Scientific Research Publishing

Advances in Remote Sensing, 2026, 15(3), 99-118
https://www.scirp.org/journal/ars
ISSN Online: 2169-2688
ISSN Print: 2169-267X

Spatiotemporal Analysis of Forest Cover Change Using Sentinel-2 Imagery and Maximum Likelihood Classification: A Case Study of Shimla, India

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How to cite this paper: Gupta, S. and Gupta, S. (2026) Spatiotemporal Analysis of Forest Cover Change Using Sentinel-2 Imagery and Maximum Likelihood Classification: A Case Study of Shimla, India. *Advances in Remote Sensing*, **15**, 99-118.
https://doi.org/10.4236/ars.2026.153006

Received: July 16, 2026
Accepted: August 25, 2026
Published: August 28, 2026

Abstract

Forests represent a critical component of land-based ecosystems, making accurate forest cover assessment essential for sustainable landscape management. This study presents a two-part methodology combining Maximum Likelihood Estimation (MLE) and Sentinel-2 satellite imagery to support forest monitoring and spatial mapping. Unlike conventional forest mapping studies that primarily report land cover statistics, our work develops an integrated hybrid classification framework combining NDVI transformation and ISODATA spectral clustering with Maximum Likelihood Classification to quantify forest canopy transitions in a complex Himalayan landscape. Remote sensing and GIS techniques were applied using NDVI classification and pixel-based extraction, with unsupervised ISODATA clustering and ERDAS Imagine software employed in the classification workflow. Forest cover was categorized into five canopy density classes: Very Dense Forest (VDF), Moderately Dense Forest (MDF), Open Forest (OF), Scrub, and Non-Forest (NF). The study area encompassed Shimla Municipal Forests in the Western Himalayas, with change detection conducted over a four-year interval from 2015 to 2019. Results revealed a net loss of 113 ha in open forest and 48 ha in non-forest areas. The classification achieved an overall accuracy of 89.2% with a Kappa coefficient of 0.86, reflecting strong agreement between classified outputs and reference data. These findings demonstrate the effectiveness of MLE paired with Sentinel-2 imagery in accurately detecting forest cover change, while also offering a cost-effective solution and beyond estimating forest extent, the proposed framework provides a reproducible workflow for analyzing canopy density transitions that can support long-term environmental monitoring and evidence-based forest management in mountainous regions on a large scale.

Keywords

Forest Cover Monitoring, Land Cover Change Detection, Maximum Likelihood Classification, Sentinel-2 Satellite Imagery, Normalized Difference Vegetation Index (NDVI)

1. Introduction

1.1. Remote Sensing

The influence of space-based technology has grown significantly in informed decision-making, especially in fields like forest resource management. Remote sensing, in particular, has provided a well-organized and layered framework for evaluating and tracking forest conditions, taking advantage of sensors with varying spatial and spectral characteristics [1].

Forest ecosystems provide humans with critical resources, including carbon sequestration, biodiversity conservation, hydrological regulation and climate stabilization. Monitoring changes in forest cover is therefore essential for sustainable forest management, particularly in ecologically sensitive mountainous regions such as the Himalayas [2]-[5].

Mapping forest extent and tracking its changes are among the most widely applied uses of satellite imagery [6] [7]. Forest monitoring with the help of satellite technology enables efficient assessment of spatial and temporal changes in ecosystem structure and land cover dynamics [6] [8]-[10].

1.2. Remote Sensing, Satellite Data and Geographical Information Systems

Advances in remote sensing and GIS technologies have significantly improved forest monitoring by enabling rapid and economical assessment of land cover dynamics across large spatial extents [11]. The availability of high-resolution multispectral satellite datasets such as Sentinel-2 has further enhanced vegetation classification and forest change detection studies.

However, achieving high levels of accuracy has often been limited by a variety of factors like spatial, spectral, and temporal limitations of widely used public datasets like Landsat and MODIS. The launch of the Copernicus Programme by the European Space Agency and the European Union marked an important advancement in this regard. In particular, Sentinel-2, operational since 2015, has improved forest mapping by providing high-resolution multispectral imagery with high frequency, enabling more detailed and reliable classification across larger areas [12]-[18].

1.3. Digital Image Classification

Digital image classification techniques are widely used in remote sensing for land cover mapping and change detection. Supervised and unsupervised classification approaches enable the identification of spectrally distinct land cover classes from multispectral imagery. Some of the most popular machine learning algorithms for this include minimum distance to mean, parallelepiped, and Gaussian maximum likelihood classifier [19]-[21]. ISODATA clustering was used to group spectrally similar pixels with Maximum Likelihood Classification used to refine the final land cover categories.

Change detection is essentially the comparative analysis of two or more remotely sensed images acquired over the same geographic area across different time periods [10]. The classification of spatial data has seen a marked rise in adoption in recent years due to its capacity to uncover meaningful patterns and generate actionable insight from complex datasets. This trajectory has been shaped by extensive empirical testing across a wide range of classifiers, leading to measurable gains in classification accuracy and overall performance. Land cover mapping through satellite image classification constitutes one of the primary remote sensing applications examined in this study. Although numerous studies have applied Sentinel-2 imagery for land cover mapping yet they do not account for forest canopy transition dynamics in rapidly urbanizing Himalayan municipal forests or an integrated hybrid classification workflow. Most previous studies emphasize classification accuracy or overall land cover statistics while limited attention has been given to quantifying inter-class forest transitions using efficient statistical approaches suitable for operational efficiency, as individual classes carry very important context. **Table 1**, as indicated below, presents an overview of related investigations that utilized a variety of remote sensing techniques and data sources, highlighting the conclusions that proved instrumental in guiding forest cover change classification and estimation.

Table 1. Compilation of tools and datasets for analyzing changes across regions.

Technology and Data Set Used	Area Studied/Objective Fulfilled	Reference
NDVI analysis using hybrid unsupervised classification	Density-Based Forest Stratification and Accuracy Assessment in the Western Himalayan Landscape	[22]
Maximum likelihood classifier	Tracking Forest Loss in Cedar Ecosystems of the Middle Atlas Mountains, Morocco	[23]
Satellite imagery with high spatial detail	Forest condition monitoring of an isolated Nepal watershed	[24]
Sentinel-2 and Landsat-8 data	Assessment and Mapping of Forest Successional Stages in a Southern Brazilian Subtropical Forest	[25]
Using MLE classification and NDVI	Spatial Mapping of Tree Species in the Azrou Forest, Middle Atlas, Morocco	[26]
Sentinel-2	Forest classification in Mediterranean environments	[15]

Continued

Sentinel-2	Use of Imagery for Automated Forest Succession Mapping in Pacze Forests, Southeastern Poland	[16]
NDVI and Sentinel-2 images	Mapped a decline in the Castelporziano State Natural Reserve by monitoring Mediterranean Oak peri-urban protected area	[27]
Sentinel-2 and Landsat 8 imagery	Forest variable prediction in the boreal region in Finland	[28]
Convoluted neural networks and Sentinel-2 satellite imagery	Forest classification work based on	[29]
Deep learning methodology Sentinel-2	In land use classification based on time series and indicated the advantages, effectiveness and utility for assessment and change detection	[30]
Multitemporal Sentinel-2 imagery	Land use/land cover mapping for analysis of forest/land cover in Dak-Nong, Vietnam	[9]
LandSat data	Land use/land cover change detection for Kaddapa region, Andhra Pradesh	[31]

1.4. Significance of the Study

Monitoring forest cover dynamics in Himalayan ecosystems is particularly important due to increasing urban expansion, tourism activity, and climate changes. Shimla represents a rapidly urbanizing mountain landscape where forest fragmentation and canopy modification can significantly influence slope stability, biodiversity, water cycles, and local climate regulation. The integration of open source Sentinel-2 imagery with statistically robust classification methods provides an efficient and scalable framework for long-term forest monitoring in mountainous environments where extensive field surveys are often difficult to conduct.

1.5. Novel Contributions

This study contributes to the existing literature by introducing an integrated remote sensing workflow for forest monitoring that combines NDVI pre-processing and ISODATA spectral clustering with Maximum Likelihood Classification using high-resolution Sentinel-2 imagery. Unlike many previous studies that limit scope to overall land cover changes, this work emphasizes detailed canopy density transition analysis across five forest classes through a transition matrix framework. The methodology achieves high classification accuracy while relying exclusively on freely available satellite imagery and widely accessible GIS tools, which is efficient and reproducible solution for forest monitoring in complex mountainous terrain like the Himalayas. Furthermore, the study establishes an updated baseline dataset for Shimla Municipal Forests that can support future ecological assessments, sustainable forest management and climate adaptation planning across the region.

2. Objectives

The study aims to evaluate spatiotemporal forest cover dynamics in Shimla Municipal Forests using Sentinel-2 multispectral imagery integrated with NDVI transformation, ISODATA clustering, and Maximum Likelihood Classification (MLC). Specific objectives include:

1) Generation of forest cover maps for 2015 and 2019,

2) Classification of forest canopy density into VDF, MDF, OF, Scrub, and Non-Forest categories,

3) Quantification of forest cover transitions using change detection matrices, and

4) Assessment of classification reliability using confusion matrix-based accuracy assessment.

5) Demonstrate the efficiency of an integrated hybrid classification workflow for forest monitoring in a sustainable manner.

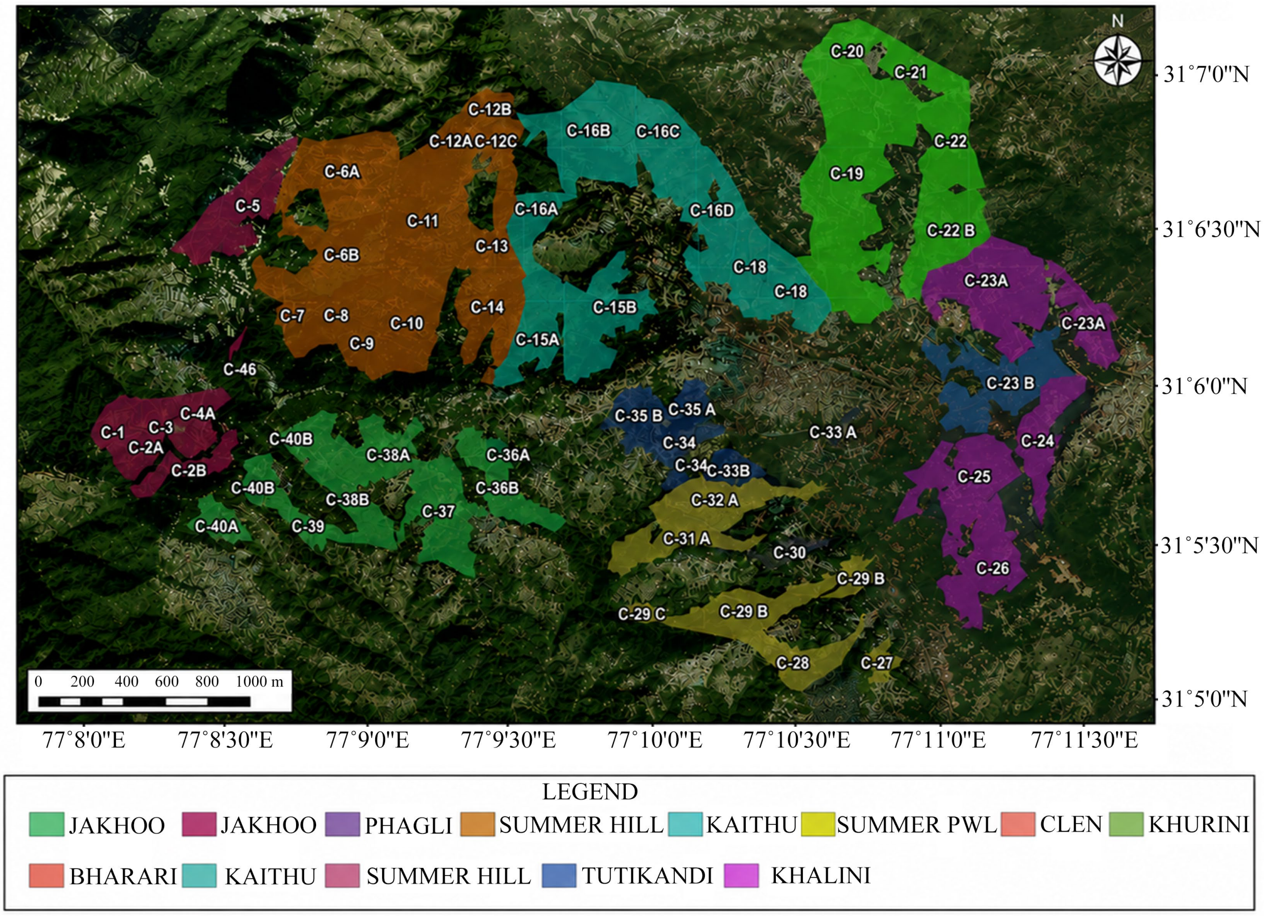
3. Study Area

Shimla Municipal Forests lie between Latitude 31˚5'N to 31˚7'N and Longitude 77˚11'E to 77˚14'E. It surrounds the Shimla town from all sides in blocks, interspersed with government estate and private property with some villages mostly on the outskirts. The classification and change detection in the analysis were conducted over a broader 2780 ha extent covering the Shimla Municipal Forests and adjoining land within the Municipal Corporation boundary, which forms the basis of the analysis. The whole area is mountainous, and the slopes are moderate to steep, with a gradient varying from 25˚ to 45˚. The forest occurs on both sides of the 6.4 kilometers along the ridge on which the town is situated. Forested areas dominate both private and government estates, excluding commercial and trading regions, while municipal forests are generally located below the cart road, except around Jakhoo Hill (**Figure 1**).

4. Materials and Methods

4.1. Sentinel-2 Data

Multispectral Sentinel-2 imagery provided by the European Space Agency was utilized for both classification and change detection, offering a spatial resolution of 10 meters and a wide swath width of approximately 290 km. The datasets for the study area were obtained from the Copernicus open-access platform for the dates 20 November 2015 and 6 November 2019. Sentinel-2 multispectral imagery with 10 m spatial resolution and five-day revisit frequency was used for forest classification and change detection. Sentinel 2 with Level 1C top of the atmosphere reflectance products were used. Bands B2 (Blue), B3 (Green), B4 (Red), and B8 (Near-Infrared) were selected at 10 m resolution. Cloud and shadow-contaminated images were excluded during image selection. Atmospheric correction, geometric pre-processing and terrain correction were performed in ERDAS Imagine



Sources: Esri, HERE,Garmin, Intermap, increment P Corp., GEBCO, USGS, FAO, NPS, NRCAN, GeoBase, IGN, Kadaster NL, Ordnance Survey, Esri Japan, METI, Esri China (Hong Kong), © OpenStreetMap contributors, and the GIS User Community

Figure 1. Geographic location of Shimla Municipal Forests within Himachal Pradesh, India.

using the Shuttle Radar Topography Mission (SRTM) 30 m Digital Elevation Model (DEM). Images acquired during November 2015 and November 2019 were selected to minimize seasonal variability and ensure consistent comparison.

Area statistics in the results section were normalized to the total surveyed extent of the Shimla Municipal Forest boundary, 2780.4 ha rather than computed directly from pixel count at nominal 10 m resolution. This normalization accounts for boundary clipping effects at the edge of the irregular study area polygon.

4.2. Forest Cover Mapping

Figure 2 shows a detailed framework for forest cover mapping and steps involved to generate forest maps as follows.

The methodological novelty of this study lies in integrating unsupervised spectral clustering with supervised statistical classification within a unified workflow that improves efficiency of assessment of forest canopy density classes while maintaining computational efficiency and reproducibility for regional forest monitoring applications. The methodology is based on digital Image processing

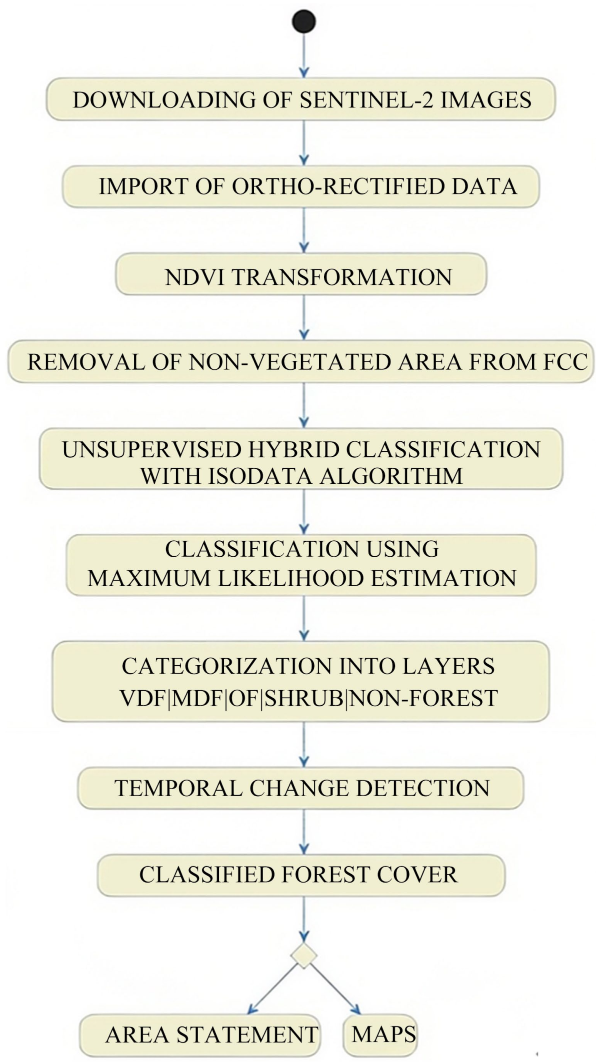


Figure 2. Methodological framework adopted for forest cover mapping and change detection using Sentinel-2 imagery and maximum likelihood classification.

and classification using ERDAS Imagine software [32] that involves the use of NDVI transformation, unsupervised hybrid classification with ISODATA algorithm and Maximum Likelihood Estimation (MLE) algorithm. The sequential steps included: 1) Data preparation (pre-processing) by downloading images, 2) ortho-rectification, 3) image interpretation, 4) categorization into layers, 5) interpretation of images to identify change areas and 6) map generation.

Both 2015 and 2019 images were ortho-rectified to a common reference system using ground control points and a digital elevation model. Registration achieved a root mean square error of 0.31 pixels within the 0.5 pixel threshold recommended for reliable change detection. This reduced false transitions between adjacent canopy classes on the steep slopes used in Section 3.

4.3. Normalized Difference Vegetation Index (NDVI) Classification

The Normalized Difference Vegetation Index (NDVI) is one of the most commonly used indicators for assessing vegetation condition, as it captures both the presence and health of vegetation by utilizing the Near-Infrared (NIR) and red portions of the electromagnetic spectrum. It is computed using the following expression:

$$\mathrm{NDVI}=\frac{\mathrm{NIR}-\mathrm{Red}}{\mathrm{NIR}+\mathrm{Red}} \tag{1}$$

NDVI values range from −1 to +1, where higher values indicate dense vegetation and lower values represent sparse or non-vegetated surfaces. The index was used to separate vegetated and non-vegetated areas prior to classification [22] [33] [34].

4.4. Unsupervised Classification Using the ISODATA Method

Unsupervised classification, which can be best described as a clustering approach because of it being largely an automated technique in which pixels with similar spectral characteristics are grouped together without prior training data. ISODATA (Iterative Self-Organizing Data Analysis Technique) is one of the most commonly used algorithms for vegetation analysis in satellite imagery. This method organizes pixels into clusters based on spectral similarity and is typically applied to separate forest classes from other land cover types. Pixels are repeatedly reassigned through an iterative process, class statistics are updated, and class boundaries are refined until stable patterns in the spectral data begin to emerge.

In this study, the vegetated portion of the imagery is classified using the ISODATA algorithm to generate categories such as Very Dense Forest (VDF), Moderately Dense Forest (MDF), Open Forest (OF), scrubland, and non-forest areas, including agriculture, land built by humans, and sparse vegetation. The algorithm operates through repeated cycles of clustering and adjustment, gradually improving the separation between land cover types based on their spectral behavior. ISODATA clustering was iteratively applied to group spectrally similar pixels into preliminary land cover classes using standard convergence and splitting criteria. Rather than using ISODATA as the final classification output the spectral clusters were subsequently refined through Maximum Likelihood Classification, which reduces spectral ambiguity between adjacent vegetation classes.

4.5. Maximum Likelihood Estimation (MLE)

Maximum Likelihood Estimation (MLE) is a supervised parametric classifier that assigns pixels to the class with the highest statistical probability based on class mean vectors and covariance matrices [35]. MLE is a supervised, parametric classification method in which the analyst first defines representative training samples, often referred to as training areas or regions of interest. These samples are used to derive statistical descriptions of each class, which are then fed into the classification algorithm. The model computes probability density functions for each class and uses them to determine the likelihood of a pixel belonging to a given category.

4.6. Classification Using Maximum Likelihood Estimation

Satellite image classification in this study was carried out using digital image processing techniques based on the Maximum Likelihood Estimation (MLE) approach. A pixel-by-pixel comparison framework was adopted to generate change information, enabling a more precise interpretation of land cover transitions through a clear "from-to" analysis of pixel categories. To quantify changes over time, classified outputs from two different dates were compared using a cross-tabulation method. This allowed the extent and nature of land cover change to be determined using Sentinel-2 datasets acquired on 20 November 2015 and 6 November 2019. For interpretation purposes, forest cover was mapped into canopy density-based classes. In total, five forest cover categories were defined, as outlined in **Table 2**.

Table 2. Forest cover classified in terms of canopy density classes.

Class	Description
Very Dense Forest	All areas with tree canopy density of 70% and above.
Moderately Dense Forest	Areas with tree canopy density ranging from 40% to less than 70%.
Open Forest	Lands with tree canopy density between 10% and less than 40%.
Scrub	Degraded forest areas where canopy density is less than 10%.
Non-Forest	All remaining land cover types not included in the above categories, including water bodies.

The canopy density thresholds in **Table 2** follow Kumar *et al.* (2007) [22]. NDVI values were binned into density ranges matching these thresholds. ISODATA clusters falling within each range were labeled Non Forest, Open Forests, Moderately Dense Forest, Scrub or Very Dense Forests to generate training areas for Maximum Likelihood Classification. The set of spectral signatures derived from unsupervised classification is stored for each image scene and subsequently used in the application of Maximum Likelihood Estimation (MLE). This approach is particularly suitable because it performs well with input data that follows a normal distribution and incorporates both variance and covariance information, making it statistically robust.

Bayesian probability theory used by the classifier evaluates each pixel by comparing it to class-level statistical parameters. Mean vector and covariance matrix derived from training data form the basis for computing class membership probabilities. A pixel is ultimately assigned to the class for which it has the highest likelihood of belonging.

$$D_c = \ln\left(a_c\right) - \left[0.5\ln\left(\left|Cov_c\right|\right)\right] - \left[0.5\left(X - M_c\right)^{\mathrm{T}}\left(Cov_c^{-1}\right)\left(X - M_c\right)\right] \tag{2}$$

In Equation (2), D_c represents the likelihood distance for class c, where X is the pixel feature vector, M_c is the class mean vector, and Cov_c is the covariance matrix derived from training samples.

The classification decision is made by assigning each pixel to the class that yields the smallest value of D, which indicates the highest likelihood of membership. When prior probabilities differ among classes, then a weighting factor can be introduced to reflect this imbalance. This modified form of the Maximum Likelihood approach is commonly referred to as the Bayesian decision rule.

A hybrid classification approach was adopted. This hybrid strategy combines the strengths of unsupervised and supervised classification by leveraging spectral clusters while using class probability distributions during final classification. Initially, ISODATA unsupervised classification was applied to identify spectral clusters and generate preliminary land cover groups. These spectral signatures were subsequently refined and used as training samples within a supervised Maximum Likelihood Classification framework to produce the final classified maps. A total of 250 training samples were delineated per image, which is 50 per class in 2015 and 2019. Samples were selected from ISODATA clusters with the highest spectral homogeneity and checked against high-resolution reference imagery. Training areas were distributed across representative slope, aspect and elevation zones. ISODATA clusters were labeled based on spectral characteristics, NDVI results, reflectance signatures for Table 2 and visual interpretation before serving as Maximum Likelihood Classification training input.

5. Results

The classification results of forest cover methodology performed on Sentinel-2 images of 2015 and 2019 are shown in Figure 3 and Figure 4. Although the broader study area encompassed a larger portion of the Shimla landscape with the detailed classification and change detection analysis were conducted on a focused subset covering the Shimla Municipal Forests to enable consistent assessment across both time periods. In addition to producing forest cover maps, the proposed framework allows detailed characterization of canopy density transitions that gives greater ecological insight than conventional area-based change statistics alone.

5.1. Classification Analysis

The outcomes of the classification analysis are presented in Figure 5 and Figure 6. Table 3 and Table 4 indicate that the study area exhibits a mixed distribution of forest cover classes for 2015. Very Dense Forest (VDF) accounts for 19.58% of the total area (544 ha), while Moderately Dense Forest (MDF) occupies the largest forested portion at 27.37% (760 ha), Open Forest covers 16.13% (448 ha), and Scrub Forest represents a small fraction of 1.15% (32 ha) and non-Forest land constitutes 35.53% (988 ha) of the total geographical extent. Overall, the Shimla Municipal Forest spans approximately 2780 hectares, with a substantial share falling outside forested categories. The 2780 ha figure refers to the total classified image extent used for change detection.

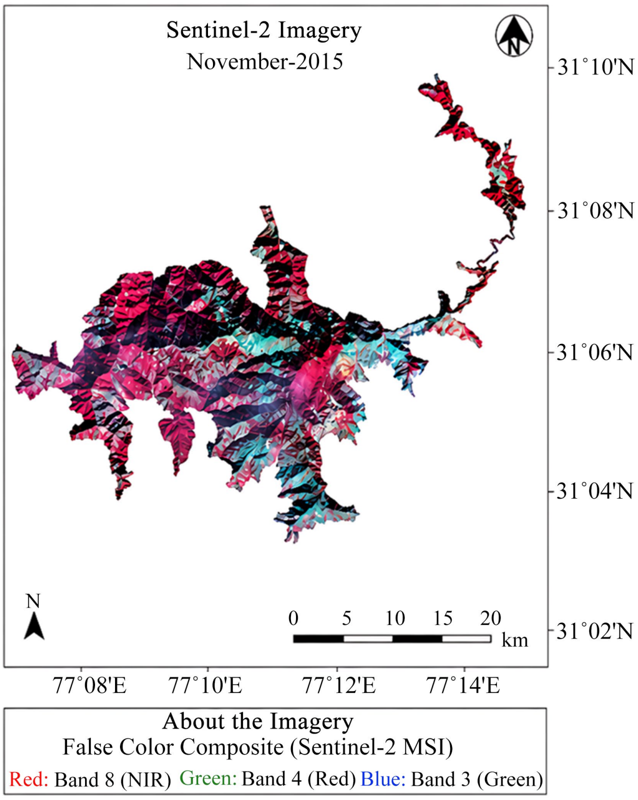


Figure 3. False Color Composite (FCC) Sentinel-2 imagery of the Shimla study area for 2015.

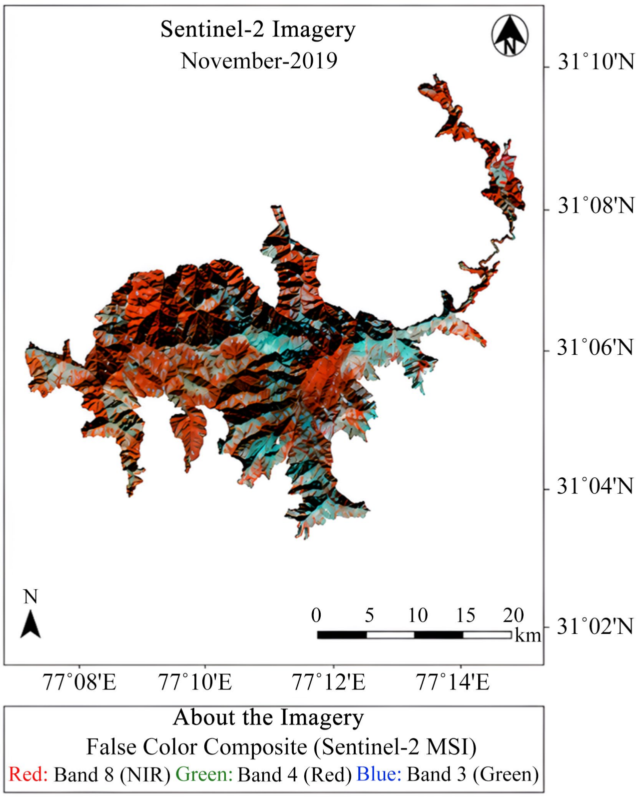


Figure 4. False Color Composite (FCC) Sentinel-2 imagery of the Shimla study area for 2019.

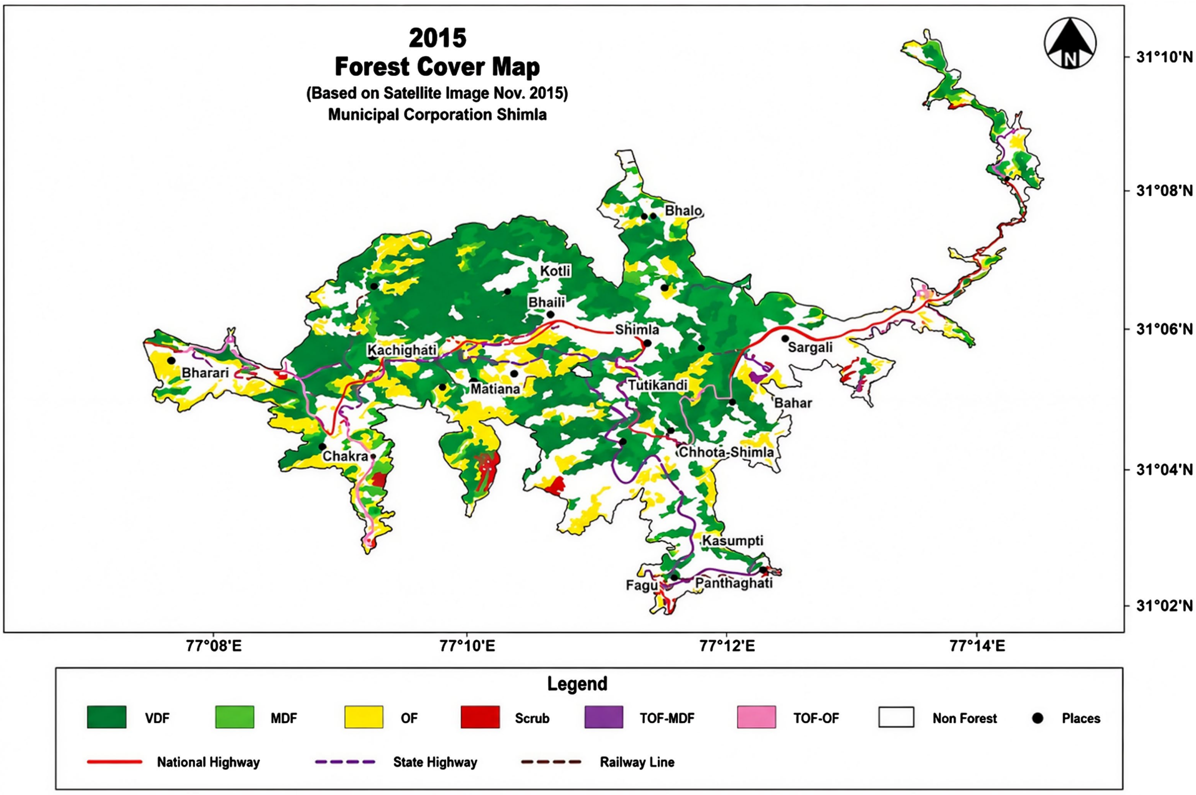


Figure 5. Classified forest cover map of Shimla Municipal Forests for 2015 with corresponding area statistics.

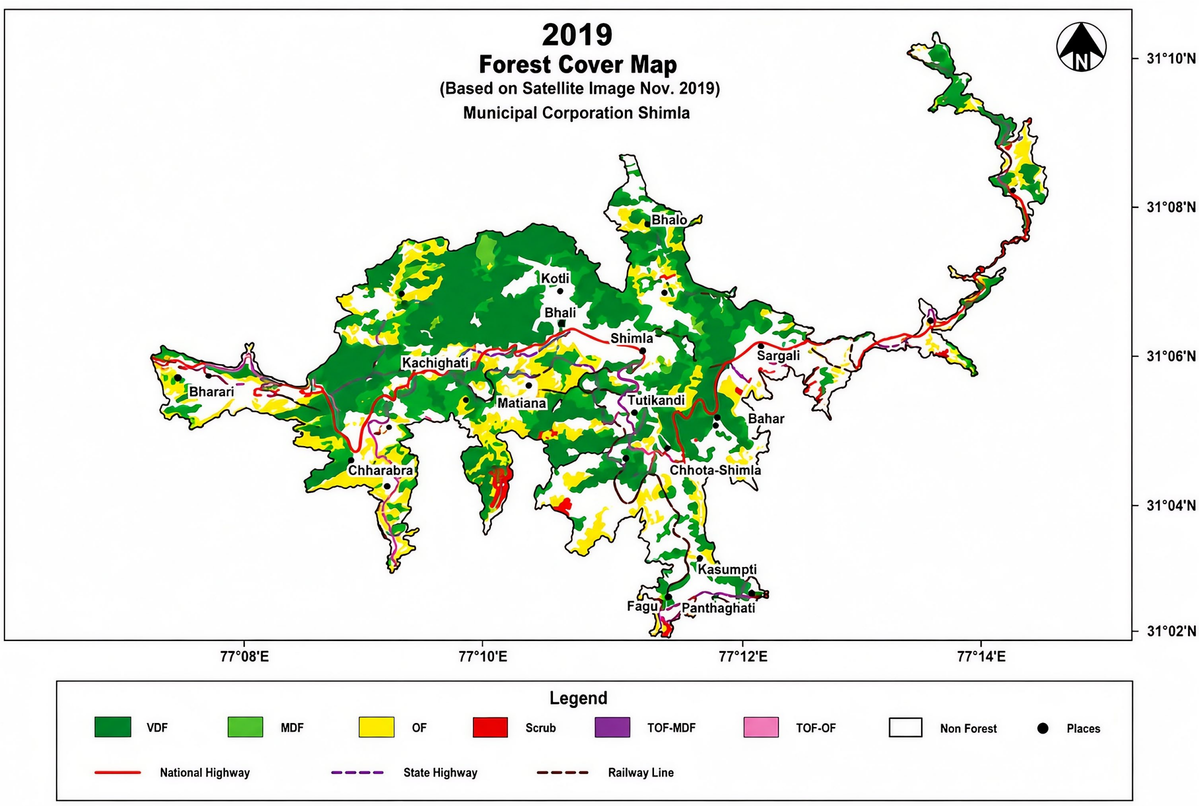


Figure 6. Classified forest cover map of Shimla Municipal Forests for 2019 derived from Sentinel-2 imagery.

Table 3. Forest cover Shimla Municipal Forest corporation in 2015 (in ha).

Class	Name	Count	Percentage	Area	Area Rounded	Area * 1.25899
2	VDF	44,534	19.58	544.42	544	685
3	MDF	62,244	27.36	760.95	760	957
4	OF	36,685	16.13	448.48	448	564
5	SCRUB	2584	1.14	31.59	32	40
7	TOF-MDF	219	0.1	2.67	3	4
8	TOF-OF	381	0.17	4.66	5	6
13	NON-FOREST	80,785	35.52	987.62	988	1244
		227,432	100	2780.4	2780	3500

Statistical analysis calculated from Figure 5.

Table 4. Forest cover municipal forest/municipal corporation in 2015 (in ha).

Class Name	Municipal Forest Area	Municipal Forest Area	Municipal Corporation Area	Municipal Corporation Area
	Area	% of GPA	Area	% of GPA
VDF	544	19.59	685	19.5
MDF	763	27.42	961	27.4
OF	453	16.17	570	16.2
Total (VDF, MDF, OF)	1760	63.18	2216	63.3
SCRUB	32	1.19	40	1.2
NON-FOREST	988	35.63	1244	35.7
Total	2780	100	3500	100

Shimla Municipal Corporation Area = 3500 ha, Shimla Municipal Forest Area = 2780 ha.

Common conversion factor is applied for extrapolating Shimla Municipal Forest area (2780 ha) to Shimla Municipal Corporation area (3500 ha).

Common Factor = 3500/2780 = 1.25899.

Municipal Corporation area estimates were derived by multiplying Municipal Forest area values by the common factor. Class areas are scaled by a factor of 0.0122 ha per pixel, which is derived from the total classified pixel count of 227,432 in Table 3 and Table 5 against the known municipal forest boundary area rather than the nominal 100 m^2 per pixel Sentinel 2 resolution.

Table 5. Forest cover Shimla Municipal Forest/corporation 2019 (in ha).

Class	Name	Count	Percentage	Area	Area Rounded	Area * 1.25899
2	VDF	49,593	21.81	606.29	606	763
3	MDF	68,424	30.09	836.50	836	1053

Continued

4	OF	27,002	11.87	330.11	330	415
5	SCRUB	4481	1.97	54.78	55	69
7	TOF-MDF	219	0.10	2.68	3	4
8	TOF-OF	819	0.36	10.01	10	13
13	NON-FOREST	76,894	33.81	940.05	940	1183
		227,432	100	2780.42	2780	3500

Statistical analysis calculated from Figure 6.

Comparison between 2015 and 2019 indicates an increase in VDF and MDF categories, whereas Open Forest area declined during the study period (Tables 5-8). Figure 6 shows the outcome of the analysis for the year 2019.

Table 6. Forest cover municipal forest/municipal corporation 2019 (in ha).

Class Name	Municipal Forest Area	Municipal Forest Area	Municipal Corporation Area	Municipal Corporation Area
	Area	% of GPA	Area	% of GPA
VDF	606	21.79	763	21.89
MDF	839	30.17	1057	29.85
OF	340	12.24	428	12.43
Total (VDF, MDF, OF)	1785	64.20	2248	64.17
SCRUB	55	1.98	69	1.98
NON-FOREST	940	33.82	1183	33.85
Total	2780	100	3500	100

Table 7. Forest cover of Shimla Municipal Forest in 2019 (in ha).

Class	Area	% of GA
Very Dense Forest	606	21.79/22
Moderately Dense Forest	839	30.17/30
Open Forest	340	12.2/12
Scrub	55	1.97/2
Non-Forest	940	33.38/34
Total	2780	100

Table 8. Area and amount of change in forest cover in municipal forest between 2015-2019 (in ha).

Year	VDF	MDF	OF	Total	Scrub	Non-Forest
2015	544	763	453	1760	32	988
2019	606	839	340	1785	55	940
Change	62	76	−113	25	23	−48

Between 2015 and 2019, VDF and MDF increased while OF decreased, indicating canopy densification and possible vegetation recovery. The 2019 forest cover distribution is given in Table 7.

The change detection between 2015 & 2019 shows that there is an increase of 62 ha in VDF, 76 ha in MDF but decrease of 113 in OF, thus an increase of 25 ha among three categories, Scrub also increased by 25 ha but non-forest shows decrease of 48 ha in Shimla Municipal Forest (Table 8).

Similarly, change detection observed in Shimla Municipal corporation shows an increase of 78 ha VDF, 96 ha MDF and decrease of 142 ha of OF, though Scrub increases by 29 ha but non-forest decreases by 69 ha as discussed in Table 9.

Table 9. Area and amount of change in forest cover in municipal corporation between 2015-2019 (in ha).

Year	VDF	MDF	OF	Total	Scrub	Non-forest
2015	685	961	570	2216	40	1244
2019	763	1057	428	2248	69	1183
Change	78	96	−142	32	29	−69

5.2. Forest Cover Change Matrix

Table 10 presents the forest cover transition matrix between 2015 and 2019.

Table 10. Forest cover change matrix for Shimla Municipal Forests between 2015 & 2019 (in ha).

2015/2019	VDF	MDF	OF	Scrub	NF	Total 2015
Very Dense Forest	482	62	0	0	0	544
Moderately Dense Forest	76	687	0	0	0	763
Open Forest	48	90	305	5	5	453
Scrub	0	0	4	27	1	32
Non-Forest	0	0	31	23	934	988
Total 2019	606	839	340	55	940	2780
Net Change	62	76	−113	23	−48	

Net change refers to the overall difference in forest cover between two time periods, obtained by combining both gains and losses observed across the study area during the two assessments.

Classification accuracy was evaluated using stratified random sampling and confusion matrix analysis with results presented in Table 11. A total of 250 reference validation points were generated across the five land cover categories using high-resolution images, Sentinel-2 true color composites, and existing forest cover maps. Accuracy assessment followed standard remote sensing validation procedures overall accuracy, and the Kappa coefficient.

Table 11. Confusion matrix and classification accuracy assessment for forest cover classification.

Reference/Classified	VDF	MDF	OF	Scrub	NF	Total
VDF	45	3	1	0	1	50
MDF	4	42	2	0	2	50
OF	1	3	40	4	2	50
Scrub	0	0	5	42	3	50
NF	1	2	1	2	44	50

The overall classification accuracy achieved was 89.2%, while the Kappa coefficient was calculated as 0.86, indicating substantial agreement between classified outputs and reference data. Producer's accuracy values ranged from 80% to 90%, whereas user's accuracy values ranged from 82% to 91% across the five land cover categories. The results demonstrate that the hybrid ISODATA and MLE framework produced reliable classification performance for mountainous Himalayan terrain. This accuracy value falls within the acceptable range reported for Sentinel-2-based forest classification studies conducted in heterogeneous mountainous environments, where overall accuracies commonly range between 80% and 90%.

6. Limitations and Future Scope

Although the study produced reliable forest cover estimates, there are still several limitations. The analysis relied primarily on multispectral satellite imagery and limited secondary reference datasets due to restricted accessibility in steep Himalayan terrain. Seasonal spectral variability and mixed pixels occurring along transitional forest boundaries may have influenced classification accuracy, particularly between Open Forest and Scrub categories.

Future research may incorporate seasonal Sentinel-2 time series, LiDAR-derived canopy metrics or machine learning classifiers such as Random Forest and Support Vector Machine to further improve performance. Integration of field-based ecological measurements and higher temporal frequency datasets would also strengthen long-term forest monitoring and biomass estimation studies in Himalayan ecosystems.

7. Discussion

The principal contribution of this study extends beyond conventional forest cover estimation by demonstrating that hybrid statistical classification can effectively quantify canopy density transitions within complex Himalayan landscapes using freely available data. The increase in Very Dense Forest and Moderately Dense Forest, together with the decline in Open Forest, can be attributed to natural regeneration and plantation initiatives in the area. The increase in Scrub area may reflect localized forest degradation, edge disturbances, or transitional vegetation states associated with urban expansion and anthropogenic pressure. Similar forest transition patterns using Sentinel-2 imagery and Maximum Likelihood Classification have been reported in Himalayan and Mediterranean forest ecosystems [9] [15] [36]-[38].

Compared to other works discussed in the literature section that primarily report overall classification accuracy, this work emphasizes transition matrix analysis that allows explicit identification of conversions between canopy density classes and thereby provides information directly relevant to forest management and planning. From an operational perspective, the proposed workflow provides an efficient alternative to advanced machine learning and deep learning models, which are expensive and not easily available to everyone due to lack of resources, while maintaining high accuracy. The study relies entirely on freely available satellite imagery and software, so it can be readily adopted by forest departments and environmental agencies operating in resource-constrained regions.

8. Conclusions

The integration of Sentinel-2 imagery with Maximum Likelihood Classification provides an effective framework for forest cover estimation in mountainous terrain like Shimla, which is easily reproducible for monitoring forest cover dynamics in mountain terrains. The combination of high resolution and novel spectral capabilities in one of the most difficult terrains of the Himalayas and frequent revisit times provides unprecedented views of this mountainous region to calculate the vegetation cover within the area using both Sentinel-2 and MLE. It is revealed that the forest cover of Shimla Municipal Forests in 2019 consisted of 1785 ha (64%), VDF (22%), MDF (30%), OF (12%), Scrub (2%) *i.e.*, 2/3 area whereas non-forest constitutes for 940 ha (34%) *i.e.*, 1/3 area that accounts for built up, open area, plantations, agriculture, and play-grounds etc. out of a total area of 2780 ha. The forest cover change matrix between 2015 and 2019 showed the net change that there was a gain of 62 ha in VDF, 76 ha in MDF, 23 ha in Scrub but loss of 113 ha in OF and 48 ha in non-forest area.

The study is limited by the absence of extensive ground-based validation and the moderate temporal range between observations. Seasonal atmospheric effects and spectral similarity between scrub and open forest classes may also influence classification accuracy. Beyond the case study presented here, the proposed workflow establishes a transferable framework that can be applied to similar regions where reliable field observations are limited but routine satellite imagery is readily available, as the transition matrix analysis further enhances the practical value of the methodology by providing actionable information on canopy density for sustainable forest management and ecological conservation.

Acknowledgements

The authors acknowledge the European Space Agency (ESA) for providing open-access Sentinel-2 imagery through the Copernicus Open Access Hub. The authors are also grateful to the Forest Survey of India and previous researchers whose studies contributed to the conceptual and methodological development of this work. Image processing and classification were performed using ERDAS Imagine 2015 and ArcGIS 10.8. Sentinel-2 Level-1C imagery was atmospherically corrected prior to analysis. This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Author Contributions

Shivam Gupta: Conceptualization, methodology, data collection, analysis, and manuscript writing.

Shivai Gupta: Review, editing, and validation of the manuscript.

Conflicts of Interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

References

[1] Franklin, S.E. (2001) Remote Sensing for Sustainable Forest Management. CRC Press.

[2] FAO (2020) Global Forest Resource Assessment 2020. Food and Agriculture Organization of the United Nations. https://openknowledge.fao.org/items/d6f0df61-cb5d-4030-8814-0e466176d9a1

[3] Gupta, H.K. (2007) Deforestation and Forest Cover Changes in the Himachal Himalaya, India. *International Journal of Ecology and Environmental Sciences*, **33**, 207-218. https://hdl.handle.net/10535/3418

[4] Hansen, M.C., Potapov, P.V., Moore, R., Hancher, M., Turubanova, S.A., Tyukavina, A., *et al.* (2013) High-Resolution Global Maps of 21st-Century Forest Cover Change. *Science*, **342**, 850-853. https://doi.org/10.1126/science.1244693

[5] Sarre, A.D. and Davey, S.M. (2021) The Sustainable Development Goals, Forests, and the Role of *Australian Forestry*. *Australian Forestry*, **84**, 41-49. https://doi.org/10.1080/00049158.2021.1920207

[6] Murthy, M.S.R. and Jha, C.S. (2010) Forest and Vegetation. In: Roy, P.S., Dwivedi, R.S. and Vijayan, D., Eds., *Remote Sensing Applications*, National Remote Sensing Centre, 49-80.

[7] Roy, P.S., Dutt, C.B.S., Joshi, P.K. and Nrsa, S. (2002) Tropical Forest Resource Assessment and Monitoring. *Tropical Ecology*, **43**, 21-37.

[8] Trotter, C.M. (1991) Remotely-Sensed Data as an Information Source for Geographical Information Systems in Natural Resource Management a Review. *International Journal of Geographical Information Systems*, **5**, 225-239. https://doi.org/10.1080/02693799108927845

[9] Nguyen, H.T.T., Doan, T.M., Tomppo, E. and McRoberts, R.E. (2020) Land Use/Land Cover Mapping Using Multitemporal Sentinel-2 Imagery and Four Classification Methods—A Case Study from Dak Nong, Vietnam. *Remote Sensing*, **12**, Article 1367. https://doi.org/10.3390/rs12091367

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

[11] Mani, J.K. and Varghese, A.O. (2018) Remote Sensing and GIS in Agriculture and Forest Resource Monitoring. In: Reddy, G. and Singh, S., Eds., *Geospatial Technologies in Land Resources Mapping, Monitoring and Management*, Springer, 377-400. https://doi.org/10.1007/978-3-319-78711-4_19

[12] Addabbo, P., Focareta, M., Marcuccio, S., Votto, C. and Ullo, S.L. (2016) Contribution of Sentinel-2 Data for Applications in Vegetation Monitoring. *Acta Imeko*, **5**, 44-54. https://doi.org/10.21014/acta_imeko.v5i2.352

[13] Topaloğlu, R.H., Sertel, E. and Musaoğlu, N. (2016) Assessment of Classification Accuracies of Sentinel-2 and Landsat-8 Data for Land Cover/USE Mapping. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, **8**, 1055-1059. https://doi.org/10.5194/isprs-archives-xli-b8-1055-2016

[14] Immitzer, M., Vuolo, F. and Atzberger, C. (2016) First Experience with Sentinel-2 Data for Crop and Tree Species Classifications in Central Europe. *Remote Sensing*, **8**, Article 166. https://doi.org/10.3390/rs8030166

[15] Puletti, N., Chianucci, F. and Castaldi, C. (2018) Use of Sentinel-2 for Forest Classification in Mediterranean Environments. *Annals of Silvicultural Research*, **42**, 32-38. https://doi.org/10.12899/asr-1463

[16] Szostak, M., Hawryło, P. and Piela, D. (2017) Using of Sentinel-2 Images for Automation of the Forest Succession Detection. *European Journal of Remote Sensing*, **51**, 142-149. https://doi.org/10.1080/22797254.2017.1412272

[17] Phiri, D., Simwanda, M., Salekin, S., Nyirenda, V., Murayama, Y. and Ranagalage, M. (2020) Sentinel-2 Data for Land Cover/Use Mapping: A Review. *Remote Sensing*, **12**, Article 2291. https://doi.org/10.3390/rs12142291

[18] Lechner, A.M., Foody, G.M. and Boyd, D.S. (2020) Applications in Remote Sensing to Forest Ecology and Management. *One Earth*, **2**, 405-412. https://doi.org/10.1016/j.oneear.2020.05.001

[19] Jensen, J.R. (1985) Introductory Digital Image Processing: A Remote Sensing Perspective. Pearson.

[20] Erbek, F.S., Özkan, C. and Taberner, M. (2004) Comparison of Maximum Likelihood Classification Method with Supervised Artificial Neural Network Algorithms for Land Use Activities. *International Journal of Remote Sensing*, **25**, 1733-1748. https://doi.org/10.1080/0143116031000150077

[21] Patil, M.B., Desai, C.G. and Umrikar, B.N. (2012) Image Classification Tool for Land Use/Land Cover Analysis: A Comparative Study of Maximum Likelihood and Minimum Distance Method. *International Journal of Geology, Earth and Environmental Sciences*, **2**, 189-196.

[22] Kumar, A., Uniyal, S.K. and Lal, B. (2007) Stratification of Forest Density and Its Validation by NDVI Analysis in a Part of Western Himalaya, India Using Remote Sensing and GIS Techniques. *International Journal of Remote Sensing*, **28**, 2485-2495. https://doi.org/10.1080/01431160600693583

[23] Haboudane, D. and El Mustapha Bahri, (2007) Deforestation Detection and Monitoring in Cedar Forests of the Moroccan Middle-Atlas Mountains. 2007 *IEEE International Geoscience and Remote Sensing Symposium*, Barcelona, 23-28 July 2007, 4327-4330. https://doi.org/10.1109/igarss.2007.4423809

[24] Uddin, K., Gilani, H., Murthy, M.S.R., Kotru, R. and Qamer, F.M. (2015) Forest Condition Monitoring Using Very-High-Resolution Satellite Imagery in a Remote Mountain Watershed in Nepal. *Mountain Research and Development*, **35**, 264-277. https://doi.org/10.1659/mrd-journal-d-14-00074.1

[25] Sothe, C., Almeida, C., Liesenberg, V. and Schimalski, M. (2017) Evaluating Sentinel-

2 and Landsat-8 Data to Map Sucessional Forest Stages in a Subtropical Forest in Southern Brazil. *Remote Sensing*, **9**, Article 838. https://doi.org/10.3390/rs9080838

[26] Mohajane, M., Essahlaoui, A., Oudija, F., El Hafyani, M. and Cláudia Teodoro, A. (2017) Mapping Forest Species in the Central Middle Atlas of Morocco (Azrou Forest) through Remote Sensing Techniques. *ISPRS International Journal of Geo-Information*, **6**, Article 275. https://doi.org/10.3390/ijgi6090275

[27] Recanatesi, F., Giuliani, C. and Ripa, M.N. (2018) Monitoring Mediterranean Oak Decline in a Peri-Urban Protected Area Using the NDVI and Sentinel-2 Images: The Case Study of Castelporziano State Natural Reserve. *Sustainability*, **10**, Article 3308. https://doi.org/10.3390/su10093308

[28] Astola, H., Häme, T., Sirro, L., Molinier, M. and Kilpi, J. (2019) Comparison of Sentinel-2 and Landsat 8 Imagery for Forest Variable Prediction in Boreal Region. *Remote Sensing of Environment*, **223**, 257-273. https://doi.org/10.1016/j.rse.2019.01.019

[29] Miranda, E., Mutiara, A.B. and Wibowo, W.C. (2019) Forest Classification Method Based on Convolutional Neural Networks and Sentinel-2 Satellite Imagery. *International Journal of Fuzzy Logic and Intelligent Systems*, **19**, 272-282. https://doi.org/10.5391/ijfis.2019.19.4.272

[30] Campos-Taberner, M., García-Haro, F.J., Martínez, B., Izquierdo-Verdiguier, E., Atzberger, C., Camps-Valls, G., *et al.* (2020) Understanding Deep Learning in Land Use Classification Based on Sentinel-2 Time Series. *Scientific Reports*, **10**, Article No. 17188. https://doi.org/10.1038/s41598-020-74215-5

[31] Rajani, A. and Varadarajan, S. (2020) LU/LC Change Detection Using NDVI & MLC through Remote Sensing and GIS for Kadapa Region. In: Mallick, P., Balas, V., Bhoi, A. and Chae, G.S., Eds., *Cognitive Informatics and Soft Computing*, Springer, 215-223. https://doi.org/10.1007/978-981-15-1451-7_24

[32] Nelson, S.A. and Khorram, S. (2018) Image Processing and Data Analysis with ER-DAS IMAGINE®. CRC Press.

[33] Reddy, R.S., Babu, G.A. and Reddy, A.R.M. (2020) Geospatial Approach for the Analysis of Forest Cover Change Detection Using Machine Learning. *Geosfera Indonesia*, **5**, 335-351. https://doi.org/10.19184/geosi.v5i3.20157

[34] Elhag, M., Boteva, S. and Al-Amri, N. (2021) Forest Cover Assessment Using Remote-Sensing Techniques in Crete Island, Greece. *Open Geosciences*, **13**, 345-358. https://doi.org/10.1515/geo-2020-0235

[35] Hagner, O. and Reese, H. (2007) A Method for Calibrated Maximum Likelihood Classification of Forest Types. *Remote Sensing of Environment*, **110**, 438-444. https://doi.org/10.1016/j.rse.2006.08.017

[36] Rawat, J.S. and Kumar, M. (2015) Monitoring Land Use/Cover Change Using Remote Sensing and GIS Techniques: A Case Study of Hawalbagh Block, District Almora, Uttarakhand, India. *The Egyptian Journal of Remote Sensing and Space Science*, **18**, 77-84. https://doi.org/10.1016/j.ejrs.2015.02.002

[37] Alam, A., Bhat, M.S. and Maheen, M. (2020) Using Landsat Satellite Data for Assessing the Land Use and Land Cover Change in Kashmir Valley. *GeoJournal*, **85**, 1529-1543. https://doi.org/10.1007/s10708-019-10037-x

[38] Roy, P.S. and Giriraj, A. (2008) Land Use and Land Cover Analysis in Indian Context. *Journal of Applied Sciences*, **8**, 1346-1353. https://doi.org/10.3923/jas.2008.1346.1353