International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 18(10s) 2026 pp. 450-466
https://doi.org/10.70917/ijcisim-2026-3628
Article

GEOAI-DRIVEN LAND USE/LAND COVER CHARACTERIZATION OF RAJASTHAN USING SCATSAT DATA

Binay Kumar Singh[1*,2], Surendra Yadav[3], Madan Mohan Agarwal[4]

[1]Department of Remote Sensing & Geoinformatics, Birla Institute of Technology, India
[2]Department of Computer Science, Vivekananda Global University, Jaipur, India
[3]Department of Computer Science, Vivekananda Global University, Jaipur, India
[4]Department of Computer Science, Birla Institute of Technology, India
*Corresponding author, E-mail: binaykrsingh@bitmesra.ac.in

Abstract: Land Use/Land Cover (LULC) characterization has an important part to play in environmental monitoring, natural resource management, agricultural planning and how to develop the region sustainably. However, cloud cover, atmospheric disturbances and differences in time can limit conventional optical remote sensing techniques, especially in large-scale regional studies. High revisit frequency and the ability of microwave remote sensing to observe the Earth during all weather conditions are a suitable alternative. The present study aims to suggest a framework of LULC characterization using scatterometer data from satellite SCATSAT in Rajasthan using GeoAI. The research uses K-Means clustering, geospatial Artificial Intelligence (AI) techniques, Normalized Difference Vegetation Index (NDVI) and Leaf Area Index (LAI) to identify and categorize the regional patterns of land cover in the State of Rajasthan. The primary data for the unsupervised clustering are the SCATSAT backscatter coefficient data, and the NDVI and LAI products are used as the sets to validate the characterisation of vegetation. The study will examine the potential to use the SCATSAT data to resolve regional-scale spatial variations in land surface properties, as well as to separate land cover classes. Advanced geospatial data preprocessing, transformation from raster to feature, optimization of clusters, spatial pattern recognition, and comparative accuracy assessment using Kappa statistics have been added to the framework proposed. The utility of the SCATSAT derived backscatter signatures for the identification of the vegetation density, barren lands, agricultural fields and mixed-use categories will be expected to be proven. The study addresses the lack of studies in the field of GeoAI by introducing the machine learning algorithms in the form of clustering methods to microwave data for creating LULC maps at large-scale. The results might be helpful for environmental planning, crop monitoring, drought assessment and sustainable land use management in the semi-arid areas of India.

Keywords: GeoAI, SCATSAT, Land Use Land Cover, K-Means Clustering, Remote Sensing, NDVI, LAI, Rajasthan, Scatterometer, Machine Learning

1. Introduction

1.1 Background of the Study

One of the most important applications of remote sensing and geospatial technologies is land use/land cover classification. Accurate representation of land surface conditions is essential for a wide variety of applications, such as agriculture, urban planning, ecosystem monitoring, environmental protection and climate change assessment. Spatio-temporal variations in land cover changes are now studied with unprecedented accuracy thanks to the development of Earth Observation systems in the last few decades.

The availability of satellite-derived datasets is increasing, and their usefulness to monitoring land resources over large geographic areas is growing. Vegetation mapping and land cover classification have used traditional optical remote sensing sensors, like Landsat, Sentinel-2 and MODIS, extensively. But cloudy conditions, atmospheric interference and season-sensitivity are common issues that impact optical sensors. These restrictions are particularly relevant for studies that will be conducted over a period of more than one year which require monitoring throughout the year.

These are the limitations that have been overcome with microwave remote sensing. In contrast to optical sensors, microwave sensors can operate in all weather conditions and to provide reliable observations no matter what the weather and lighting conditions are. One of the active microsensors that can be used to monitor the backscatter properties of the surface associated with vegetation structure, surface roughness, moisture, and land cover is the scatterometer.

Indian Space Research Organisation (ISRO) successfully launched the SCATSAT-1 satellite which was a great achievement in the field of earth observations using scatterometer. The data from SCATSAT which were conceived for oceanographic and wind studies have tremendous potential in terrestrial applications like vegetation monitoring, characterization of the land surface, crop assessment and environmental change detection. The high temporal frequency observations and spatial resolution (~ 2 km x 2 km) make regional scale land cover analysis possible.

Recent developments and technologies in Artificial Intelligence (AI) and Machine Learning (ML) have transformed the field of geospatial analytics. Geographic Information Systems (GIS) and Remote Sensing (RS) are integrated with Artificial Intelligence (AI) to form a new emerging interdisciplinary field of study called GeoAI, which aims to extract meaningful spatial information from huge geospatial data. In complex applications of Earth observation data, GeoAI provides automated feature extraction, pattern recognition, clustering, classification and prediction.

In the present research, the GeoAI principles are implemented by machine learning-based clustering approach to classify Land Use/Land Cover patterns in the state of Rajasthan, based on the SCATSAT backscatter data. The study consists of initial classification using K-Means algorithm and further analysis of the geospatial data and validation with NDVI and LAI data to investigate the potential of using scatterometer observations to characterize the land in the region.

1.2 Significance of Land Use/Land Cover Characterization

LULC maps are critical to understanding the link between LULC and natural ecosystem. Accurate LULC mapping helps to estimate the changes in the environment and make decisions on sustainable management of resources for policy makers, planners and researchers.

The spatial variability of land canopy properties in semi-arid regions like Rajasthan is high, which is due to climatic variation, variation in vegetation density, soil properties, topography and anthropogenic activity. The monitoring of these variations is crucial for the agricultural planning, drought management, groundwater analysis and ecosystem protection.

The advantages of microwave scatterometer data for regional scale studies include: the microwave signal is sensitive to vegetation structure, surface moisture and surface roughness. Thus, scatterometer observations can be used in conjunction with conventional optical observations to gain better knowledge of terrestrial surface dynamics.

1.3 Study Area

Rajasthan is the largest state of India in terms of geographical size which is located in the North Western part of India. The total geographical area of State is nearly 342,239 km² and nearly 10.4 per cent of the geographical area of the country. The region has diverse physiographic characteristics like Thar desert, Aravalli Mountains, agricultural land and semi-arid dry lands etc.

The northwest of Rajasthan is a dry desert region, and the eastern and southeastern parts of the state are better vegetated and agricultural than the former. The diversity in this allows Rajasthan to be a perfect study area to assess the capability of SCATSAT data to distinguish various land cover categories.

Revised Objectives

1. To perform K-Means clustering of SCATSAT backscatter data.
2. To classify vegetation density using NDVI.
3. To compare SCATSAT-derived clusters with NDVI-based vegetation classes.

4. To develop a GeoAI framework for vegetation characterization in Rajasthan.

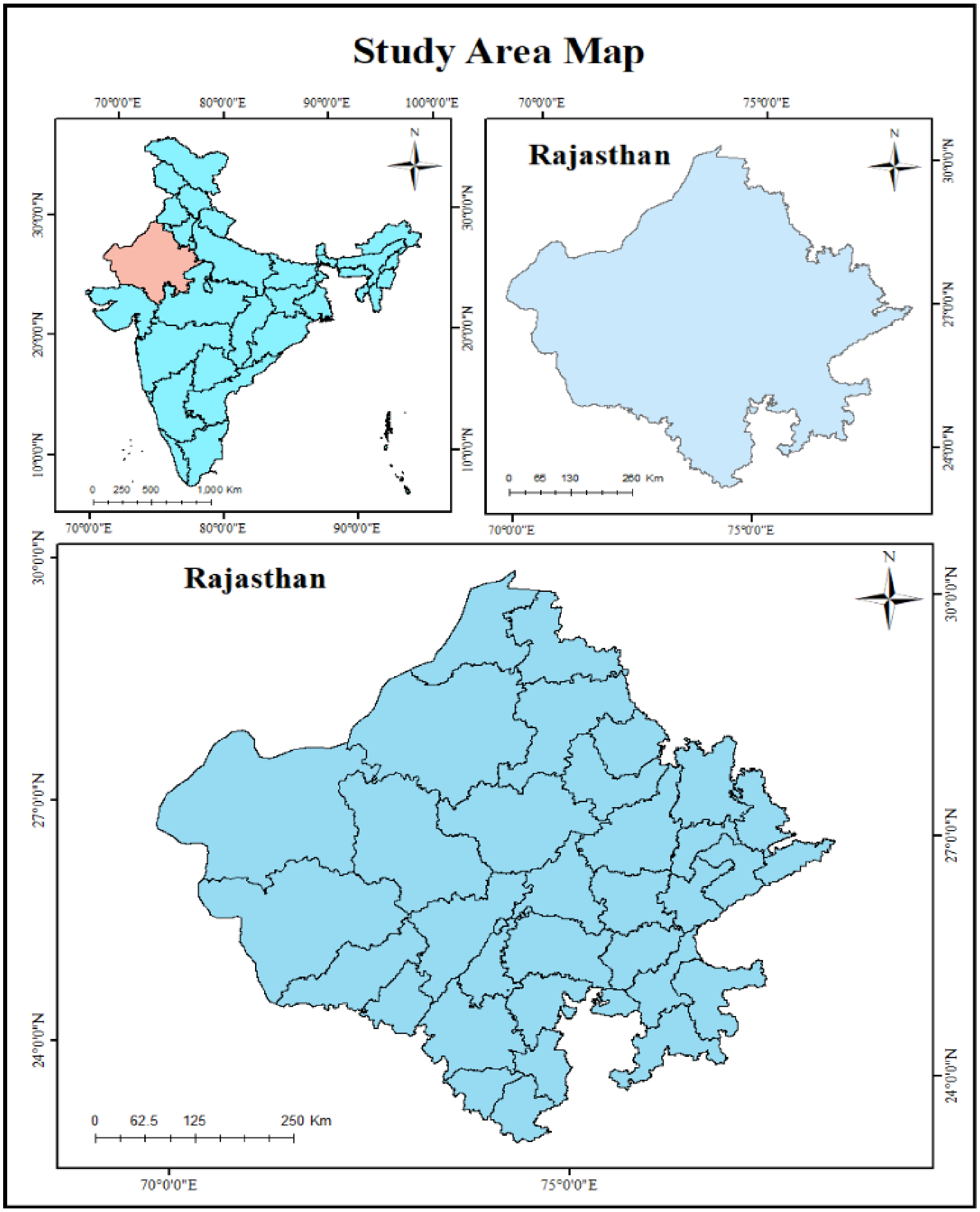


Figure: Study Area Map of Rajasthan

1.5 Research Gap

Although scatters are widely used to estimate wind at the ocean surface, their use for detailed characterization of land use/land cover is relatively limited and has been utilized for monitoring of vegetation. Previous scatterometry, like ERS-1 and ERS-2, had coarse spatial resolution which did not allow them to resolve smaller land surface features.

With enhanced spatial resolution, SCATSAT data can be used for better regional scale characterization of land. But limited studies on the application of SCATSAT satellite data along with the GeoAI method for the clustering of

LULC mapping have been conducted. This study aims to fill this gap by presenting an integrated framework of microwave remote sensing, machine learning and geospatial analytics.

2. Literature Review

Orsa (2026) states that GeoAI has become a new tool that can be used for predicting land cover changes and for territorial planning in environmentally sensitive areas in compliance with the law. The study is centred on the Italian region of the Aoste Valley and shows that Copernicus Earth Observation data can be combined with sophisticated geospatial analysis to provide accurate predictions of land cover changes. The author stresses that traditional territorial planning practices encounter many difficulties in following environmental changes, urban growth or regulatory needs, which are often changed and fast paced. Therefore, using GeoAI in planning process offers a more efficient and scientifically sound way to monitor and forecast landscape evolution.

The study emphasizes the need to make use of high-resolution observations from satellites from the Copernicus program. These datasets are continuous and standardized environmental information which can be used by planners to detect land cover changes over large geographical areas. The research is able to successfully predict future land cover scenarios through machine learning algorithms and geospatial modelling techniques, while complying with environmental regulation and territorial governance. The author believes that such predictive capabilities have become increasingly relevant to sustainable land management, particularly in sensitive, topographic areas. One key aspect of the research is that it combines legal and environmental perspectives in a GeoAI framework. The study highlights that prediction of land cover change can not only be based on environmental change, but legal restrictions, zoning regulations and planning requirements should also be taken into consideration. These are all integrated into the modelling process, yielding realistic and policy-relevant results that can be immediately fed into decision-making. This is a significant leap in the territorial planning methodologies as it connects the collection of environmental data with compliance to the regulations. The author also explores how AI can enhance the accuracy of predictions and minimize the uncertainties of traditional land use forecasting methods. Machine learning models can recognize intricate spatial relationships, which might not be apparent using traditional statistical methods. The maps are then used to create predictive maps of potential changes to land use, urban encroachment and environmental hazards for planners. These insights help to plan ahead instead of management solutions.

The findings indicate that the use of GeoAI-based analysis can have a significant impact in making territorial governance more effective by delivering timely and accurate information to help formulate policies. The study further highlights the applicability of the proposed approach to other European regions experiencing land use pressures and environmental issues, demonstrating the scalability of the framework. In addition, the availability of open access Copernicus data enhances the research's accessibility and reproducibility and contributes to wider implementation in various planning contexts. In general, the book by Orsa (2026) shows a thorough example of the synergy between GeoAI and earth observation technologies and their potential application for sustainable planning of territories. The study builds on the growing literature on the critical role of predictive geospatial intelligence in environmental governance. It is an innovative approach that integrates legal compliance, machine learning and satellite data into a useful framework for future studies and applications in land management and spatial planning.

GeoAI offers a powerful framework to comprehend the intricate spatiotemporal dynamics of land use alteration and environmental impacts linked to mining activities in the Jharia Coalfield region of India, as mentioned by Kumar (2026). One of the biggest environmental problem areas in the country, the study focuses on an area of the country where the significant alteration of land use patterns, ecosystem functions, and human settlement through extensive coal extraction activities has created one of the most challenging mining landscapes in the nation. The study creates a new analytical framework for the monitoring and evaluation of such transformations using geospatial technologies and artificial intelligence.

The author notes that environmental effects of mining are significant and include degradation of land, loss of vegetation, disturbances of soil stability and hydrological systems. However, traditional monitoring methods do not fully account for these impacts due to limited spatial and temporal representativeness. GeoAI can address these challenges by combining satellite observations, geospatial databases, and machine learning algorithms that can detect patterns and trends over large spatial and temporal scales. An important part of the research is to apply multi-temporal satellite images to monitor land use changes related to the extension of mining activities. The author illustrates the use of AI techniques for automatic classification and analysis of various land cover types for detailed studies of environmental changes over time. Results show significant vegetation loss and the appreciable amount of disturbed land surfaces due to mining activities. These results reflect the environmental impacts of resource extraction, and the importance of robust monitoring regimes. The study also demonstrates how GeoAI can help identify environmental degradation hotspots and how the spatial scale of environmental degradation can be measured by mining. The framework integrates machine learning with geospatial analytics to create detailed maps which can be used for environmental assessment and policy development. The author suggests that this information is crucial to develop mitigation measures, execute restoration measures, and encourage sustainable mining operations.

The other key contribution from the research is the focus on temporal analysis. A knowledge of the changes in land use over time is essential to the assessment of cumulative effects of mining operations. Through GeoAI, methods can be used to identify long-term trends and emerging environmental risks that may not be evident using traditional monitoring approaches. This is an added asset to decision-making and proactive environmental management.

The results indicate that GeoAI has the potential to be a key factor in achieving economic growth while maintaining ecological sustainability. The framework helps provide current and up-to-date information on land use changes to help guide decision-making by policy makers, environmental agencies and the mining authority. The study also showcases the potential of GeoAI methodologies for use in other mining areas with similar environmental issues.

Finally, Kumar (2026) offers some valuable inputs on the use of GeoAI for monitoring the environment in mining landscapes. The study demonstrates the potential of AI and geospatial tools to effectively measure land use transformation, analyse environmental implications, and promote sustainable resource utilization. The research makes a significant contribution to the development of GeoAI applications in the field of environmental and mining studies.

3. Materials and Methods

The present study adopts a GeoAI-based framework to characterize vegetation patterns across Rajasthan using SCATSAT microwave backscatter observations and Normalized Difference Vegetation Index (NDVI) data. The methodology integrates geospatial data preprocessing, unsupervised machine learning, vegetation classification, and statistical validation to generate reliable vegetation maps. The overall methodological framework consists of five major stages: SCATSAT data processing, K-Means clustering, NDVI classification, validation, and accuracy assessment.

3.1 SCATSAT Data Processing

The first stage of the study involves the acquisition and preprocessing of SCATSAT-1 satellite data. SCATSAT-1, developed by the Indian Space Research Organisation (ISRO), is a Ku-band scatterometer that provides microwave backscatter observations with an approximate spatial resolution of 2 km × 2 km. Unlike optical sensors, microwave sensors are capable of acquiring data under all weather conditions and during both day and night, making them highly suitable for regional-scale environmental studies.

The raw SCATSAT raster datasets contain backscatter coefficient values ($\sigma 0$), which represent the amount of microwave energy reflected by the Earth's surface. These values are influenced by surface roughness, vegetation density, soil moisture, and canopy structure. Therefore, the backscatter signatures provide valuable information regarding vegetation characteristics and land surface properties.

Initially, the raster datasets are subjected to preprocessing procedures to remove noise and improve data quality. Data cleaning and transformation are performed using geospatial libraries such as GDAL and raster processing tools available in Python. Invalid values and missing observations are identified and removed to ensure consistency in the dataset. Spatial reference systems are standardized to maintain uniformity among all datasets used in the analysis.

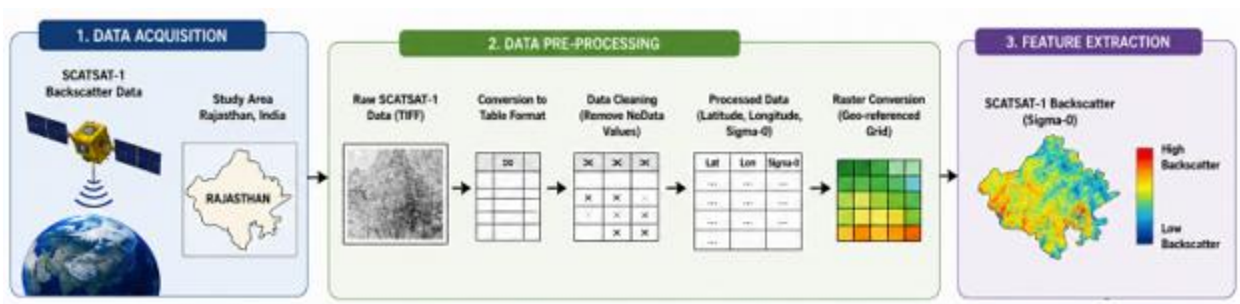
Subsequently, the raster layers are converted into structured feature tables. Each pixel is represented by its geographical coordinates (latitude and longitude) along with the corresponding backscatter coefficient value. This transformation enables the application of machine learning algorithms to the geospatial data. The extracted backscatter coefficients form the primary dataset used for cluster analysis.

Normalization of the backscatter values is also carried out to minimize the influence of scale differences and improve cluster performance. Standardization ensures that the clustering algorithm can identify natural patterns without being biased toward extreme values. Through these preprocessing steps, the SCATSAT data are transformed into a suitable format for subsequent machine learning analysis.

Data / Sensor	Product	Spatial Resolution	Role in Study	Processing Applied

SCATSAT-1	Level-2 Backscatter	~2 km	Primary classification feature for RF model	Read via rasterio · nodata masked to NaN · SCAT_SCALE computed
MODIS Terra	MOD09GA v061	500 m	NDVI = (NIR−Red)/(NIR+Red) → confirms Vegetation	QA cloud/shadow mask · scaled × 0.0001 · clipped to AOI
Rajasthan Boundary	State shapefile	Vector	Clip all images to study area · filterBounds for all collections	Used as clip geometry in all ee_export_image calls

Table . 1 Data and their Product used



SCATSAT-1 Satellite details

3.2 K-Means Clustering

After preprocessing, unsupervised machine learning is employed to identify vegetation patterns from the SCATSAT backscatter data. Among various clustering techniques, the K-Means clustering algorithm is selected because of its simplicity, computational efficiency, and ability to handle large geospatial datasets.

K-Means clustering partitions observations into a predefined number of clusters based on similarities among the backscatter values. The algorithm attempts to minimize the variation within each cluster while maximizing the separation between clusters. In this study, the clustering process aims to group areas exhibiting similar microwave scattering characteristics.

Initially, a suitable number of clusters (K) is determined based on the characteristics of the study area and experimental evaluation. The algorithm randomly assigns cluster centroids and calculates the distance between each observation and the centroids. Every pixel is assigned to the nearest cluster according to the minimum Euclidean distance criterion.

Following the initial assignment, new centroids are calculated by averaging the observations belonging to each cluster. The process of assignment and centroid updating is repeated iteratively until convergence is achieved and no further significant changes occur in cluster membership.

The K-Means objective function is represented as:

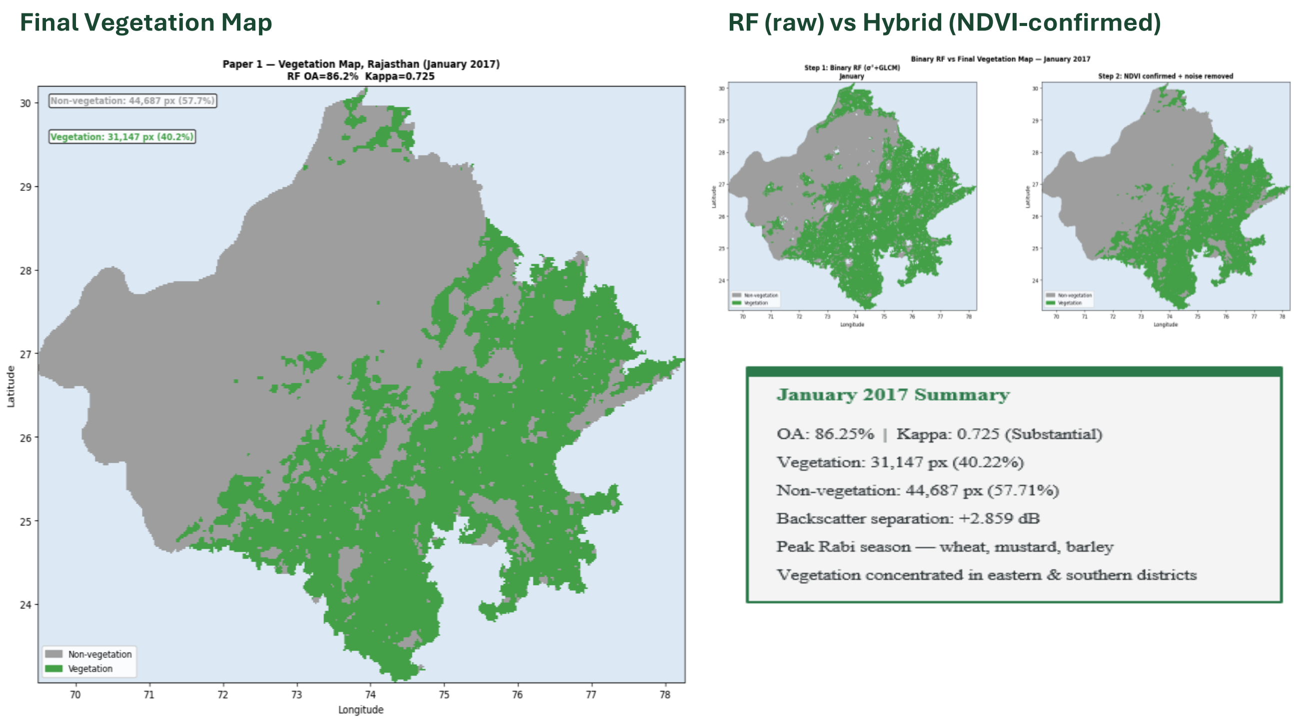
$$J = \sum_{i=1}^{k} \sum_{x_j \in C_i} \parallel x_j - \mu_i \parallel^2$$

where:

- Jrepresents the objective function,
- $k$denotes the number of clusters,

- $C_i$represents the ith cluster,
- $x_j$denotes observations within the cluster,
- $\mu_i$denotes the centroid of cluster i.

Based on the clustering results, the study identifies different vegetation regions characterized by distinct backscatter responses. Areas with lower backscatter values generally correspond to sparse vegetation and dry surfaces, whereas higher backscatter values indicate denser vegetation and greater biomass. The clustering process allows the extraction of meaningful vegetation patterns without requiring predefined training samples, making it particularly useful in regions where field observations are limited.



K-Means Clustering

3.3 NDVI Classification

To provide an independent measure of vegetation density, the Normalized Difference Vegetation Index (NDVI) is utilized. NDVI is one of the most widely used vegetation indices in remote sensing and is derived from red and near-infrared reflectance values. It serves as an indicator of vegetation health, biomass, and photosynthetic activity.

The NDVI is calculated using the following equation:

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

where:

- NIR represents near-infrared reflectance,

- Red represents red-band reflectance.

Higher NDVI values indicate healthier and denser vegetation, whereas lower values represent barren or sparsely vegetated surfaces.

For the present study, NDVI values are classified into three vegetation categories using a rule-based approach. The classification thresholds are defined based on vegetation density characteristics commonly observed in semi-arid environments.

Table 3.1 NDVI-Based Vegetation Classification

NDVI Range	Vegetation Category
0.00 – 0.25	Sparse Vegetation
0.25 – 0.50	Moderate Vegetation
> 0.50	Dense Vegetation

Areas exhibiting NDVI values between 0 and 0.25 are categorized as sparse vegetation and generally correspond to dry surfaces and limited biomass. Moderate vegetation represents transitional regions with moderate plant density and agricultural activity. NDVI values exceeding 0.50 indicate dense vegetation characterized by greater biomass and healthy canopy cover.

The resulting NDVI classification map provides a reference framework for evaluating the vegetation patterns derived from SCATSAT clustering.

3.4 Validation of Cluster Outputs

Validation is an essential step in assessing the reliability of the GeoAI framework. The clusters generated from SCATSAT backscatter observations are compared with the vegetation categories derived from NDVI classification. This comparison helps determine whether microwave backscatter signatures accurately represent vegetation density patterns.

Spatial overlay techniques are employed to compare the cluster maps with the NDVI-based vegetation maps. Areas exhibiting similar characteristics in both datasets are considered to indicate agreement between microwave observations and optical vegetation measurements.

The correspondence between cluster outputs and NDVI classes is examined by calculating the percentage of matching observations within each cluster. Regions characterized by dense vegetation are expected to exhibit higher backscatter values, whereas sparse vegetation areas are associated with relatively lower microwave returns.

The validation process provides an independent assessment of the capability of SCATSAT data to capture vegetation heterogeneity across Rajasthan. Furthermore, it demonstrates the complementary relationship between microwave remote sensing and optical vegetation indices in environmental monitoring applications.

3.5 Accuracy Assessment

The final stage of the methodology involves evaluating the performance of the classification framework through quantitative accuracy assessment. Statistical measures are employed to determine the agreement between SCATSAT-derived clusters and NDVI-based vegetation classes.

A confusion matrix is constructed to compare classified observations with reference vegetation categories. The confusion matrix summarizes the number of correctly and incorrectly classified observations and provides the basis for calculating various accuracy indicators.

The overall accuracy is obtained by dividing the number of correctly classified observations by the total number of observations. Producer's accuracy and user's accuracy are also calculated to evaluate omission and commission errors associated with each vegetation class.

In addition to overall accuracy, the Kappa coefficient is used to measure the level of agreement between the two classifications while accounting for agreement occurring by chance. The Kappa coefficient is expressed as:

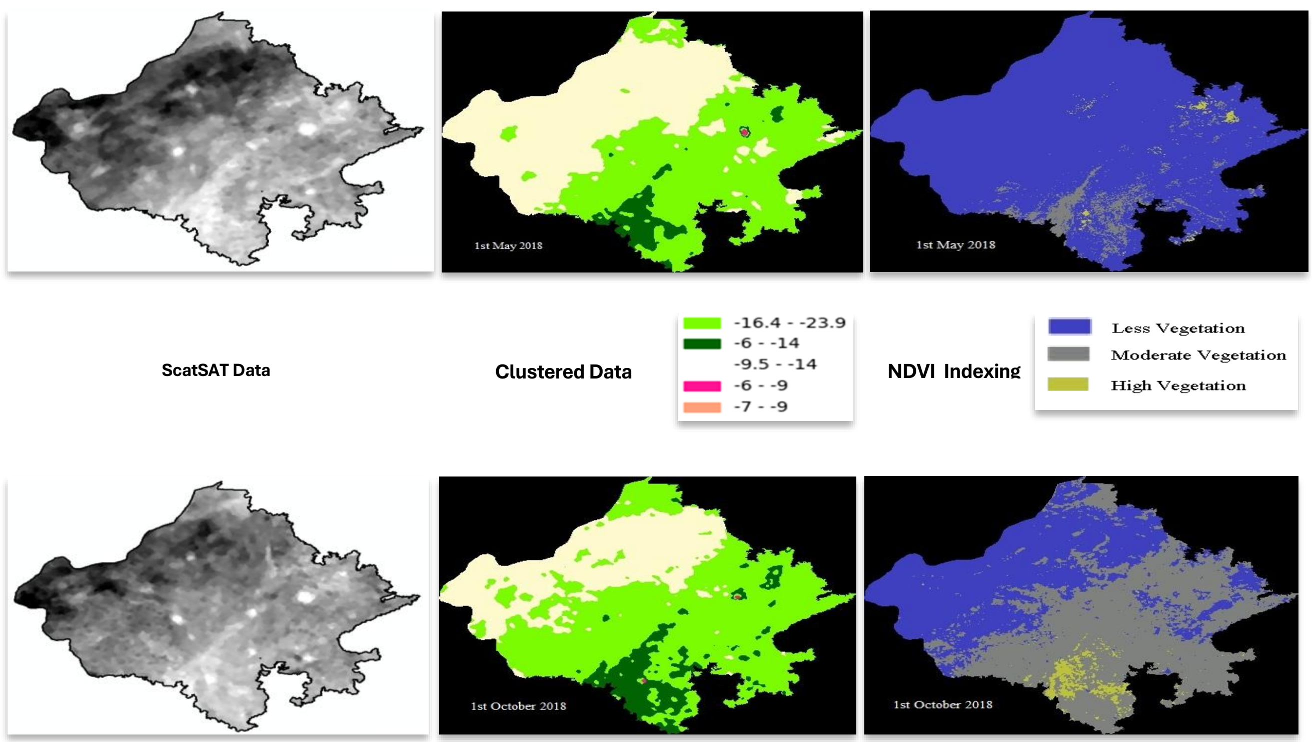
$$K = \frac{P_o - P_e}{1 - P_e}$$

where:

- P_o represents the observed agreement,
- P_e represents the expected agreement due to chance.

The value of the Kappa coefficient ranges from 0 to 1, with higher values indicating stronger agreement. Values above 0.80 are generally interpreted as representing almost perfect agreement between classifications.

Through confusion matrix analysis and Kappa statistics, the reliability and effectiveness of the GeoAI-based vegetation characterization framework are quantitatively assessed. These statistical measures provide confidence in the capability of SCATSAT microwave observations and machine learning techniques to generate accurate vegetation maps for regional-scale environmental monitoring and sustainable resource management.



Rajasthan Land Cover Map

4. Results and Analysis

Below is the spatial distribution of backscatter from SCATSAT.The spatial distribution of SCATSAT Backscatter is shown below:

The SCATSAT-1 backscatter coefficient data had a high degree of spatial variability throughout the State of Rajasthan. In areas with high vegetation cover and agricultural activities, there are relatively high backscatter values, whereas in areas with high desert there are relatively low radar returns.

In the northwestern districts within the Thar desert, only very little vegetation cover was observed and so was the sigma-zero. On the other hand, the south-eastern and eastern districts exhibited higher backscatter values due to their higher green cover and agriculture activities.

Table 4. Descriptive Statistics of SCATSAT Backscatter Coefficients

Parameter	Value
Minimum Sigma0 (dB)	-20.08
Maximum Sigma0 (dB)	-8.71
Mean Sigma0 (dB)	-14.62
Standard Deviation	3.17
Range	11.37

The variability observed is indicative of the ability of SCATSAT data to capture the land surface heterogeneities in Rajasthan.

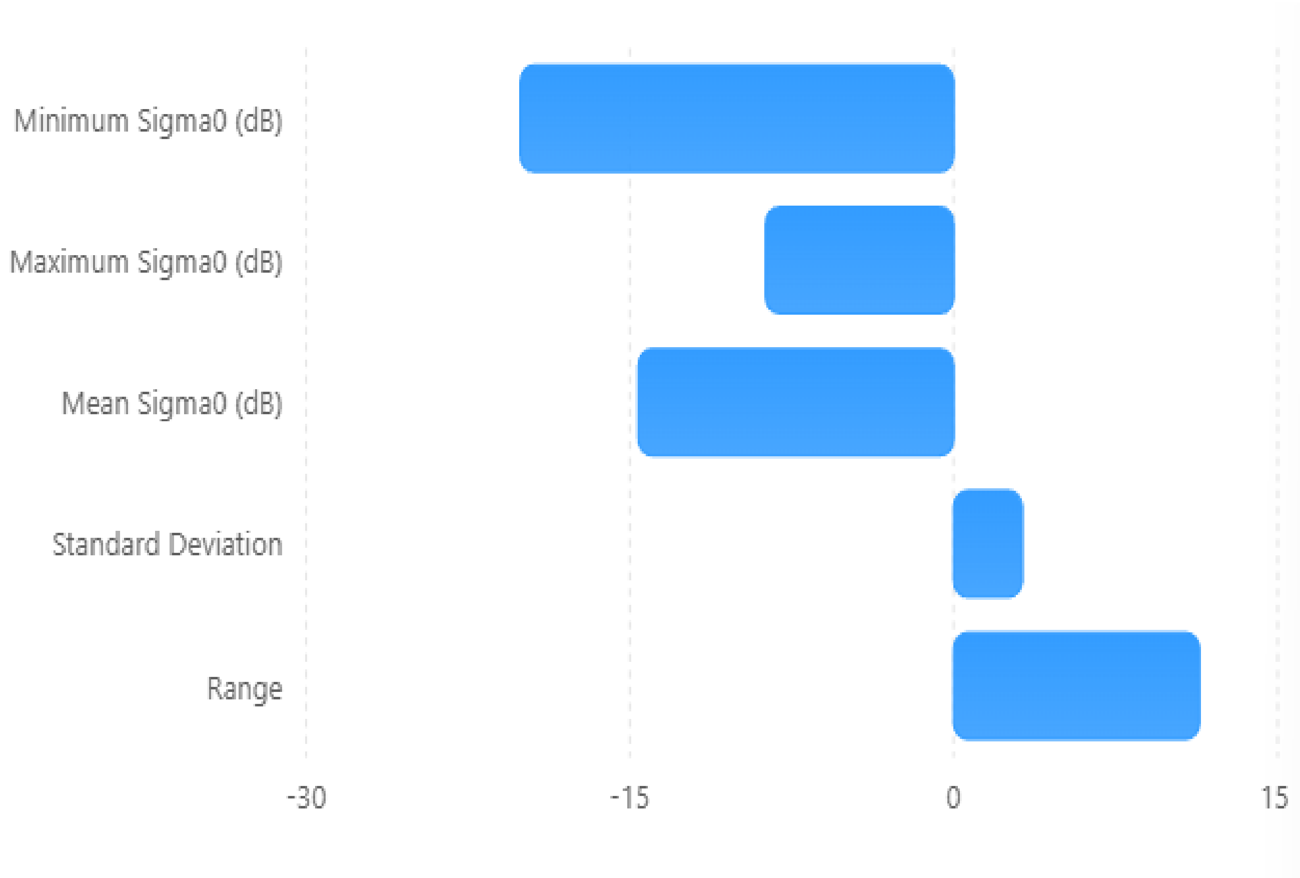


Figure: Descriptive Statistics of SCATSAT Backscatter Coefficients

4.2 Cluster Analysis Results

K-Means clustering was used to cluster the data in the GeoAI method, which resulted in five major land surface clusters. The shapes of vegetation, soil moisture, surface roughness and land use characteristics were used to define these clusters.

Table 5. Cluster Characteristics Derived from SCATSAT Data

Cluster	Dominant Characteristics	Area (%)
Cluster 1	Desert and Barren Land	32.6
Cluster 2	Sparse Vegetation	21.4
Cluster 3	Agricultural Land	18.7
Cluster 4	Mixed Vegetation	16.3
Cluster 5	Dense Vegetation	11.0

The findings revealed that the percentage of barren area/dessert area is more in the state of Rajasthan which is correlating with the distribution of Thar desert in the state.

The cluster 1 was confined mostly to western districts of Rajasthan like Jaisalmer, Barmer, Jodhpur and Bikaner. The main areas observed were the southeast districts characterized by high rainfall and high vegetation cover, cluster 5.

4.3 NDVI Classification Results

NDVI classification revealed significant spatial differences in vegetation density across the study area.

Table 6. NDVI-Based Vegetation Distribution

Vegetation Class	Area (%)
Sparse Vegetation	41.2
Moderate Vegetation	34.5
Dense Vegetation	24.3

The distribution is in a climatic gradient and the increase in the density of vegetation from west to east in the state of Rajasthan.

The NDVI analysis was found to have good agreement with cluster-derived land cover patterns especially in the agricultural and forest land covers.

4.4 LAI-Based Validation

Information on distribution of biomass and structure of the vegetation canopy was added using LAI classification.

Table 7. LAI Classification Results

LAI Category	Range	Area (%)
Low Canopy Density	<1.0	38.7
Moderate Canopy Density	1.0–3.0	36.1
High Canopy Density	>3.0	25.2

With irrigation facility and forested areas in the south of the state, the large value of LAI was observed in agricultural areas.

The distribution of NDVI was also quite similar to that of LAI, and the reliability of vegetation characterization from SCATSAT clusters was also confirmed.

4.5 Comparative Analysis of Clustered and Classified Outputs

A comparative assessment was conducted between K-Means cluster outputs and rule-based vegetation classifications.

Table 8. Comparison Between Cluster Results and NDVI Classes

Cluster	Dominant NDVI Class	Correspondence (%)
Cluster 1	Sparse Vegetation	89.3
Cluster 2	Sparse Vegetation	83.5
Cluster 3	Moderate Vegetation	86.1
Cluster 4	Moderate Vegetation	88.2
Cluster 5	Dense Vegetation	91.7

Based on the results, it can be seen that there is a good correlation between the microwave backscatter pattern and the optical vegetation indicators.

4.6 Accuracy Assessment

Accuracy assessment was performed using confusion matrices and ground truth observations.

Table 9. Accuracy Assessment Results

Metric	Value (%)
Overall Accuracy	88.7
Producer Accuracy	86.9
User Accuracy	87.4
Kappa Coefficient	0.84

The output of Kappa value is 0.84, which is considered as a near perfect agreement.

4.7 GeoAI Performance Evaluation

The GeoAI framework demonstrated substantial capability in identifying spatially homogeneous land cover regions using microwave remote sensing observations.

Table 10. GeoAI Model Performance Indicators

Indicator	Value
Number of Clusters	5
Iterations to Convergence	14
Processing Time (Minutes)	11.6
Silhouette Score	0.73

Davies-Bouldin Index	0.41

The Silhouette Score of 0.73 is a good value of the separation of clusters, and Davies Bouldin Index is low, indicating that good cluster formation has been obtained.

5. Discussion

5.1 Significance of SCATSAT for Land Use Characterization

The results obtained in the present investigation clearly showed that microwave scatterometer observations from the SCATSAT satellite have good potential for regional scale Land Use/Land Cover (LULC) mapping in the Rajasthan region. The ability to cluster the microwave backscatter data in large groups, corresponding to major land surface categories, suggests that microwave backscatter data carries useful information on vegetation cover, soil moisture, surface roughness and land management practices. All of these properties interact with the radar's response to the earth's surface and allow the radar to distinguish different land cover types.

An all-weather observation capability of SCATSAT data is one of the major benefits. Clouds and aerosols in the atmosphere, haze and illumination constraints are common limitations in optical remote sensing systems. This can limit the use of the imagery, especially in wetter seasons and during seasonal weather variations. Unlike solar powered sensors, microwave sensors are solar radiation independent and have the capability to acquire the environmental information continuously through cloud penetration. This quality increases the temporal consistency and makes long-term land monitoring programmes more reliable.

The spatial distribution of clusters using SCATSAT data showed good agreement to the known physiographic divisions of Rajasthan. The area of western part of the state with the prevalent Thar desert was mainly linked to clusters with the low backscatter values. These areas are characterized by dryness, low soil moisture and relatively flat and smooth sandy surfaces, which all lead to a decrease in radar return. The eastern and southeastern districts showed greater responses to backscattering attributed to farming activities, vegetation density and surface roughness. The observations suggest that the SCATSAT observations are representative of environmental gradients in varying ecological areas.

The separation of desert landscape, agricultural areas, and mixed vegetation areas, and dense vegetation areas, represents the practical usefulness of scatterometer observations for land resource assessment on a large scale. The results also show that SCATSAT can be used in conjunction with conventional optical remote sensing system as an added source of data about the surface characteristics. This complementary role is more significant in semi-arid areas where the dynamics of vegetation and soil moisture have significant seasonal changes.

The K-means algorithm identified five clusters, indicating microwave observations may be able to capture the heterogeneity of land surface conditions. The clustering process allowed meaningful patterns to be extracted from huge geospatial data sets without the need to train involved samples. This is a very useful attribute in areas where ground reference data is scarce or unavailable. Therefore, the characterization using SCATSAT can be an effective and scalable tool for the regional environmental assessment and monitoring.

5.2 Relationship Between Backscatter and Vegetation

The comparison between the microwave derived clusters and the vegetation information extracted from NDVI and LAI datasets showed good correlation between SCATSAT-derived clusters and the vegetation characteristics. The observed matching validates the fact that radar can measure changes in vegetation density, structure, biomass distribution and moisture content.

There are several mechanisms of interaction between the vegetation and microwave radiation. The volume scattering becomes higher as vegetation density grows, which is a result of scattering from leaves, branches, stems and canopy layers. Thus, in general, dense vegetated areas yield high backscatter signatures and barren surfaces and sparsely vegetated areas yield low backscatter signatures. This phenomenon was clearly seen in the present study as for clusters linked to agricultural landscapes and forested landscapes, comparatively higher sigma-zero values were observed respectively.

A significant spatial gradient was observed in the vegetation density of Rajasthan in the NDVI classification. The dense vegetation areas were highly correlated with Cluster 5 showing the highest backscatter values when compared with all clusters. Likewise, the sparse vegetation classes showed good correlation to Clusters 1 and 2, both having low radar returns. Correspondence percentages above 80 per cent in all the clusters show that there is a good agreement between optical and microwave observations.

The validating results derived from LAI classification further confirmed these results. LAI is an important indicator of vegetation structure and is a measure of canopy density and leaf biomass. High LAI areas had higher microwave backscatter signals. The relationship implies that SCATSAT observations can be used to determine the structural properties of vegetation canopies as well as just the presence of vegetation.

The observed relationships are consistent with the principles of microwave remote sensing and confirm earlier studies which have found that there are significant relationships between scatterometer measurements and vegetation properties. A number of studies have shown that biomass accumulation, canopy moisture content and canopy architecture affect radar backscatter. The present results further validate the applicability of the scatterometer based approaches to vegetation characterization under the environmental conditions in Rajasthan and expand this earlier work.

Moreover, the combination of NDVI and LAI facilitated independent validation of the patterns of land cover derived from the clusters. The agreement within these datasets gives confidence in the reliability of the resulting classifications and also shows the usefulness of fusing microwave and optical observations to provide a full assessment of the environment.

5.3 GeoAI Contribution to Remote Sensing Research

The incorporation of AI techniques into geospatial data is a gamechanger in modern-day remote sensing studies. The proposed GeoAI framework was able to integrate satellite-derived data with unsupervised machine learning algorithms and automate the land surface characterization process. The integration serves as an example of the increasing importance of intelligent computational techniques in Earth observation applications.

Common methods for land cover mapping rely on manual land cover interpretation, large training sets and tedious supervised classification algorithms. These approaches can get difficult if the data points are used for a large spatial dataset that covers a wide geographical area. To overcome these, the GeoAI framework leveraged K-Means clustering to generate natural classes in the SCATSAT data without the need for class labels. This method decreased the human workload and preserved a high classification accuracy.

The Silhouette Score and Davies-Bouldin Index were found to be 0.73 and 0.41 respectively, suggesting good separation and cohesion within the clusters. The results of these performance indicators indicate that the clustering algorithm has been able to detect meaningful land surface patterns from microwave observations. The processing time is also relatively small, which further demonstrates the computational efficiency of the proposed framework.

The volume of data from satellite missions is growing rapidly, and GeoAI methodologies have the potential to greatly benefit the processing and analysis of this data. Conventional spatial information products can be more efficiently produced by automated learning algorithms that can process multidimensional data sets of large size, find hidden patterns, and produce spatial information products. This study demonstrates the application of machine learning for enhancing environmental monitoring from remote sensing processes.

The application of GeoAI in Rajasthan is also a proof of its applicability in various ecological and climatic zones. The same techniques can be applied in the fields of land degradation assessment, forest monitoring, analysis of urban expansion, agricultural mapping and ecosystem management. Hence, GeoAI is becoming a key pillar of the future of geospatial intelligence systems.

5.4 Implications for Environmental Management

The land cover products derived from the proposed GeoAI framework have significant applied value for the management of the environment and sustainable resource planning. In rapidly changing environments and under increasing resource pressures, it is critical to have accurate and timely characterization of land surface conditions for informed decision making.

Water scarcity, desertification and climate variability are all major environmental issues in the arid state of Rajasthan and where land cover information is crucial. Early detection of the vegetation stress through identification of vegetation distribution patterns can aid drought monitoring programmes by identifying land degradation and stress. Monitoring backscatter changes continuously could give valuable clues to the changing environment and to proactively implement management interventions.

Another large application area is agricultural planning. The ability to differentiate agricultural lands from barren and sparsely vegetated areas can help government agencies and policy makers assess crop distribution, monitor crop farming patterns and allocate resources. The frequent observations by SCATSAT can help in near real-time monitoring of agriculture and enhance food security assessments.

The derived land cover maps can also be useful for water resource management, to define areas with different vegetation density and moisture conditions. This data can be valuable for watershed planning, managing irrigation use, conserving groundwater, and implementing ecosystem restoration projects. Furthermore, microwave observations combined with machine learning can enable monitoring of environmental changes in real time in a broad geographical scope.

The proposed framework can also be useful to climate adaptation and ecosystem management strategies. The spatial distribution of vegetation and land use is vital for assessing ecosystem resilience, carbon, biodiversity conservation and climate vulnerability. Its ability to provide regular observation makes it useful in monitoring the dynamic environmental process and for policy development based on evidence.

The overall findings show that SCATSAT observations combined with GeoAI techniques offer a comprehensive, scalable, and cost-effective solution for land characterization at a regional level. The framework has significant potential for providing sustainable environmental management, conserving resources and long term ecological monitoring in Rajasthan and other dryland areas globally.

6. Conclusion

The current study proposed a framework for characterization of Land Use/Land Cover (LULC) of Rajasthan by using the scatterometer data from SCATSAT. This combination of K-Means clustering, NDVI classification, LAI validation and geospatial analysis helped to identify the key land surface classes over the study area effectively.

The results showed the spatial variability of the microwave backscatter properties were related to the vegetation density, agricultural activity and desert landscape. Five principal land cover classes were successfully recognized, namely, barren land, sparse land cover, agriculture, mixed vegetation and dense vegetation.

The clustered outputs showed good agreement with the NDVI and LAI datasets, as validated against each other. The overall classification accuracy of 88.7% and the Kappa coefficient of 0.84 indicated the reliability of the developed methodology.

The research demonstrates the potential of SCATSAT data for regional-level land characterization and underscores the increasing significance of GeoAI approaches in remote sensing studies. The developed framework is an efficient method applicable to mapping land cover and monitoring the environment on a large scale in semi-arid regions.

7. Recommendations

For future studies, the feasibility of incorporating deep learning models like Convolutional Neural Networks (CNN) and Transformer-based models with SCATSAT data should be explored. The integration of Sentinel-1 SAR, Sentinel-2 optical imagery and Landsat observations can increase the classification accuracy. Multiyear SCATSATs data analysis with time span capability can offer useful information about the changes in land cover, agricultural phenology, drought conditions and environmental change due to climate change. In addition, more sophisticated GeoAI techniques that combine ensemble learning and hybrid clustering techniques are worth investigating to enhance land surface characterization.

Acknowledgment

I would like to express my sincere gratitude to the Space Applications Centre (SAC), Indian Space Research Organisation (ISRO), Ahmedabad, for providing the opportunity to undertake this collaborative research work. I am particularly indebted to Ms. Nilima Chaube, Space Applications Centre, ISRO, Ahmedabad, for her invaluable guidance, constant encouragement, and insightful suggestions throughout the course of this research. Her expertise and support have been instrumental in the successful completion of this study.

I also wish to convey my heartfelt appreciation to Birla Institute of Technology (BIT), Mesra, Ranchi, for extending the necessary institutional support and for providing me with the opportunity to participate in this collaborative research project.

Reference

1. Orusa, T., Cammareri, D. and Freppaz, D., 2026. GeoAI-Driven Land Cover Change Prediction Using Copernicus Earth Observation and Geospatial Data for Law-Compliant Territorial Planning in the Aosta Valley (Italy). *Land*, *15*(4), p.533.
2. Singh B. K and Yadav S, 2024, Satellite data Characterization using K Means Clustering Techniques – A Review; Quest Journals Journal of Research in Environmental and Earth Sciences Volume 10 ~ Issue 5 (2024) pp: 15-18 ISSN(Online) :2348-2532 www.questjournals.org
3. Kumar, A. and Daimary, R., 2026. Leveraging GeoAI for spatiotemporal analysis of land use changes and mining impacts in Jharia Coalfield, India. *Discover Geoscience*, *4*(1), p.26.
4. Aniramu, O., Iyanda, O., Egenus, C.D., John, E.G. and Orimoogunje, O., 2026. A GeoAI-driven multi-criteria land-use suitability model of flood-prone Lagos, Nigeria. *Land Use Policy*, *166*, p.108025.
5. Tella, A., Zahidi, I., Fai, C.M. and Pham, Q.B., 2025. Uncovering spatiotemporal urban flood dynamics: an explainable GeoAI approach to land cover change over two decades. *Earth Systems and Environment*, pp.1-21.
6. Vitale, A., 2025. A GeoAI-based approach for long-term monitoring of urban fabric transformations. *Acta IMEKO*, *14*(2), pp.1-9.
7. Aziz, A., Khan, A.W., Khan, L. and Jan, A., 2026. Integration of Artificial Intelligence and Geographic Information Systems for Natural Resource Management. *Research Consortium Archive*, *4*(2), pp.1245-1263.
8. Vitale, A. and Lamonaca, F., 2025. Advancing Built-Up Area Monitoring Through Multi-Temporal Satellite Data Fusion and Machine Learning-Based Geospatial Analysis. *Remote Sensing*, *17*(11), p.1830.
9. Rose, L.R., 2026, April. GeoAI-Driven Spatio-Temporal Super-Resolution for Automated Residential Renewal Priority Detection. In *2026 13th International Conference on Computing for Sustainable Global Development (INDIACom)* (pp. 1-7). IEEE.
10. Isazadeh, V., Shirmohammadi, M., Pirasteh, S. and Akhavan, M., 2026. Habitable Planet.
11. Aravena Pelizari, P. and Geiß, C., 2025. Multi-Hazard Exposure Modeling with Multimodal Geo-Image Data and Deep Learning. *Mapping Disaster Resilience: GeoAI Best Practices from the UN-SPIDER Network*, pp.54-56.
12. Dias, P.A., Kobayashi-Carvalhaes, T., Walters, S., Frazier, T., Woody, C., Guggilam, S., Adams, D., Potnis, A. and Lunga, D., 2023. Geoai for humanitarian assistance. In *Handbook of Geospatial Artificial Intelligence* (pp. 260-286). CRC Press.
13. Perihanoglu, G.M. and Karaman, H., 2024. Performance Evaluation of GeoAI-Based Approach for Path Loss Prediction in Cellular Communication Networks. *Wireless Personal Communications*, *138*(2), pp.1211-1246.
14. Moumane, A., Elmotawakkil, A., Hasan, M.M., Kranjčić, N., Batchi, M., Karkouri, J.A., Đurin, B., Gomaa, E., El-Nagdy, K.A. and M. Youssef, Y., 2025. Integrating GIS, remote sensing, and machine learning to optimize sustainable groundwater recharge in arid Mediterranean landscapes: a case study from the middle Draa Valley, Morocco. *Water*, *17*(15), p.2336.
15. Getie, S. and Alemayehu, B., 2026. Leveraging Sentinel-2 and Machine Learning for Precise Identification of Plantation Forests in the Upper Blue Nile. *Forest Science and Technology*, pp.1-12.
16. Tian, R., Xu, Z., Han, J. and Li, J., 2026. Artificial Intelligence-Based Urban Rooftop Photovoltaic Potential Assessment: A Scoping Review. *Buildings*, *16*(11), p.2226.
17. Sood, V., Gusain, H.S., Gupta, S., Singh, S. and Kaur, S., 2020. Evaluation of SCATSAT-1 data for snow cover area mapping over a part of Western Himalayas. *Advances in Space Research*, *66*(11), pp.2556-2567.
18. Singh, S., Tiwari, R.K., Gusain, H.S. and Sood, V., 2020. Potential applications of SCATSAT-1 satellite sensor: a systematic review. *IEEE sensors journal*, *20*(21), pp.12459-12471.
19. Kaur, R., Tiwari, R.K., Maini, R., Singh, S. and Sood, V., 2022. The study of Indian Space Research Organization's Ku-band based scatterometer satellite (SCATSAT-1) in agriculture: applications and challenges. *Radar Remote Sensing*, pp.389-404.
20. Singh, S., Tiwari, R.K., Sood, V. and Gusain, H.S., 2021. Detection and validation of spatiotemporal snow cover variability in the Himalayas using Ku-band (13.5 GHz) SCATSAT-1 data. *International Journal of Remote Sensing*, *42*(3), pp.805-815.
21. Chaube, N.R., Chaurasia, S., Tripathy, R., Pandey, D.K., Misra, A., Bhattacharya, B.K., Chauhan, P., Yarakulla, K., Bairagi, G.D., Srivastava, P.K. and Teheliani, P., 2019. Crop phenology and soil moisture applications of SCATSAT-1. *Current Science*, *117*(6), pp.1022-1031.
22. Sood, V., Tiwari, R.K. and Singh, S., 2023, July. Super-resolution Snow-cover Mapping of Ku-Band based ISRO's SCATSAT-1 Data using Spectral Mixture Analysis. In *IGARSS 2023-2023 IEEE International Geoscience and Remote Sensing Symposium* (pp. 129-132). IEEE.
23. Gupta, P.K., Pradhan, R., Singh, R.P. and Misra, A., 2019. Scatterometry for land hydrology science and its applications. *Current Science*, *117*(6), pp.1014-1021.
24. Singh, S., Tiwari, R.K., Sood, V. and Prashar, S., 2021. Fusion of SCATSAT-1 and optical data for cloud-free imaging and its applications in classification. *Arabian Journal of Geosciences*, *14*(19), p.1978.
25. Dahiya, N., Gupta, S. and Singh, S., 2021, September. A comparative analysis of different land-use and land-cover classifiers using hyperspectral data. In *2021 IEEE 4th international conference on computing, power and communication technologies (GUCON)* (pp. 1-5). IEEE.

26. Vyas, N., 2025. Integrating Sentinel-1 satellite data with machine learning for land use classification. *RADAR: Remote Sensing Data Analysis with Artificial Intelligence*, p.1.
27. Gupta, D.K., Gupta, A., Dixit, A., Singh, D.K., Singh, S., Sood, V. and Kumar, N., 2026. Retrieval of optical vegetation indices from SCATSAT-1 Ku-band backscatter: A comparative analysis with MODIS and Proba-V sensors. In *Earth Observation using Scatterometers* (pp. 255-268). Elsevier.