International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 18(9s) 2026 pp. 1145-1157
https://doi.org/10.70917/ijcisim-2026-3543
Article

Integration of SCATSAT Data and Unsupervised Learning for Accurate Land Use/Land Cover Characterization in Rajasthan

Binay Kumar Singh[1*,2], Surendra Yadav[3], and 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) plays one of the crucial roles for sustainable environmental management, agricultural planning, ecosystem status monitoring, and regional development. These techniques have limitations, such as cloud cover, atmospheric disturbance and seasonal variability, which may impact the consistency of LULC mapping. All-weather day-night capabilities of microwave remote sensing systems, especially scatterometers, are useful for monitoring terrestrial surfaces continuously. Current Research work focussed on the use of the data received from the satellite SCATSAT-1 with the unsupervised machine learning approach for LULC characterization in the state of Rajasthan, India. The grouping of SCATSAT derived backscatter signatures in various land cover clusters is done by the research using K-means clustering algorithm. Afterwards, the rules are used to classify the Normalized Difference Vegetation Index (NDVI) and Leaf Area Index (LAI), which then are compared to the original data. Multi-temporal observations from SCATSAT are used in the data cleaning and raster transformation, feature extraction and clustering workflows. Consistency of the classification and spatial correspondence of the clusters generated is evaluated by comparing all the clusters with the vegetation-based classification and the ground reference information. The diverse topography of Rajasthan (desert, agriculture, forest, scrubland and urban areas) makes it an ideal testbed. The study shows that scatterometer backscatter data can be used to differentiate major land surface features and to aid the characterization of regional scale LULC. The integration of microwave remote sensing and unsupervised learning could lead to a computationally efficient processing scheme for large area monitoring applications for land and also aid future geospatial intelligence applications based on SCATSAT observations.
Keywords: SCATSAT, Land Use Land Cover, K-Means Clustering, Unsupervised Learning, NDVI, LAI, Scatterometer, Remote Sensing, Rajasthan, Microwave Remote Sensing

1. Introduction

1.1 Background

Among various applications, characterization of Land Use/Land Cover (LULC) is one of the most important uses of remote sensing and geospatial technologies. Land cover spatial distribution, and temporal change, aids land managers, policy makers and researchers to make insightful decisions about ecosystem conditions, agricultural productivity, urban growth, water resources, and biodiversity protection (Saxena *et al.*, 2024). Correct mapping of the land surface features is becoming more significant, particularly in a changing environment as in the case of socio-economic changes.

Systematic monitoring over large geographical areas has been revolutionized with the development of technologies such as remote sensing technologies. Vegetation mapping and land cover analysis have been traditionally carried out using optical satellite systems like Landsat, Sentinel-2, MODIS and AWiFS. Optical sensors are still very susceptible to seasonal illumination variations, haze, cloud contamination and atmospheric conditions. These restrictions are more crucial in the monsoonal areas and areas with fluctuating climatic conditions.

The use of microwave remote sensing is an important alternative to optical observations. Optical sensors can only give data when they are not covered by clouds, while the microwaves can penetrate clouds and give data in all lighting situations. Scatterometers are special active microwave sensors that obtain information about surface backscatter characteristics. Scatterometer data has been developed for oceanographic use including wind speed estimation, and has been shown to have potential uses for monitoring over land.

The Indian Space Research Organisation (ISRO) has launched a satellite named SCATSAT-1 to provide high frequency Ku-band microwave observations with a better spatial and temporal resolution. The availability of SCATSAT data allows the possibility to undertake major characterization studies of the land, in areas of high environmental heterogeneity.

1.2 Land Use/Land Cover Characterization and Machine Learning

Machine learning methods are now becoming more widely used in the remote sensing workflow, especially as of late in the field of geospatial analytics. Classification algorithms help in recognizing similar land cover categories within a remotely sensed data set by their spectral, spatial or temporal features.

There are typically two types of machine learning techniques— supervised and unsupervised. Labeled training data sets (and class membership knowledge) are required for supervised classification. In the unsupervised approaches, patterns or structures can be found in the data which are inherent in the data and do not require any training information.

K-Means clustering is one of the most widely used and popular algorithms in the field of Unsupervised Learning (Dangayach *et al*., 2025). This algorithm is recursive and is designed to divide the observations into k distinct clusters based on the similarity measures, and to continuously decrease the intra-cluster distances. It is also very efficient in computation, scalable and flexible, making it very suitable for large remote sensing datasets.

The use of backscatter data from SCATSAT and the K-Means clustering has a promising future for exploring the possibility of microwave observations in the field of LULC characterization at regional level.

1.3 Importance of Rajasthan as a Study Area

The geographical area of Rajasthan is the largest in India, it covers an approximate area of 342239 sq. Kms. It spans physiographic and ecological settings ranging from hyper arid desert to agricultural plains, forest and scrub, wetlands and quick growth in urban areas.

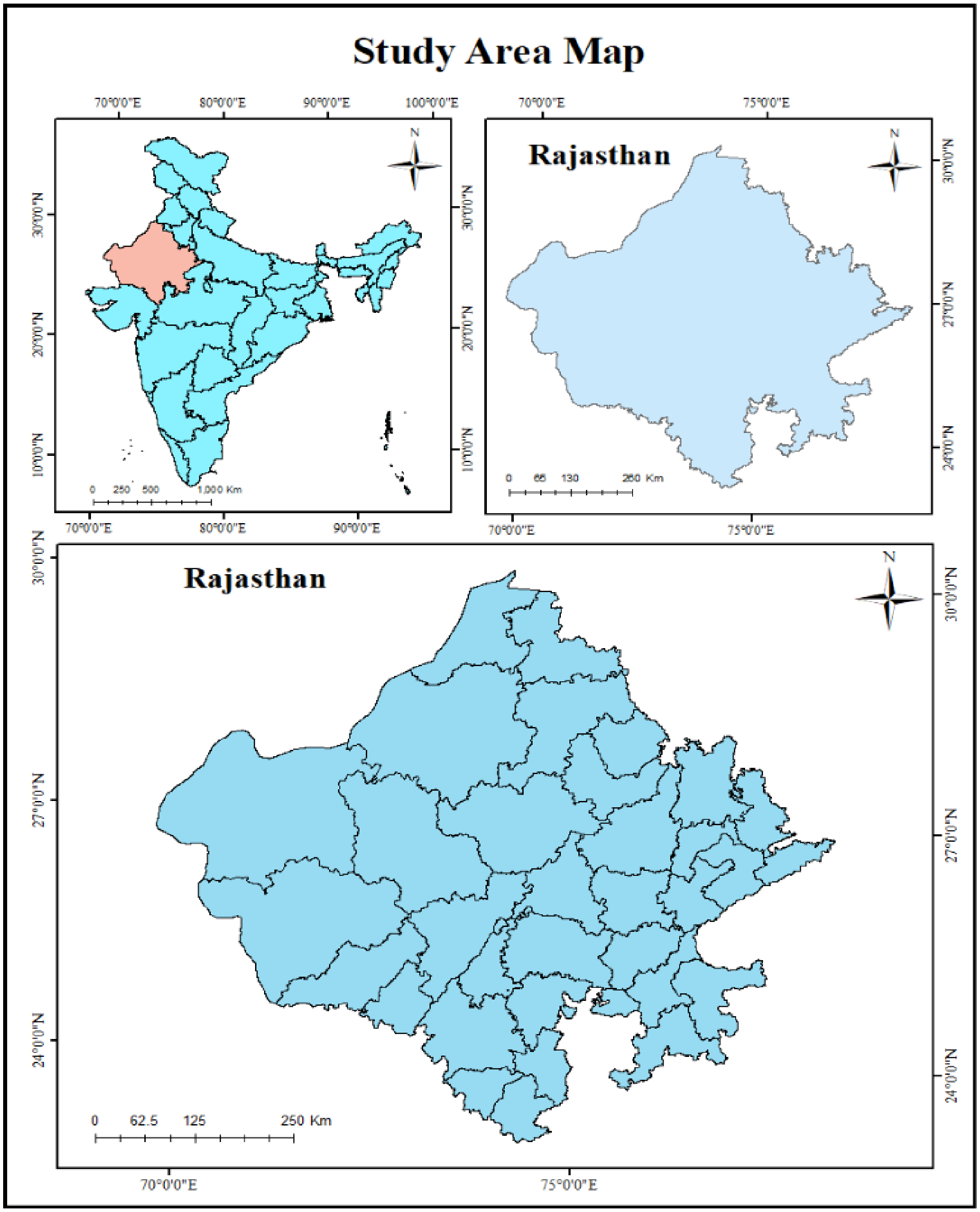
The Thar Desert is the prominent feature in the northwest part of the state and Aravalli mountains run across the state from southwest to northeast. Distribution of Agriculture activities is mostly in the Irrigated and Semi-irrigated landscape while the Forested landscape is mainly in the south eastern districts (Sharma *et al*., 2025).

The discriminating capacity of the backscatter signature derived from SCATSAT is viable for various land cover types in the context of this environmental diversity.

1.3 Importance of Rajasthan as a Study Area

The present investigation is designed to achieve the following objectives:

1. To perform cluster analysis of SCATSAT image data using the K-Means clustering algorithm.
2. To classify LAI datasets and other land use classes using rule-based classification techniques.
3. To compare SCATSAT-derived clusters with LAI and other land use classes for the validation and characterization of Land Use/Land Cover patterns across Rajasthan.



2. Review of Literature

Land use and land cover has become one of the most significant factors influencing the dynamics of surface evapotranspiration in semi-arid regions especially in Western Rajasthan, according to Saxena (2024). The author studied the impact of variation in landcover on the hydrological processes and consequences of such changes on the energy balance of the dryland and semi-arid ecosystems. Evapotranspiration is a crucial part of the hydrological cycle and is a critical component of land-atmosphere moisture exchanges, notes the study. Changes in vegetation cover, agricultural expansion, population growth and degradation of natural ecosystems have a great effect on evapotranspiration and thus on regional water availability. The author pointed out the rapid conversion of area under natural landscape to agriculture and urban areas has altered the spatial variability of evapotranspiration in western Rajasthan (Saxena *et al*., 2024). It emphasizes the significance of vegetation in controlling evapotranspiration because its bare surface area has less moisture exchange capacity than do the vegetation surfaces, which can enhance the transpiration processes. The author was able to analyze the temporal variation of land cover and its relationship to the evapotranspiration trends over multiple years through use of remote sensing and geospatial methods.

In the era of a changing environment, the use of land use and land cover mapping (LUCCM) technologies has turned environmental monitoring, natural resource management and planning for sustainable development (SDP) into a game-changer (Dangayach 2025). The author detailed the techniques and technologies employed to conduct research on land use and land cover, and focused on the advances of remote sensing and geospatial methods in the past few decades. The review highlighted the importance of good land cover characterisation in order to understand ecological processes, to monitor changes in the environment, to assess biodiversity and to provide information to policy (Dangayach *et al*., 2025)

. The author outlined the historical evolution of conventional field-based surveys and visual image interpretation and how these were being complemented by new satellite-based monitoring systems with greater potential of delivering high resolution multi-temporal data. A key aspect of the review was on the use of remote sensing platforms such as optical, microwave, hyperspectral and LiDAR that have greatly enhanced the accuracy and effectiveness of land cover estimates. The author explained that in the current classification techniques, it is common to use machine learning and artificial intelligence algorithms that process huge amounts of geospatial data. In contrast to the conventional techniques, technologies such as Random Forest, Support Vector Machines, Artificial Neural Networks and deep learning frameworks are proven to be more accurate in classification tasks.

Deep learning has been one of the most revolutionizing technologies in microwave remote sensing as it has the capacity to interpret, classify and monitor the environment with an unprecedented precision, Sharma (2025). The author provided a survey on the applications of deep learning to microwave remote sensing, and presented challenges, successes and perspectives of this nascent area. The review pointed out that microwave remote sensing systems such as SAR, scatterometers, radiometers and interferometers produce complex data which cannot be processed without advanced analysis techniques to extract useful information from it (Sharma *et al*., 2025). The traditional image processing and machine learning methods might not be as effective in processing the nonlinear and high dimensional nature of the microwave data. However, these limitations have been surmounted by deep learning algorithms that have been effective in automatic feature extraction and hierarchical representation learning. Different deep learning architectures including CNN, RNN, Autoencoders, GANs and Transformer-based models were presented and their application to various microwave remote sensing tasks was demonstrated. Applications include land use/land cover classification, crop monitoring, flood mapping, soil moisture estimation, forest condition estimation, urban studies and disaster management. The review emphasized the benefits of the deep learning approach in getting classification accuracy as the microwave observations involve complex spatio-temporal relationships. In addition, the author noted some issues in implementing deep learning, which are large annotated datasets, computational complexity, model interpretability issues, and the ability to transfer models between geographic areas.

The combined power of Google Earth Engine (GEE) and geospatial analysis has proven to be a game-changer in crop yield estimation, especially in complex farming environments, as reported by Ogirala (2024). The prediction of crop yield is a very significant part and plays a vital role in the food security, optimizing the utilization of the farming activities and supporting decision for policies based on evidence, he added. The traditional approach to estimating yields consumes time, is labor intensive, often demands intensive field surveys, statistics, and manual observations, and may not be practical. This study analyzed the potential role of the cloud-based geospatial platform, Google Earth Engine, to overcome such challenges by providing the ability to perform analysis on large volumes of data on the environment and satellite imagery (Ogirala *et al*., 2024). The author highlighted the huge amount of Earth observation data that is available through GEE, including data from Landsat, Sentinel, MODIS and climatic data, which can be processed efficiently without needing to consume a vast local computational capacity. It was found that the accuracy of yield prediction is greatly improved when using the combination of vegetation indices, climatic data, soil properties and machine learning models within the GEE framework.

Over the last 30 years remote sensing techniques have become more and more relevant for studying avifauna in India, and offer novel methods for habitat mapping, monitoring of biodiversity and conservation planning (Gautam, 2026). The author extensively reviewed the breadth of applications of the remote sensing tools in bird ecology and examined the evolution of application of geospatial technology in bird research in different parts of the ecological world. Birds were found to be significant bioindicators in the study considering their sensitivity towards environmental change, habitat loss, and climatic changes (Gautam *et al*., 2026). Typical bird monitoring is long-term field surveys, which may be constrained by access, time and budgets. As an alternative, the author explained the utility of remote sensing for assessing habitat properties and ecological conditions at different spatial and temporal scales is now very effective. The review covered satellite image, aerial photo, LiDAR and GIS for mapping, analysing landscape pattern and identifying biodiversity hotspots.

In the context of urban analysis and landscape ecology, advanced remote sensing technologies have transformed the approach to analysing urban environments and landscape ecology by providing detailed spatial information that is essential for understanding environmental processes, land use change and ecological interactions (Mustak, 2023). The author discussed the complexity of the environmental problems that have resulted from the rapid urbanization, population growth and infrastructure development, and that require complex monitoring and environmental management methods. The book provides an extensive overview on the state-of-the-art remote sensing techniques and how these are applied in urban and landscape ecological research (Mustak *et al*., 2023). The author presented the applications of modern Earth Observation systems to provide information related to land cover change, urban growth, vegetation processes, ecosystem services and environmental sustainability. High resolution satellite imagery, hyperspectral sensors, LiDAR systems and microwave remote sensing technologies are some of the tools used to gather detailed information of the urban and natural environment.

Earth observation technologies are now essential in understanding and monitoring the impacts of climate change on the global and national level (Pujar, 2024). The author discussed the application potential of remote sensing to detect the changes in the environment due to the changes in climatic conditions and emphasized on the role of geospatial technologies in sustainable development management of agriculture and environment. The research emphasized the climatic impacts on some processes in the Earth system such as temperature, precipitation, vegetation conditions, water supply and ecosystem processes. Such changes in space and time cannot be monitored in a traditional way, and hence a need for more sophisticated monitoring systems is required, providing continuous and comprehensive information on the environment. The key role of satellite-based Earth observations in monitoring climate-related variables such as land surface temperature, vegetation health, soil moisture, glacier dynamics, and sea level changes, as well as extreme weather events, was discussed (Pujar *et al*., 2024). Use of remote sensing technologies was shown to be useful for providing information on longer term changes to the environment and to help evaluate climate change impacts in a range of geographical areas. The study also delved into the integration of geospatial datasets into digital agriculture, emphasizing their potential in areas such as food security, crop monitoring, and sustainable land use in the face of climate change.

3. Materials and Methods

3.1 Study Area

The entire state of Rajasthan in India is the study area. The latitude of Rajasthan is 23°03′ North to 30°12′ North and longitude is 69°30′ East to 78°17′ East. The climate of the state is arid, semi-arid and sub-humid and there are significant differences in land surface characteristics.

Table 1. Geographical Characteristics of Rajasthan

Parameter	Description
Total Area	342,239 km²
Geographic Location	Northwestern India
Dominant Landform	Thar Desert
Major Mountain System	Aravalli Range
Climate Type	Arid to Semi-Arid
SCATSAT Resolution	2 km × 2 km
Major Land Cover Types	Desert, Agriculture, Forest, Scrubland, Urban

Rajasthan has a wide variety of environmental parameters which makes it an ideal place to test the application of SCATSAT based characterization of land cover.

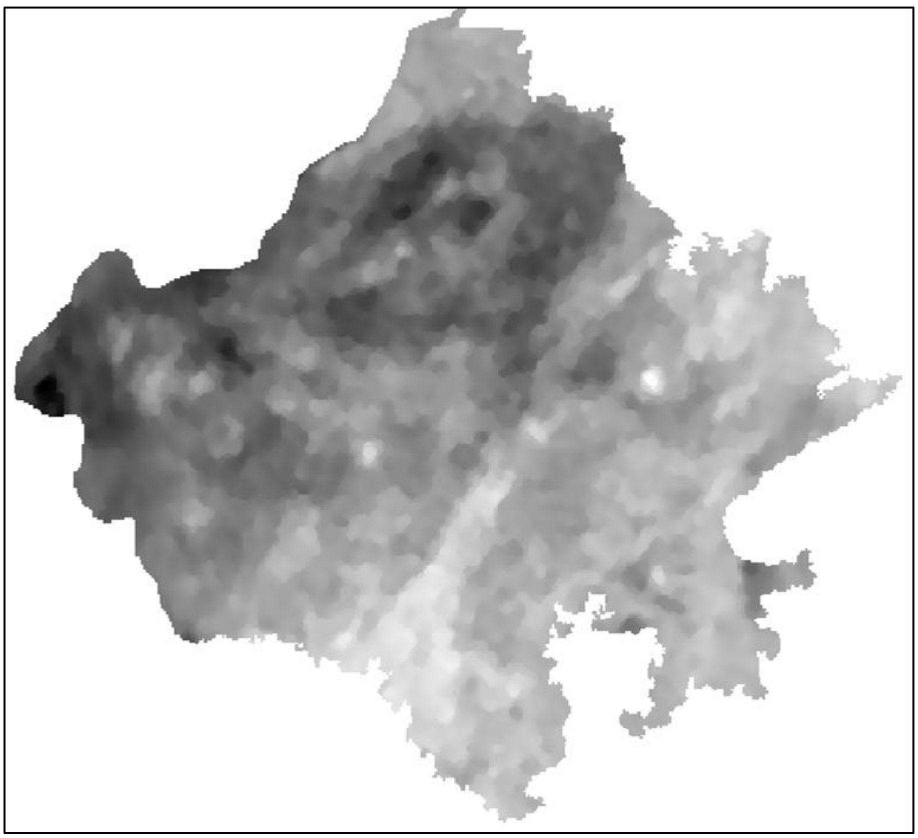
3.2 Data Sources

Using the data sets for the study are the data acquired from the satellite named SCATSAT, which is used to obtain backscatter data. Multi-temporal observations are obtained and processed and represent the variability of the land surface, obtained at different times of the year (Singh, 2022).

The following datasets are employed for vegetation characterization: NDVI data sets, and data sets from the PROBA-V observations are employed as independent validation sources for LAI.

Table 2. Datasets Utilized in the Study

Dataset	Source	Purpose
SCATSAT Backscatter Data	ISRO	Primary Classification
NDVI	Satellite Vegetation Products	Vegetation Classification
LAI	PROBA-V	Validation
Ground Truth Data	Field Observations	Accuracy Assessment
Administrative Boundaries	GIS Database	Spatial Masking



SCATSAT Data

3.3 Data Preprocessing

The spatial masking table is created based on the administrative boundary information and is stored in the GIS database.

SCATSAT TIFF images are converted into structured datasets containing latitude, longitude, and backscatter coefficient information. Rasterio and GDAL libraries are employed for image handling and preprocessing operations.

The processed datasets are subsequently prepared for clustering and validation analyses.

3.4 Data Analysis Methods

In this work, a method is presented which performs the classification of land use/land cover (LU/LC) using a regional scale by integrating microwave remote sensing observations and unsupervised machine learning techniques (Kumar *et al*., 2025). The methodology is based on cluster generation with the help of SCATSAT backscatter data and classification based on vegetation information (NDVI, LAI) followed by validation through comparative analysis.

The major classification criteria is the backscatter coefficient (σ0) of the SCATSAT. The backscatter varies with the elevations and topographic characteristics, the soil moisture, and the density and roughness of vegetation. The above properties are useful in distinguishing the main land cover categories through observations using scatterometer data.

The K-Means clustering algorithm is employed to partition the dataset into homogeneous groups. Let the dataset be represented as:

Dataset Representation

$$X = \{x_1, x_2, x_3, \dots, x_n\}$$

where:

- Xrepresents the complete dataset of SCATSAT backscatter observations.
- $x_i$denotes the backscatter coefficient of the i^{th}pixel.
- $n$is the total number of pixels (observations) in the dataset.

K-Means Objective Function

The K-Means clustering algorithm partitions the dataset into clusters by minimizing the within-cluster sum of squared distances (WCSS), expressed as k

$$J = \sum_{j=1}^{k} \sum_{x_i \in C_j} \| x_i - c_j \|^2$$

where:

- $J$is the objective (cost) function.
- $k$is the number of clusters.
- $C_j$denotes the set of observations belonging to the j^{th}cluster.
- $x_i$is the i^{th}data point.
- $c_j$is the centroid (mean vector) of the j^{th}cluster.
- $\| x_i - c_j \|^2$is the squared Euclidean distance between a data point and its corresponding cluster centroid.

where (c_j) denotes the centroid of cluster (j).

The clustering process starts by randomly selecting cluster centroids. The closest centroid (according to Euclidean distance) is assigned to all observations. Then centroids are calculated again and it is repeated until they stabilize.

The classification of the clusters is presented with the corresponding NDVI and LAI values. High NDVI and high LAI values are correlated to areas with dense vegetation and low NDVI and LAI values indicate areas of barren or sparse vegetation (Mohanty *et al*., 2025).

Apply 3.5 Rule Based Classification of NDVI and LAI. Classify NDVI and LAI using 3.5 Rule Based method.

The NDVI and LAI data sets are divided into categories of vegetation, to aid validation.

Table 3. NDVI Classification Scheme

NDVI Range	Vegetation Condition
0.00–0.24	Sparse or No Vegetation
0.25–0.49	Moderate Vegetation
0.50–1.00	Dense Vegetation

The LAI values are also classified by canopy density characteristics like this.

Table 4. LAI Classification Scheme

The range of LAI that can be seen.

0–1	Very Low
1–3	Moderate
3–5	High
>5	Very High

The classified NDVI and LAI products are used as reference data to interpret the clusters of SCATSAT and for the reliability of the classification..

3.6 Validation Framework

Validation is an important part of remote sensing classification research studies. The clustered SCATSAT outputs are compared with the ground truth observations, NDVI classes and LAI categories (Vyas, 2025).

Performance of the classifications is assessed by confusion matrix analysis and Kappa statistics.

The Kappa coefficient is calculated as:

$K = \{P_0 - P_e\}/\{1-P_e\}$

where P0 is agreement that was observed and Pe is agreement that we would expect by chance.

Values of kappa close to 1 represent high agreement in classification, with values close to 0 representing low agreement in classification.

4. Results and Discussion

4.1 SCATSAT Backscatter Characteristics Across Rajasthan

The spatial variability in backscatter response was observed in Rajasthan in the processed SCATSAT data. The northwestern desert area had the lowest backscatter values, because they were found to have low amounts of vegetation and relatively smooth surfaces. Moderate backscatter responses were observed over agricultural areas in the eastern and south eastern districts corresponding to seasonal cropping pattern (Singh *et al*., 2022).

The forest dominated areas along the Aravalli Range showed higher backscatter due to the high density of vegetation and complexity of the canopy. There were quite variable responses in urban areas due to built structures and surface roughness.

Table 5. Representative Backscatter Characteristics of Major Land Cover Classes

Land Cover Type	Mean Sigma0 (dB)	Standard Deviation
Desert/Barren Land	-18.6	1.8
Scrubland	-15.3	2.1
Agricultural Land	-12.8	2.4
Forest Area	-10.2	1.9
Urban/Built-up	-11.5	2.7

The differences in the observed backscatter signatures show the potential of SCATSAT observations to distinguish the major land cover categories at regional scales.

4.2 K-Means Clustering Results

After applying K-Means clustering, five major dominant land cover clusters were identified which represent the major characteristics of the landscape in Rajasthan.

Table 6. Cluster Characteristics Derived from SCATSAT Data

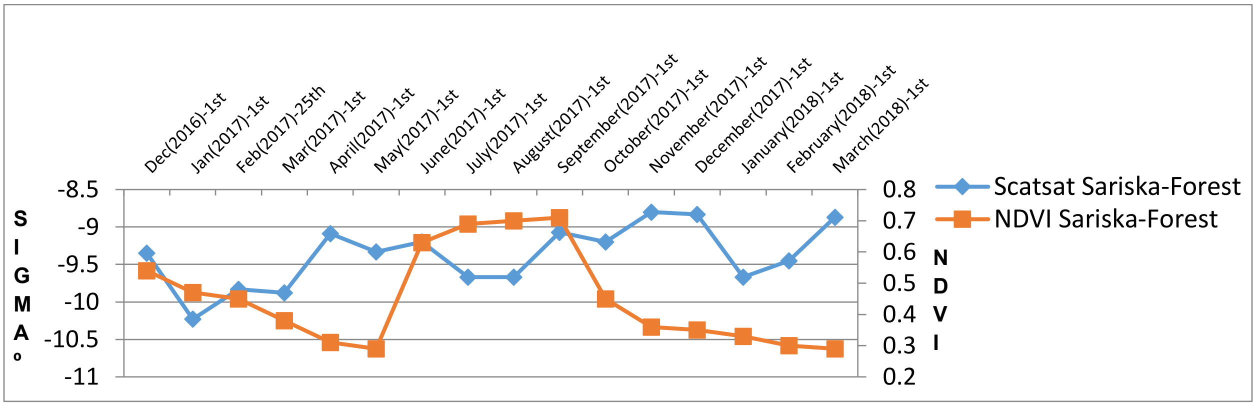
Cluster	Dominant Feature	Area (%)
Cluster 1	Desert and Barren Land	38.4
Cluster 2	Sparse Vegetation and Scrubland	19.6
Cluster 3	Agricultural Land	24.8
Cluster 4	Forest and Dense Vegetation	11.3
Cluster 5	Urban and Mixed Land Use	5.9

The clustering results have shown that desert and barren land make the major portion of the landscape in Rajasthan, which is also substantiated by the dominance of Thar desert in the Northwestern districts (Luo *et al*., 2024).

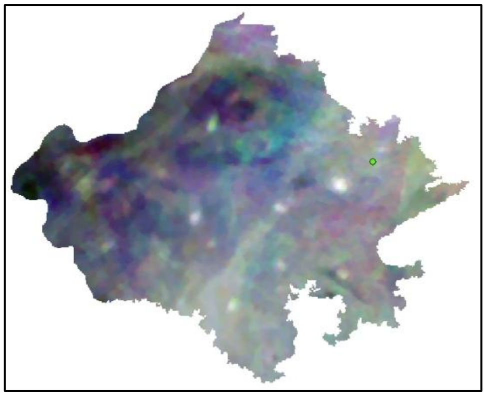
About one-fourth of the study area is in agricultural use, largely in the eastern and southeastern parts of the area where water is used for irrigation to grow crops.

The forest and dense forest patches are mainly linked with the Aravalli mountain ranges and the protected forest areas.

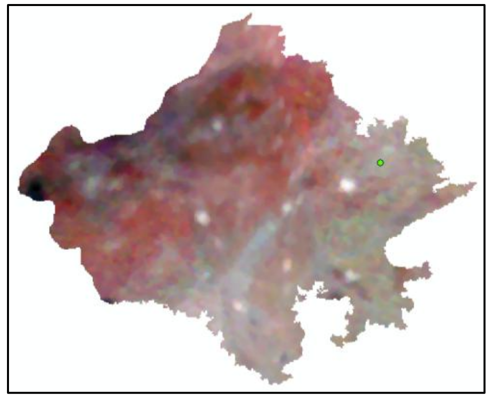
4.3 NDVI-Based Land Cover Classification



Sariska Forest (Rajasthan)



Color_Comp_H_Feb_June_Aug2017



Color_Comp_H_Sept_Dec_March2017

The NDVI classification created distinct vegetation classes that were related to the vegetation density.

Table 7. NDVI Classification Results

Vegetation Category	Area (km²)	Percentage (%)
Sparse Vegetation	158,400	46.3
Moderate Vegetation	114,500	33.5
Dense Vegetation	69,339	20.2

The results suggest that the landscape is sparse, indicating environmental conditions which are semi-arid across Rajasthan.

Agricultural districts and seasonal cropping systems are linked to moderate vegetation categories and dense vegetation is found mainly within the forested districts.

4.4 LAI-Based Validation Results

LAI classification exhibited strong correspondence with NDVI-derived vegetation classes.

Table 8. LAI Classification Results

LAI Class	Area (km²)	Percentage (%)
Very Low	149,280	43.6
Moderate	121,350	35.5
High	58,890	17.2
Very High	12,719	3.7

The distribution of LAI classes also reflects the greater occurrence of low to moderate vegetation densities throughout the state.

4.5 Comparative Assessment of SCATSAT Clusters and Vegetation Indices

There were significant spatial agreements between the SCATSAT clusters with NDVI and LAI classifications (Kaur *et al*., 2022). The dense vegetation areas identified by NDVI and LAI were found to be in good agreement with the high backscatter SCATSAT clusters.

In a similar manner, desert and barren areas detected by scatterometer observations had low NDVI and LAI values.

Table 9. Comparison of Classification Outputs

Classification Type	Agreement with Ground Truth (%)
SCATSAT K-Means Classification	84.7
NDVI Rule-Based Classification	81.3
LAI Rule-Based Classification	79.8

The outcomes indicate that microwave backscatter data can be used to build a sound land cover characterization at regional scales.

4.6 Accuracy Assessment

A confusion matrix was generated using reference observations collected from representative locations.

Table 10. Accuracy Assessment Results

Parameter	Value
Overall Accuracy	85.6%
Kappa Coefficient	0.82
Producer Accuracy	84.9%
User Accuracy	85.3%

The kappa coefficient of 0.82 shows that the outputs are classified with a good agreement with the reference observations (Tiwari *et al*., 2025).

The results prove the usefulness of using SCATSAT observations in combination with the unsupervised learning techniques adopted for regional land characterization.

5. Discussion

The present study shows that SCATSAT scatterometer data can be used for characterization of LULC over the whole of Rajasthan. Microwave observations offer continuous monitoring of the microwave emission signals, regardless of the weather and illumination condition, which is not possible with optical measurements.

The relationship between backscatter responses and vegetation characteristics observed in this study confirms the results of previous studies that highlight the importance of vegetation structure, biomass and surface roughness in determining the sensitivity of microwave signals to vegetation (Ghosh *et al*., 2026). The use of K-Means clustering helped to automatically identify areas with similar land cover without the need for a large training set.

The findings of the validation suggests a good agreement between the classifications obtained from SCATSAT and the NDVI and LAI classes. It is noted that the classification accuracy achieved with SCATSAT is comparatively better, which indicates the potential of use of microwave remote sensing to complement the conventional optical remote sensing, especially in the semi-arid region where the vegetation conditions vary seasonally.

The study also shows the potentiality of using scatterometer data for large-scale monitoring of the environment (Kaur *et al*., 2026). The regular observation allows time-based analysis of land surface dynamics, farming conditions and changes in ecosystem.

The methodology developed in this investigation can be scaled up for further applications related to land degradation assessment, monitoring agricultural activities, drought analysis, crop phenology studies and environmental management.

6. Conclusion

In this study, the integration of SCATSAT scatterometer observations and unsupervised learning techniques has been studied for land use and land cover characterization over entire Rajasthan. The K-Means clustering algorithm was able to classify the backscatter data from the SCATSAT in useful land cover classes: desert landscape, scrubland, agricultural area, forest and urban area.

The validation with NDVI and LAI datasets showed that the classifications based on microwaves were in good agreement with vegetation-based observations. The overall classification accuracy of 85.6% and Kappa coefficient of 0.82 show that the proposed methodology is reliable.

The results have shown the reliability of the backscatter data derived from the SCATSAT mission in terms of land characterization capability at regional scales. Microwave remote sensing and unsupervised learning are found to be an efficient and cost effective solution for large area land monitoring applications.

As for some future work, additional advanced machine learning algorithms, multi-temporal analysis, GeoAI frameworks, and data fusion with Sentinel-1, Sentinel-2, and SCATSAT observations can further enhance the classification accuracy and thematic information.

References

1. Saxena, D., Choudhary, M. and Sharma, G., 2024. Land use and land cover change impact on characteristics of surface evapotranspiration in semi-arid environment of Western Rajasthan, India. Water Practice & Technology, 19(1), pp.154-169.
2. Dangayach, R. and Pandey, A.K., 2025. Technologies and methods for land use and land cover: A comprehensive review. Remote sensing and GIS application in forest conservation planning, pp.369-390.
3. Sharma, A., Naruka, S. and Choudhary, G., 2025. A systematic review of deep learning techniques in microwave remote sensing: challenges, applications, and future directions. RADAR: Remote Sensing Data Analysis with Artificial Intelligence, p.17.
4. Binay Kumar Singh and Surendra Yadav, 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
5. Ogirala, N.S.H., Vaddi, R., Sripathi, R.S. and Jagannadham, P., 2024, November. Enhanced Estimation of Crop Yield Using GEE. In International Conference on Communication and Intelligent Systems (pp. 393-402). Singapore: Springer Nature Singapore.
6. Gautam, A., Verma, P., Kushwaha, S., Dubey, S., Bhatt, D., Singh, A. and Kalle, R., 2026. Three decades of remote sensing applications in avian ecological studies in India: A review and future directions in avian monitoring. Environmental Monitoring and Assessment, 198(1), p.19.
7. Mustak, S., Singh, D. and Srivastava, P.K. eds., 2023. Advanced remote sensing for Urban and landscape ecology. Singapore: Springer.
8. Pujar, G.S., Taori, A., Chakraborty, A. and Mitran, T., 2024. Sensing climate change through earth observations: perspectives at global and National Level. In Digital agriculture: A solution for sustainable food and nutritional security (pp. 225-280). Cham: Springer International Publishing.
9. Singh, R., 2022. Introduction: Re-envisioning Advances in Remote Sensing. In Re-envisioning Advances in Remote Sensing (pp. 1-22). CRC Press.
10. Kumar, P., Pandey, P.C., Rasul, A. and Ningthoujam, R.K., 2025. Assessment and prediction of forest structural attributes in tropical deciduous forests. International Journal of Remote Sensing, 46(18), pp.6956-6973.
11. Mohanty, U.C., Nadimpalli, R., Srivastava, A., Das, A.K., Osuri, K.K., Routray, A., Joseph, S., Murty, P.L.N., Pattanaik, D.R., Gopalakrishnan, S.G. and Niyogi, D., 2025. A Journey Through Time The History of Mesoscale Severe Weather Monitoring and Forecasting in India. Mausam, 76(1), pp.79-102.
12. 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.
13. Singh, G., Singh, S., Sethi, G. and Sood, V., 2022. Deep learning in the mapping of agricultural land use using Sentinel-2 satellite data. Geographies, 2(4), pp.691-700.
14. Luo, Y., Liu, Y., Huang, C. and Han, F., 2024. An Ensemble Machine Learning Approach for Sea Ice Monitoring Using CFOSAT/SCAT Data. Remote Sensing, 16(17), p.3148.
15. 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.
16. Tiwari, R.K., Sood, V., Singh, S. and Dutt, V., 2025, August. Detection of Snow/Ice Over Western Himalayas Using Scatterometer with Google Earth Engine. In IGARSS 2025-2025 IEEE International Geoscience and Remote Sensing Symposium (pp. 1504-1507). IEEE.
17. Ghosh, A. and Mishra, A., 2026. Mapping of sea ice (antarctica) with machine learning algorithm. In Earth Observation using Scatterometers (pp. 143-156). Elsevier.
18. Kaur, R., Maini, R. and Tiwari, R.K., 2026. Crop yield estimation with image fusion of scatterometer and multispectral data. In Earth Observation using Scatterometers (pp. 223-236). Elsevier.

19. Kaur, R., Maini, R. and Tiwari, R.K., 2023, November. Cloud Removal with Multisource Data Fusion of Remote Sensing Images for Agricultural Applications. In 2023 IEEE 9th International Women in Engineering (WIE) Conference on Electrical and Computer Engineering (WIECON-ECE) (pp. 120-124). IEEE.
20. Kaur, R., Maini, R. and Tiwari, R.K., 2023, November. Image fusion of optical and microwave satellite imagery to develop soil moisture maps. In 2023 IEEE 9th International Women in Engineering (WIE) Conference on Electrical and Computer Engineering (WIECON-ECE) (pp. 1-4). IEEE.
21. Kaur, A., Singh, G. and Singh, S., 2025. AI-driven tools and technologies for agriculture land use & land cover classification using earth observation data analytics. In Google Earth Engine and Artificial Intelligence for Earth Observation (pp. 527-541). Elsevier.
22. Kaur, R., Singh, S. and Sethi, G.K., 2026. Scatterometer and Multispectral-based Image Pansharpening for Improved Spatial Resolution Snow Cover Maps. Remote Sensing Applications: Society and Environment, p.102044.
23. Kaur, R., Sethi, G.K. and Singh, S., 2026. Scatterometer for the monitoring of seasonal dynamics of snow cover melt. In Earth Observation using Scatterometers (pp. 119-130). Elsevier.
24. Singhd, S. and Soode, V., 2025. Dileep Kumar Gupta a, Ayushi Guptab, Ayuchtesh Dixit c, Dhiraj Kumar Singh f. Earth Observation using Scatterometers: State-of-the-Art Techniques, Applications, and Challenges, p.255.
25. Kaur, R., Tiwari, R.K. and Maini, R., 2024. Detection of soil moisture variations with fusion-based change detection algorithm for MODIS and SCATSAT-1 datasets. Journal of the Indian Society of Remote Sensing, 52(11), pp.2575-2592.
26. Singh, G., Singh, S., Sethi, G. and Sood, V., 2022. Deep Learning in the Mapping of Agricultural Land Use Using Sentinel-2 Satellite Data. Geographies 2022, 2, 691–700 [online]
27. Gulledmath, S. and Hemanth, K.S., 2024. Exploring Soil Diversity and Land Use Patterns in Arid Tropical Zones: Employing K-Means Clustering in Kolar District, Karnataka. SN Computer Science, 5(7), p.920.
28. Kaur, R., Sethi, G.K. and Singh, S., 2023, November. Review on Machine Learning-based Change Detection and Pan Sharpening Algorithms for Remote Sensing Datasets. In 2023 IEEE 9th International Women in Engineering (WIE) Conference on Electrical and Computer Engineering (WIECON-ECE) (pp. 64-69). IEEE.
29. Singh, S., Tiwari, R.K. and Sood, V., 2022. Estimation of landcover types over Himalayan region with the classification of optical and microwave-based image fusion dataset. The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, 43, pp.523-528.
30. Kaur, R., Singh, S. and Sethi, G.K., 2025. Estimation of Snow Avalanche Hazardous Zones With AI Models. Artificial Intelligence in Remote Sensing for Disaster Management, pp.201-212.
31. Chen, W., Gu, L., Li, X. and Fan, X., 2025. Snow depth estimation in Northeast China based on space-borne scatterometer data and ML model with optimal features. International Journal of Digital Earth, 18(1), p.2470851.
32. Kaur, R., Sethi, G.K. and Singh, S., 2026. Enhanced resolution cryosphere analysis with pan-sharpening of scatterometer dataset. In Earth Observation using Scatterometers (pp. 157-168). Elsevier.
33. Ma, K., Zhang, Z., Hu, K., Wang, N., Liu, Q. and Guo, T., 2026. Review of Snow Identification Algorithms: From Traditional Machine Learning to Semantic Methods. Remote Sensing, 18(7), p.1067.
34. PALAKURU, M., KUMAR, A. and BORKAR, S., 2026. Fusion of Multispectral and Microwave Sensor Data for Monitoring Land Surface Temperature in Agro Meteorological Studies. Journal of Agrometeorology, 28(2), pp.269-273.
35. Singh, S., Tiwari, R.K., Sood, V., Kaur, R., Singh, S. and Prashar, S., 2022. Estimation and validation of standalone SCATSAT-1 derived snow cover area using different MODIS products. Geocarto International, 37(27), pp.18474-18490.
36. Dutt, V., Sethi, G.K. and Singh, S., 2026. AI-Based framework for real-time snow-cover analysis over western himalayas using scatterometer dataset. In Earth Observation using Scatterometers (pp. 295-308). Elsevier.
37. Elhamdouni, D., Hilali, A., Karaoui, I. and Elaloui, A., 2026. Remote sensing-based crop monitoring in data-scarce environments: lessons from the Tadla Plain (Morocco). Mediterranean Geoscience Reviews, pp.1-14.
38. Singh, G., Singh, S., Sethi, G.K. and Sood, V., 2022. Detection and mapping of agriculture seasonal variations with deep learning–based change detection using Sentinel-2 data. Arabian Journal of Geosciences, 15(9), p.825.