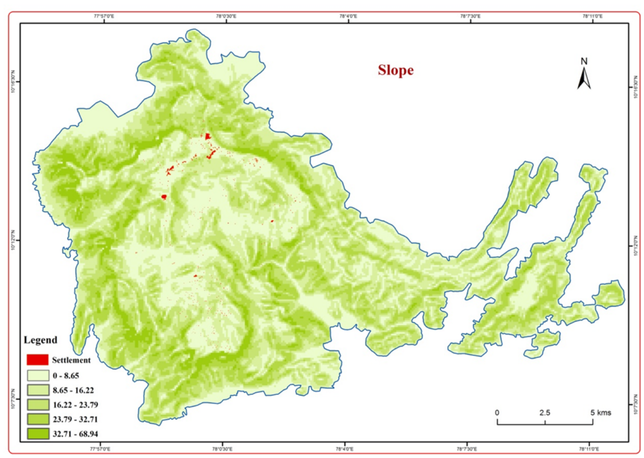

Fig. 5. Slope map and its range from 0° to 68.94° red color indicate the settlement located over the top of the hill slope range from 0° to 8.65°

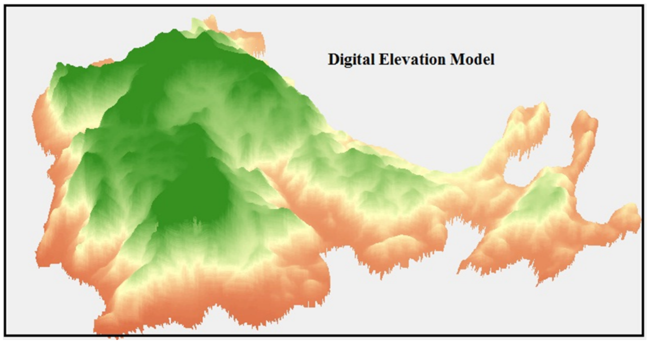

Fig. 6. Digital Elevation Model map and its range of 218m to 1369m from the mean sea level (MSL). Lowest MSL indicate in red and highest MSL depict dark green. Many watersheds are clearly distinguishable

Table 3. Degree of slope range and land cover land use category

S.No	Slope Range in degree	Slope area in sqkm	LCLU category
1	0 - 8.65	71	Settlement
2	8.65 - 16.22	73	Agriculture
3	16.22 -23.79	84	Dense forest
4	23.79 - 32.71	66	Sparse vegetation
5	32.71 - 68.94		

2.7 NDVI variation based on elevation division

The NDVI (Normalized Difference Vegetation Index) is a widely used metric for assessing vegetation health, derived from optical remote sensing by combining red and near-infrared (NIR) bands. Previous studies have demonstrated that NDVI can provide valuable insights into vegetation dynamics (Mather, 1999; Foody et al., 2001; Li X. et al., 2007 [(27)]). For this study, we utilized band-4 (Red) and band-8 (NIR) for NDVI calculations.

resents the band values used, and the NDVI was computed using the specified formula after performing geometric correction on the raw imagery. The spectral reflectance values for the pixels ranged from -0.02 to 0.82. Typically, NDVI values range from -1 (indicating no vegetation) to 1 (indicating dense vegetation). The variation observed in NDVI values across different elevation zones provides insights into vegetation distribution and health in relation to elevation changes.

NDVI calculated from the following formula:

$$NDVI = \frac{(NIR - Red)}{(NIR + Red)}$$

2.8 Multiple linear regression model

A fishnet grid was established for raster data extraction with cell dimensions of 1000 x 1000 meters, comprising 21

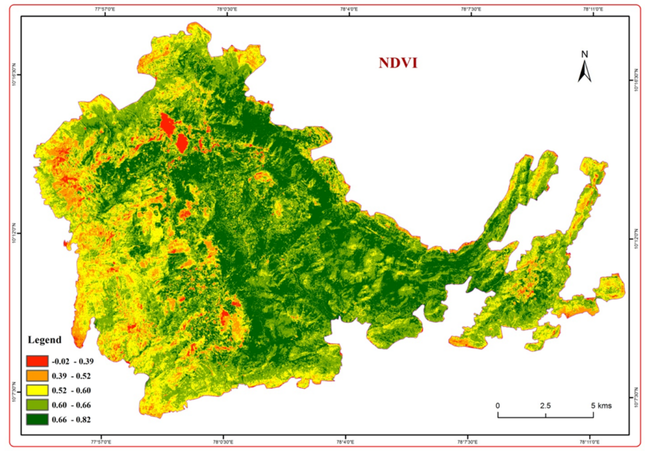

Fig. 7. Normalized Difference Vegetation Index shows vegetated and non-vegetated areas

rows and 31 columns. This setup was utilized to analyze the correlation between Land Cover/Land Use (LCLU), Normalized Difference Vegetation Index (NDVI), and slope in the context of a multiple linear regression (MLR) model. NDVI values were interpreted as follows: values below 0 represent non-vegetated areas such as rocky surfaces or soil reflections, negative values indicate built-up areas or water bodies, values between 0.5 and 0.6 correspond to grassland and sparsely vegetated areas, and values above 0.6 signify densely vegetated areas with healthy vegetation.

For scatter plots, ensure that the x-axis and y-axis are labeled correctly as ”Slope” and ”LCLU,” respectively. Each data point should be plotted with a trend line to visualize the best fit among the data sets. The scatter plot should illustrate the dispersion of points both above and below the trend line, indicating variability in the data.

The MLR model showed a significant correlation between settlement and slope. A total of 294 samples were analyzed, incorporating LCLU, slope, and NDVI. The regression statistics revealed a multiple R value of 0.4, with both R^2 and adjusted R^2 values at 0.2, and a standard error of 0.3. The intercept coefficient was 3.03, while NDVI and slope coefficients were -2.7 and -0.007, respectively, suggesting that lower NDVI and slope values are associated with increased settlement activity. The model's significance is underscored by an F-value of 42.66, indicating strong statistical significance.

Figure 8 illustrates the scatter plot showing the relationship between slope and LCLU. The trend line demonstrates a positive correlation, indicating that a reduction in slope from 18 to 16 degrees is associated with an increase in agricultural land, while slopes below 16 degrees are more favorable for settlement construction.

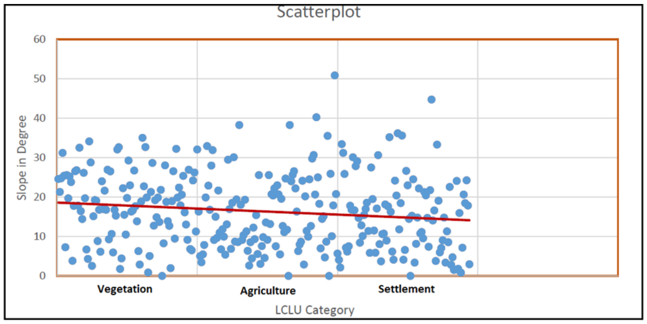

Fig. 8. Scatter plot correlation for LCLU and slope. Y axis slope in degree and X axis collect the LCLU category of dense forest, sparse vegetation, agriculture and settlement. The trend line (red color) start from more than 19 degree which occupied forest vegetation and trend line cross 19 to 16 degree slope area occupied by forest agriculture, when the trend line cross below 16 degree slope influence for settlement

3 Conclusion

Understanding the distribution of forested land, agricultural areas, settlements, and water bodies is crucial for local tribes and communities. This study highlights that topography, particularly slope, significantly impacts vegetation indices, as evidenced by variations in NDVI. The analysis of land cover and land use (LCLU) in conjunction with slope data reveals that slope plays a pivotal role in influencing settlement patterns. Settlements tend to be concentrated in areas with slopes between 8 to 16 degrees, while regions with slopes less than 8 degrees are more likely to feature linear settlement patterns.

The research indicates a strong correlation between slope and settlement growth, with built-up areas decreasing as slope increases. Currently, there remains a potential area of 70.04 sq km within favorable slope ranges that could be utilized for development purposes. Effective forest landscape management could enhance economic benefits for tribes, improve agricultural development, and elevate living standards.

Future recommendations include investigating plant species variations based on elevation and slope, identifying landslide-prone zones to prevent construction in vulnerable areas, and utilizing high-resolution imagery and GPS for better planning of agricultural and residential infrastructure**.**

Author Contribution

Corresponding author Dr Chandramohan Karuppiah prepared the manuscript, co-authors supported the preparation of study area details, reviewed the paper, and suggested their comments.

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