



IJRASET

International Journal For Research in
Applied Science and Engineering Technology



INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14 **Issue:** IV **Month of publication:** April 2026

DOI: <https://doi.org/10.22214/ijraset.2026.80752>

www.ijraset.com

Call:  08813907089

E-mail ID: ijraset@gmail.com

Pattern Recognition Methods for Remote-Sensing-Based Land Use and Land Cover Analysis

Ann Maria EC, Asst Prof. Karthik K Krishna

Dept. of Computer Science and Engineering Vimal Jyothi Engineering College, Kannur

Abstract: Pattern recognition is critical for obtaining useful information from remote sensing data and improving land-use and land-cover (LULC) classification. With the increased availability of multispectral, hyperspectral, LiDAR, and high-resolution data, sophisticated algorithms are needed to address issues such as spectral similarity, geographical heterogeneity, atmospheric distortions, and mixed pixels. Recent research has shown that machine-learning models such as SVM, Random Forest, Ensemble Learning, and ELM, as well as deep-learning architectures such as CNNs, U-Net, and hybrid spectral-spatial networks, improve classification accuracy and environmental monitoring. Semantic alignment, open-vocabulary mapping, spatial point pattern analysis, and novel-class discovery are all emerging technologies that promote adaptability in dynamic contexts. The use of GIS, Monte Carlo simulations, and multi-modal data fusion improves the modelling of environmental processes and long-term changes. Overall, the reviewed research demonstrates that sophisticated pattern-recognition approaches offer dependable, scalable, and data-driven solutions for remote-sensing applications, thereby promoting sustainable resource management, urban planning, ecological conservation, and climate-resilient development.

Keywords -Pattern Recognition, Remote Sensing, Land Use and Cover (LULC), Hyperspectral Imaging, Open Vocabulary Mapping, Spatial Point Pattern Analysis, GIS, Monte Carlo Simulation, and Environmental Monitoring.

I. INTRODUCTION

The tremendous rise in remotely sensed data brought about by the quick development of Earth observation technologies presents both new opportunities and difficulties for the analysis of land-use and land-cover (LULC) trends. With the ability to automatically extract useful information from multispectral, hyperspectral, LiDAR, and high-resolution satellite data, pattern recognition has become a key technique in remote sensing. Pattern recognition techniques, in contrast to conventional manual interpretation approaches, can effectively manage massive amounts of diverse data, facilitate multi-temporal analysis, and enhance environmental monitoring accuracy.

Remote-sensing images frequently include high spectral similarity between classes, spatial heterogeneity, atmospheric aberrations, and mixed pixels, which complicate classification and change detection tasks. To address these issues, researchers have developed advanced approaches that combine spectral, spatial, textural, and temporal features, which are supported by machine-learning algorithms such as Support Vector Machines (SVM), Random Forest (RF), Ensemble Learning, and Extreme Learning Machines (ELM), as well as deep-learning models such as CNNs, U-Net, and hybrid 2D-3D networks, all of which significantly improve classification robustness and precision. Recent advances go beyond typical closed-set classification to include semantic alignment, open-vocabulary mapping, spatial point-pattern modelling, and the development of novel land-cover classes in fast changing metropolitan situations. Furthermore, the ability to model environmental processes, evaluate radiation exposure, analyse ecological relationships, and forecast long-term landscape dynamics has improved due to the integration of GIS, Monte Carlo simulation frameworks, and multimodal data fusion. All things considered, pattern recognition provides a thorough and scalable framework for obtaining high-quality data from remote-sensing datasets, supporting essential applications in urban planning, ecological conservation, disaster management, climate-resilient development, and sustainable resource monitoring. This study expands on these developments by examining current approaches and proving their efficacy in enhancing the dependability of LULC mapping and environmental analysis.

II. LITERATURE SURVEY

Leila M.G. Fonseca et al. [1] undertook a thorough investigation on the use of pattern recognition and remote sensing techniques for mapping Land Use and Land Cover (LULC) in the Brazilian Savannah, often known as the Cerrado biome.

The study sought to address the growing issues of sustainable land management in this critical ecological area, which is characterised by fast agricultural development and deforestation.

The researchers used pattern recognition and image processing tools to investigate how natural vegetation transformed into agricultural and pasture lands during a 20-year period. Their method merged standard pixel-based classifiers such as Maximum Likelihood Classification (MLC) and Spectral Angle Mapper (SAM) with object-based algorithms that employed Geographic Object-Based Image Analysis (GEOBIA) to increase spatial and contextual accuracy. They also employed multi-temporal classification with Satellite Image Time Series (SITS) data to identify seasonal shifts and minor land-cover transitions. To improve classification performance, the study used machine learning methods such as Random Forest (RF) and Support Vector Machines (SVM), as well as deep learning models like U-Net, to segment satellite pictures. These techniques demonstrated great accuracy, with Random Forest achieving up to 93% accuracy in pasture mapping and deep learning models reaching around 95% accuracy in identifying deforestation. The study used textural features from the Gray-Level Co-occurrence Matrix (GLCM) as well as phenological metrics from dense Landsat and Sentinel time series to classify vegetation types and crop patterns. The authors also incorporated environmental datasets such as topography, soil type, and drainage networks into their classification procedures, demonstrating that combining contextual features with spectral and temporal data dramatically improved land-cover categorisation. The findings demonstrated the successful identification and mapping of various vegetation types, pasture kinds, agricultural methods, and deforestation rates throughout the Cerrado. However, the study identified persistent issues such as spectrum confusion in transition zones, cloud interference, and data imbalances between vegetation classifications. Fonseca et al. stated that hierarchical classification frameworks, time-series analysis, and context-aware segmentation are the most promising approaches for future LULC mapping. They emphasised the need for hybrid deep learning systems that combine geographical and temporal data, such as CNN-LSTM models, to improve scalability and resilience while monitoring broad areas. Overall, their findings demonstrated that integrating pattern recognition and remote sensing enables for accurate and long-term monitoring of environmental changes in complex biomes such as the Brazilian Cerrado, which can aid in improved policymaking and ecological conservation efforts.

Haoyan Xie et al. [2] did extensive research on applying pattern recognition techniques to categorise land-cover remote-sensing photos. Their study sought to increase the accuracy of remote-sensing picture categorisation by addressing the limitations of standard pixel-based approaches that rely solely on spectral data. To manage the complexity of remote-sensing data, the researchers created a powerful hybrid system that integrates machine vision, statistical analysis, and machine learning algorithms. The authors applied both supervised and unsupervised classification algorithms on high-resolution satellite photos from Nanjing's Yuhuatai District (2018-2019), which had a spatial resolution of 2.5 meters. They used a variety of methods, including Maximum Likelihood Classification (MLC), Support Vector Machines (SVM), Decision Tree (C5.0), Fuzzy C-Means (FCM) clustering, and ensemble techniques combining Extreme Learning Machines (ELM) and SVM. The Ensemble-ELM models significantly improved classification performance on the PaviaU dataset, with an overall accuracy (OA) of 91% and a Kappa coefficient of 0.88. This resulted in a nearly 20% improvement over normal ELM and a 10% increase over SVM classifiers. The Indian Pines dataset achieved an overall accuracy of 86.2%, with a 13% improvement in average accuracy (AA) and a Kappa score of 0.84. However, with the Salinas dataset, the improvement was moderate at around 5%, indicating performance variability depending on the dataset. The authors also investigated optimising kernel functions in SVM and proposed two new strategies for improving noise resistance and parameter flexibility. The combination of FCM segmentation with SVM classification significantly decreased the "salt-and-pepper" effect seen in pixel-based classifications. Beyond algorithmic breakthroughs, the work established object-oriented image analysis (OBIA) principles, which enable context-aware categorisation by combining spatial, textural, and geometric characteristics. This strategy improved the recognition of complicated land-cover categories such as urban structures, vegetation, water bodies, and bare soil. The study also used LCNNet-27, a convolutional neural network-based model that enhanced accuracy via multi-scale feature extraction and texture fusion. The authors demonstrated that deep learning architectures such as LCNNet-27 outperform traditional SVM and ELM models when trained on spectral-textural inputs, resulting in smoother classification maps with fewer misclassifications. Xie et al. stated that when paired with ensemble and deep learning approaches, pattern recognition provides a powerful framework for remote-sensing image classification. Their research demonstrated the significance of combining spectral, spatial, and texture features for effective land-cover analysis. To improve classification accuracy and generalisability, they proposed further research into hybrid models that combine CNNs, SVMs, and ELMs, as well as data-fusion techniques that use multispectral and hyperspectral sources. Overall, their findings represent a significant step forward in the modernisation of remote-sensing classification and will lead to smarter, automated systems for accurately mapping land cover.

Thomas U. Omali et al. [3] investigated the use of pattern recognition (PR) techniques to remote sensing picture processing. They demonstrated how these strategies increase the accuracy of land-use and land-cover categorisation (LULC). Their research combines theoretical underpinnings with practical applications to analyse environmental changes over time. To ensure high-quality analysis, the authors developed a methodical PR procedure that included pattern capture, picture preprocessing, feature extraction, classification/regression, and post-processing. They employed preprocessing techniques such as geometric correction to remove spatial distortions, radiometric correction to minimise sensor and ambient noise, and pan-sharpening to increase image resolution. The study used both supervised and unsupervised classification approaches using multitemporal Landsat images collected between 2015 and 2020 to identify six broad land-cover classes: dense vegetation, sparse vegetation, barren land, built-up area, rock outcrop, and agriculture. Their findings revealed major land-cover changes. Built-up areas increased from 30.69% in 2015 to 38.57% by 2020, whereas sparse vegetation decreased from 26.14% to 21.99%. This suggests that urbanisation and vegetation loss will continue. The study's accuracy evaluation indicated that supervised classification gave more reliable findings thanks to well-defined training samples. Omali and Umoru emphasised that pattern recognition offers a systematic, data-driven framework for recognising environmental patterns and tracking landscape changes. They concluded that integrating pattern recognition with GIS considerably enhances land-cover mapping precision and clarity. In order to acquire more reliable and automated remote sensing analysis, they also advised adopting machine learning techniques such as Random Forest, SVM, and deep learning models in future study.

Xibo Ma et al. [4] created a thorough, region-sensitive methodology that integrates Monte Carlo simulations, GIS analysis, and remote-sensing datasets to forecast indoor gamma-ray dosage location factors (LFs) after ground deposition of ^{137}Cs . Their goal was to satisfy the increasing need following nuclear accidents like Fukushima and Chernobyl for precise, spatially explicit dose prediction. In order to represent urban and land-cover characteristics such as building density, vegetation cover, and permeable-surface fractions that have a significant impact on indoor radiation attenuation, the authors developed the Local Radiation Environment Zone (LRZ) classification, which is based on the well-known Local Climate Zone (LCZ) framework. They produced dose-distance response matrices for combinations of LRZ types using PHITS-based Monte Carlo photon-transport simulations, taking into consideration variations in shielding environments and biological half-lives of pollutants on soil versus paved surfaces. They created LRZ maps by preprocessing multispectral Landsat images and GIS layers. These maps led to the distribution of simulation results to actual geographic locations, allowing for spatially resolved LF estimation over time for both first- and second-floor indoor environments. The study's findings showed significant temporal and regional fluctuations in indoor LFs, which were caused by variations in building morphology, land-cover types, and the environmental behaviour of deposited ^{137}Cs . Sparately constructed and vegetated areas showed greater initial doses, whereas compact urban zones showed lower LFs due to stronger shielding from densely built structures. Long-term exposure patterns are strongly impacted by ecological half-life differences between soil and concrete surfaces, according to temporal assessments. Strong qualitative agreement with available measurement datasets and earlier modelling research was demonstrated by the LF maps produced by the combined simulation-GIS technique. Notwithstanding its advantages, the authors pointed out some drawbacks, such as oversimplified building material assumptions, the omission of complicated topography, and errors in real deposition patterns. They suggested improving deposition inputs, using a variety of building kinds, and refining LRZ criteria in future study. All things considered, this approach offers a scalable, scientifically based instrument for post-accident radiation assessment, assisting with public health risk management, emergency response, and long-term relocation planning.

Zermatten et al. [5] investigated the limitations and practical problems of employing classical deep-learning models for land-cover mapping, particularly when applied to real-world remote-sensing datasets with varying class definitions and nomenclatures. They recognised the potential of high-resolution aerial photography and current segmentation architectures for enhancing land-cover prediction, but said that little progress had been made towards true semantic flexibility or interoperability between datasets. They identified two major issues: first, most land-cover models are trained using rigid, fixed label sets, which means the model learns class names as isolated categories rather than semantic concepts; and second, even well-trained supervised models do not transfer effectively to new regions or datasets because of variances in label nomenclature, class hierarchy, and local definitions, the learnt representations are not generalisable. To address these challenges and guide future research, the authors developed the TACOSS framework, which incorporates language-driven semantic alignment into open-vocabulary land-cover mapping. Instead of using predefined labels, the Text-Aligned component defines classes semantically using natural-language descriptions produced from encoders like as CLIP, GloVe, or SBERT. The Contrastive element matches pixel-level visual data with text embeddings using a supervised contrastive loss that is augmented by a B-cos similarity function to boost discriminative ability.

To represent real-world linguistic variation, the Contextual Semantic component employs text-augmentation tactics, such as expanding class descriptions with synonyms and different wording. Finally, the Open-Vocabulary Segmentation feature allows the model to react to any text queries and Harmonise labels across datasets, addressing the ongoing problem of mismatched taxonomies. The authors advocated for a shift away from solely label-dependent supervised models and towards models that demonstrate a clear, semantically grounded alignment of language and visual features. They contended that by combining language semantics and text augmentation, remote-sensing systems can generate more adaptable, transportable, and practically usable land-cover models. Their findings indicate that, while TACOSS loses some closed-set accuracy, it enables robust cross-dataset application and constitutes an important step towards operational, interoperable land-cover mapping.

Jing Du et al. [6] introduced Land Cover Discovery Mapping (LCDM) and 3DLCDM, an end-to-end hybrid-supervision framework intended to identify and map new urban land-cover classes from 3D point clouds.

LCDM is motivated by the authors' observation that quickly changing urban surroundings generate previously unannotated characteristics (adaptive facades, temporary fixtures, renewable energy installations, etc.) that static label sets are unable to capture. In order to address this, 3DLCDM combines unsupervised novel-class discovery with full supervision for known classes: a shared MinkUNet34C backbone extracts features that feed a supervised head for labelled categories and a dual unsupervised head (a primary fixed-prototype branch plus an over-segmentation branch with progressive prototype scheduling) for unknown classes. The method mitigates the severe class imbalance typical of urban point clouds by using a dynamic weighting technique (batch + global momentum) and temporal Sinkhorn-Knopp normalisation with adaptive temperature scheduling to produce resilient pseudo-labels. In order to make the method scalable to large 3D datasets, the study describes preprocessing and block-partitioning methodologies for two testbeds (DALES and H3D), voxelization settings, and training/inference procedures. The practical value of 3DLCDM is demonstrated by experimental results, which show that the method significantly improves novel-class mIoU (upto +16.95% on DALES and +24.43% on H3D) across multiple base/novel splits and preprocessing protocols, while also boosting base-class and overall mIoU in comparison to strong baselines (NOPS, CHNCD). Detailed split-level results demonstrate significant gains for difficult withheld classes (e.g., ground, cars, low vegetation, impervious surfaces), and qualitative visualisations confirm superior boundary delineation and finer feature discovery; ablation studies validate superior boundary delineation. The authors also examine computational trade-offs (voxelization, partitioning strategies) and validate robustness across datasets (DALES, H3D, SemanticPOSS) and partitioning schemes, highlighting 3DLCDM's preparedness for operational land-cover discovery mapping in changing urban environments.

Sangeetha et al. [7] presented a complete review of hyperspectral image (HSI) classification techniques. They focused on the challenges that high-dimensional spectral data create and the improvements in feature extraction and band-selection strategies. Their approach addressed the main drawbacks of conventional pixel-based classifiers, which frequently experience classification noise in varied landscapes, spectral redundancy, and the Hughes phenomenon. The authors looked at popular public datasets, such as Indian Pines, Pavia University, Salinas, Houston, and Botswana, emphasising their spectral properties and applicability in evaluating contemporary classifiers. The study offered a thorough analysis of dimensionality reduction techniques, including nonlinear approaches like kernel PCA, manifold learning, t-SNE, and autoencoder-based models, as well as linear approaches like PCA, ICA, LDA, MNF, and NMF. Unsupervised band-selection techniques were given special attention, especially clustering-based methods, which have been demonstrated to successfully reduce redundancy while maintaining spectral bands with a wealth of information. The study also emphasised the increasing trend of spectral-spatial classification frameworks, pointing out that scenes with high spatial complexity are difficult for solely spectral models. Effective methods for capturing spatial texture and structure included morphological profiles, superpixel segmentation, GLCM, Gabor filters, LBP, and 3D transforms. Recent deep learning developments, such as 2DCNNs, 3DCNNs, hybrid 2D+3D architectures, graph convolutional networks (GCNs), attention-based transformers, and hypergraph models, were found to be the main drivers of state-of-the-art classification performance on benchmark datasets. According to their survey, hybrid and deep learning models beat conventional classifiers like SVM and Random Forest, achieving nearly flawless accuracy on datasets like Pavia University and Salinas. The scientists also examined end-to-end spectral-spatial fusion networks, evolutionary and swarm-based band-selection methods, and ensemble approaches, highlighting the importance of spatial-context modelling and efficient dimensionality reduction for better performance. Limited labelled samples, atmospheric variability, mixed pixels, and the high computing cost of transformer-based models are some of the major issues noted. In order to improve resilience across datasets, they suggested future avenues include explainable AI, multimodal fusion with LiDAR/SAR, lightweight real-time architectures, and transfer learning. Overall, the study shows that the accuracy of land-cover categorisation is significantly increased when band selection, spectral-spatial characteristics, and sophisticated deep networks are combined.

Costa et al. [8] conducted a detailed study on the cooling effectiveness of Nature-Based Solutions (NBS). They used remote-sensing indices and machine-learning prediction models. By addressing the shortcomings of conventional land-surface temperature (LST) calculations, which frequently ignore spatial context and land-cover interactions, their research sought to improve the accuracy of urban heat assessments. In order to model the relationship between land-cover patterns and thermal behaviour, the study created a solid framework that integrated spatial measures, ensemble learning algorithms, and remote-sensing indicators. Using Landsat-8 data of the Guimarães region from 2014 to 2023, the authors calculated important indices such as NDVI, NDBI, and GNDVI in addition to elevation, distance to roads and streams, and NBS effect zones. To forecast current and near-future land-surface temperatures, these variables were included in many machine learning models, such as Random Forest (RF), XGBoost, Bagging Regressor, AdaBoost, and K-Nearest Neighbour (KNN). With a R^2 of 0.957, XGBoost outperformed RF (0.942) and Bagging (0.946) as the tested model with the highest predictive accuracy. With a Kappa of 0.873 and a total accuracy of 91.7%, Random Forest's land-cover classification was also dependable. The MOLUSCE CA-ANN model projected future land-cover changes with a Kappa of 0.894, showing stable transitions and growing NBS influence on urban temperatures. Despite slight offsets, the study also verified good relationships between ground-measured air temperature and satellite-derived LST. Overall, the authors point out that using sophisticated machine learning models in conjunction with spatial-context data, including proximity to vegetation, greatly enhances thermal prediction and promotes climate-resilient urban development.

Kosarevych et al. [9] conducted a study on improving environmental remote-sensing analysis by combining convolutional neural networks (CNNs) with spatial point-pattern analysis (SPPA). The goal of their research was to overcome the shortcomings of conventional remote-sensing procedures, which frequently only use pixel-based classification and are unable to record ecological interactions across different landscapes. In order to close this gap, the scientists presented a unique system that uses CNN architectures (EffNet and LeNet) to first classify remote-sensing picture patches. The identified outputs are then converted into marked spatial point patterns that reflect various land-cover kinds. One of the study's main innovations was a new data-augmentation technique based on spatiotemporal similarity, which expanded the training dataset by using several satellite photos taken over the same area at various times. This method demonstrated its appropriateness for remote-sensing contexts with minimal labelled data by improving classification accuracy by more than 7% when compared to typical augmentation techniques. The authors demonstrated through extensive tests utilising Landsat-8 imagery of the Shatsk National Nature Park that, with the backing of huge, enriched datasets, even basic CNN architectures may achieve high accuracy (up to 97% top-1). Using second-order statistics, such as K-functions, g-functions, and mark-correlation metrics, the produced point-pattern maps allowed for a thorough ecological interpretation that revealed interactions like the proximity of forests to water and the spatial exclusion between forested and built-up areas. Their findings showed that point-pattern representation may simulate interspecific or interclass interactions at various geographical scales and captures ecological complexity more successfully than conventional raster-only techniques. The work highlighted the wider potential of integrating deep learning with SPPA to identify biotic linkages, track habitat changes, and provide ecosystem-level analysis in addition to classification. Future research needs, such as incorporating sophisticated CNN models, enhancing zero-model point-process formulations, and creating more reliable frameworks for dynamic ecological processes, were underlined by the authors.

Alawode et al. [10] conducted a thorough study of land-use and land-cover (LULC) changes in the Mödling municipality of Austria. They used a 24-year collection of Landsat-7 ETM+ and Landsat-8 OLI/TIRS images from 1999 to 2022. Their main goal was to produce precise LULC maps at the municipality level that get around the drawbacks of regional datasets with coarse resolution, like CORINE. In order to accomplish this, the scientists developed a reliable remote-sensing workflow that includes sun-angle normalisation, radiometric correction, top-of-atmosphere reflectance conversion, and Maximum Likelihood supervised classification. High classification reliability was assured by extensive ground-truthing utilising GPS coordinates, orthophotos, Google Earth sampling, and CORINE comparison. With total accuracies ranging from 91.9% to 94.4% and Kappa coefficients between 0.897 and 0.929, the produced LULC maps showed excellent performance, demonstrating the efficacy of combining supervised classification with GIS-based spatial analysis for local environmental monitoring. The study assessed vegetation dynamics using NDVI and SAVI in addition to LULC mapping, allowing for a comparison between supervised forest classifications and index-based predictions. The authors discovered that whereas SAVI continuously overstated forest cover, NDVI closely matched supervised forest patterns, indicating the sensitivity of soil-adjusted indices in peri-urban environments with fragmented vegetation. Significant land-cover changes were identified by the multi-temporal analysis: built-up areas rose significantly (by more than 1,500 hectares) due to persistent urban growth, while forest cover decreased by 2.61 percentage points (about 743 hectares). These results demonstrate how settlement growth is putting increasing strain on natural and semi-natural regions.

The study showed how remotesensingandGIS together provide a thorough, useful understanding of landscape change by combining multi-temporal Landsat data, pixel-level post-classification comparison, and vegetation-index analysis. This provides a useful evidence base for urban planning, conservation strategies, and long-term environmental management in rapidly urbanising regions.

III. CONCLUSION

This study emphasises how important pattern recognition is for increasing remote sensing data processing and land-use and land-cover (LULC) categorisation accuracy. It is clear from the reviewed works that combining spectral, spatial, textural, and temporal features with contemporary machine-learning and deep-learning techniques greatly improves classification performance, lowers noise, and facilitates more accurate interpretation of complex landscapes. The shortcomings of conventional closed-set systems are further addressed by emerging techniques like semantic alignment, open-vocabulary models, spatial point-pattern analysis, and novel-class discovery, which provide more flexibility for practical applications. Understanding environmental processes, radiation exposure, ecological interactions, and landscape dynamics is further improved by the integration of GIS, Monte Carlo simulations, and multimodal data fusion. All things considered, recent developments in pattern recognition offer robust, scalable, and data-driven solutions for remote sensing analysis, promoting climate resilience, ecological conservation, sustainable urban development, and well-informed decision-making. The literature's observations show that sustained innovation in this area will be crucial for addressing upcoming environmental issues and enhancing the accuracy of LULC mapping.

REFERENCES

- [1] L. M. Fonseca, T. S. Ko'ring, H. d. N. Bendini, C. D. Girolamo-Neto, A. K. Neves, A. R. Soares, E. C. Taquary, and R. V. Mareto, "Pattern recognition and remote sensing techniques applied to land use and land cover mapping in the Brazilian savannah," *Pattern Recognition Letters*, vol. 148, pp. 54–60, 2021.
- [2] H. Xie and H. Huang, "Classification of land cover remote-sensing images based on pattern recognition," *Scientific Programming*, vol. 2022, no. 1, p. 8319692, 2022.
- [3] T. U. Omali and K. Umoru, "Pattern recognition in remote sensing image analysis: Theory, methods, and a case study of Rijiyar Donor in Katsina, Nigeria," *Int. J. Sci. Res. in Computer Science and Engineering*, vol. 11, no. 6, 2023.
- [4] X. Ma, Z. Wang, Y. Ishida, and H. Kobayashi, "Land-cover-based indoor gamma-ray dose after a nuclear accident: location factor mapping via Monte Carlo simulation, GIS, and remote sensing," *Journal of Environmental Radioactivity*, vol. 291, p. 107853, 2026.
- [5] V. Zermatten, J. Castillo-Navarro, D. Marcos, and D. Tuia, "Learning transferable land cover semantics for open vocabulary interactions with remote sensing images," *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 220, pp. 621–636, 2025.
- [6] J. Du, J. Zelek, D. Zhang, and J. Li, "3dLcdm: Hybrid supervision for land cover discovery mapping of emerging urban structures in 3d remote sensing," *Remote Sensing of Environment*, vol. 331, p. 115018, 2025.
- [7] V. Sangeetha and L. Agilandeeswari, "Artificial intelligence enabled spectral-spatial feature extraction techniques for land use and land cover classification using hyperspectral images—an inclusive review," *The Egyptian Journal of Remote Sensing and Space Sciences*, vol. 28, no. 3, pp. 455–467, 2025.
- [8] P. C. Toscan, K. Seong, J. Jiao, C. A. L. R. Ribeiro, F. A. C. Carvalho, M. L. Oliveira, and E. B. Pereira, "Impact of nature-based solutions (NBS) on urban surface temperatures and land cover changes using remote sensing and machine learning," *Remote Sensing Applications: Society and Environment*, p. 101721, 2025.
- [9] R. Kosarevych, O. Lutsyk, B. Rusyn, O. Alokina, T. Maksymyuk, and J. Gazda, "Spatial point pattern generation from remote sensing data using convolutional neural networks with further statistical analysis," *Scientific Reports*, vol. 12, no. 1, p. 14341, 2022.
- [10] G. L. Alawode, T. V. Oluwajuwon, R. A. Hammed, K. E. Olasuyi, A. Krasovskiy, O. C. Ogundipe, and F. Kraxner, "Spatio-temporal assessment of land use and land cover dynamics in Molding district, Austria, using remote sensing techniques," *Heliyon*, vol. 11, no. 11, 2025.



10.22214/IJRASET



45.98



IMPACT FACTOR:
7.129



IMPACT FACTOR:
7.429



INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Call : 08813907089  (24*7 Support on Whatsapp)