Intelligent land use and land cover classification using Sentinel-2 multispectral imagery

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Article Info

Article history:

Received Oct 2, 2024
Revised May 28, 2026
Accepted Jul 23, 2026

Keywords:

Land use land cover
Maximum likelihood classifier
Neural networks
Precision agriculture
Remote sensing
Sentinel-2

ABSTRACT

Accurate land use and land cover (LULC) classification is essential for environmental monitoring, agricultural planning, and sustainable resource management. This study investigates the effectiveness of Sentinel-2 multispectral satellite imagery for LULC classification by comparing the performance of three supervised classification algorithms: maximum likelihood classifier (MLC), minimum distance classifier (MDC), and neural networks (NN). Before classification, Sentinel-2 imagery underwent comprehensive preprocessing, including atmospheric correction, radiometric calibration, and cloud masking using ERDAS software to improve image quality and classification reliability. The Villupuram district of Tamil Nadu, India, was selected as the study area due to its diverse land cover characteristics. Classification performance was evaluated using overall accuracy (OA), producer's accuracy (PA), user's accuracy (UA), and the Kappa coefficient. Experimental results demonstrate that the MLC achieved the highest OA of 94.81% with a Kappa coefficient of 0.9308, outperforming MDC (90.65%, 0.8753) and NN (84.38%, 0.7917). These findings confirm that supervised classification of Sentinel-2 multispectral imagery provides reliable and accurate LULC mapping, offering valuable geospatial information to support precision agriculture, environmental monitoring, land resource management, and sustainable regional planning.

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1. INTRODUCTION

Accurate land use and land cover (LULC) information plays a fundamental role in environmental monitoring, urban planning, agricultural management, natural resource conservation, and sustainable development. Rapid urbanization, population growth, industrial expansion, and climate change have accelerated landscape transformation worldwide, creating an urgent need for reliable techniques capable of continuously monitoring changes in land cover. Timely and accurate LULC mapping enables governments, environmental agencies, and decision-makers to evaluate ecosystem dynamics, monitor agricultural productivity, assess environmental degradation, and formulate effective land management policies [1]. Consequently, the development of efficient LULC classification techniques has become a major research focus within the fields of remote sensing, geospatial intelligence, and computer vision.

Remote sensing has emerged as one of the most effective technologies for large-scale LULC monitoring because it provides repetitive, non-invasive, and cost-effective observations over extensive geographical regions. Compared with conventional field surveys, satellite-based remote sensing offers high spatial, spectral, and temporal resolutions while significantly reducing labor, time, and operational costs. Continuous observations acquired from Earth observation satellites enable researchers to investigate long-term environmental changes, detect land transformation patterns, and support sustainable management of natural resources [2]. As satellite sensors continue to improve in spatial resolution and spectral capability, remote sensing has become an indispensable tool for monitoring vegetation dynamics, water resources, urban expansion, forest degradation, and agricultural activities.

Among the various Earth observation missions, the European Space Agency (ESA) Sentinel-2 satellite constellation has become one of the most widely adopted platforms for LULC mapping due to its freely accessible, high-resolution multispectral imagery. Sentinel-2 is equipped with a multispectral instrument that captures imagery across 13 spectral bands covering the visible, near-infrared (NIR), and short-wave infrared (SWIR) regions with a swath width of approximately 290 km [3], [4]. The availability of multiple spectral bands allows the extraction of rich spectral signatures from different surface materials, enabling accurate discrimination among vegetation, agricultural fields, water bodies, bare soil, and built-up areas. Furthermore, its frequent revisit cycle supports continuous environmental monitoring and facilitates multi-temporal analysis of landscape dynamics [5].

The increasing availability of Sentinel-2 imagery has significantly advanced the application of remote sensing in precision agriculture. Precision agriculture integrates geospatial technologies, remote sensing, geographic information systems (GIS), and data analytics to optimize agricultural production while minimizing environmental impacts. Multispectral satellite imagery provides valuable information regarding vegetation health, crop vigor, soil moisture conditions, irrigation efficiency, and nutrient variability, enabling farmers to make informed management decisions. By integrating historical observations with near-real-time satellite data, agricultural practitioners can optimize planting schedules, irrigation management, fertilizer application, and harvesting strategies, thereby improving productivity while reducing operational costs and environmental impacts [6], [7]. Consequently, reliable LULC classification derived from Sentinel-2 imagery contributes not only to agricultural planning but also to broader environmental sustainability and resource management objectives.

Recent advances in artificial intelligence (AI), machine learning, and image processing have substantially improved the accuracy of satellite image classification. Traditional supervised classification methods, such as MLC and minimum distance classifier (MDC), remain popular because of their computational efficiency and ease of implementation. However, modern machine learning algorithms have demonstrated superior capability in learning complex nonlinear relationships within high-dimensional multispectral data. Artificial neural networks (ANNs), support vector machines (SVMs), random forests (RFs), convolutional neural networks (CNNs), and other deep learning architectures have increasingly been adopted to enhance classification accuracy by automatically extracting discriminative spectral and spatial features from remote sensing imagery [8], [9]. These intelligent approaches have enabled more robust LULC classification under diverse environmental conditions and heterogeneous landscapes.

Several previous studies have investigated the effectiveness of various classification algorithms using different satellite datasets. CNN-based methods applied to Sentinel-2 imagery achieved an overall classification accuracy of 96.57%, demonstrating the ability of deep learning to extract complex spatial features, although computational complexity remains a significant challenge [10]. Comparative studies utilizing Sentinel-2 and Landsat-9 imagery reported Kappa coefficients of 0.78 and 0.72, respectively, indicating the superior spatial resolution of Sentinel-2 for LULC applications [11]. Another study integrated InceptionResNetV2 with a UNet framework in an ensemble deep learning model, achieving 98.21% classification accuracy on multi-year Sentinel-2 imagery [12]. Furthermore, comparative analyses involving SVM, KNN, RF, and DT classifiers on Landsat 8 OLI data demonstrated that SVM achieved the highest accuracy of 90.74% [13].

Beyond Sentinel-2, several studies have investigated alternative satellite platforms for LULC classification. A comparative evaluation of RF, ANN, SVM, fuzzy ARTMAP, SAM, and MD classifiers found RF achieved the highest agreement (Kappa = 0.89), closely followed by ANN and SVM, in mapping agriculture, settlement, vegetation, and wetland classes [14]. Moderate resolution imaging spectroradiometer (MODIS) imagery combined with Sentinel-2 and auxiliary data using random forest classifiers achieved overall accuracies ranging from 88.10% to 92.38% for land cover classification on Google Earth Engine [15]. Sentinel-1 synthetic aperture radar (SAR) imagery combined with object-oriented classification achieved overall accuracies of approximately 95% for crop classification, although performance depended heavily on plot size [16]. Similarly, WorldView-3 imagery processed using RF, ANN, and CNN classifiers achieved overall accuracies up to 77% for large-scale land cover classification, requiring extensive preprocessing due to its very high spatial resolution [17].

Numerous studies have investigated LULC classification using diverse satellite platforms and image classification algorithms. Their reported performances vary considerably according to the spatial and spectral characteristics of the imagery, preprocessing techniques, classifier design, and landscape complexity. Recent advances have increasingly incorporated machine learning and deep learning algorithms to improve classification accuracy; however, conventional supervised classifiers remain attractive because of their computational efficiency, interpretability, and ease of implementation. Table 1 compares representative studies on satellite-based LULC classification, highlighting the satellite datasets, classification methods, reported performance, strengths, and limitations. The comparison reveals that although advanced deep learning models generally achieve higher classification accuracies, they often require greater computational resources and extensive model training. Conversely, conventional supervised classifiers continue to provide competitive performance while offering lower computational complexity, making them suitable for practical operational applications.

Table 1. Comparison of satellite-based LULC classification methods

Satellite	Methodology	Characteristics	Limitations	Source
Sentinel-2	CNN[a]	96.57% overall accuracy.	High computational cost.	[10]
Sentinel-2 and Landsat-9	RGB and NIR[b] bands for classification and comparison	Kappa statistics of 0.78 and 0.72 for Sentinel-2 and Landsat-9.	Lower resolution of Landsat-9.	[11]
Sentinel-2	IRNV2UN[c]	98.21% accuracy	Requires large multi-year training data	[12]
Landsat-8	DT[d], SVM[e], KNN[f], RF[g]	90.74% accuracy for SVM	Lower spatial resolution than Sentinel-2	[13]
Multi-Sensor	Multiple ML Algorithms	RF highest (Kappa=0.89); SVM and ANN close behind	Computationally intensive on large datasets.	[14]
MODIS + Sentinel-2	RF	88.10%–92.38% accuracy	Requires careful RF parameter tuning	[15]
Sentinel-1	OBIA[h]	~95% accuracy for large-plot crop classification	Depends on plot size relative to resolution	[16]
WorldView-3	RF, ANN, CNN	Up to 77% accuracy for large-scale mapping	Requires extensive preprocessing for high-resolution data.	[17]

Footnotes: [a]Convolutional Neural Networks, [b]Near-Infrared (NIR), [c]InceptionResNetV2+UNet, [d]Decision Tree, [e]Support Vector Machine, [f]K-Nearest Neighbour, [g]Random Forest, [h]Object-Based Image Analysis.

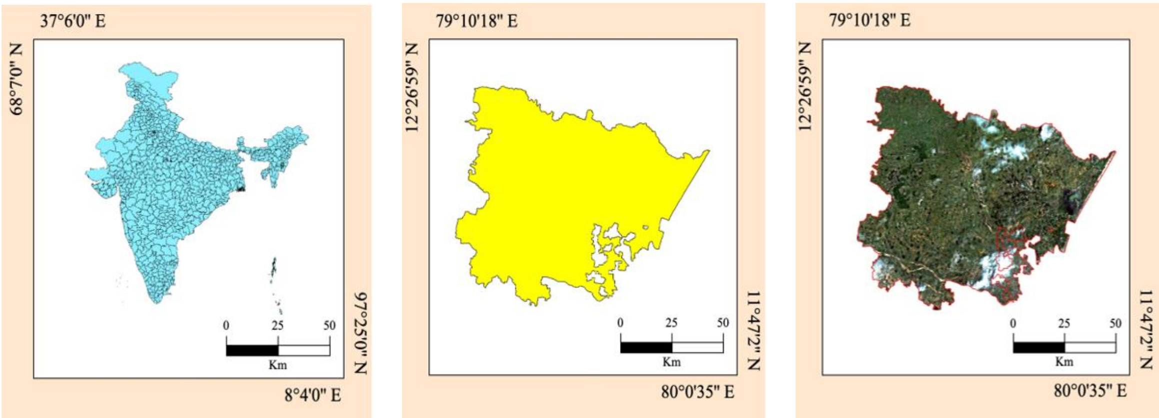
Despite the considerable progress achieved by recent machine learning and deep learning approaches, relatively few studies have comprehensively compared conventional supervised classification algorithms using Sentinel-2 multispectral imagery under identical preprocessing conditions and evaluation criteria. Moreover, the trade-offs between classification accuracy, computational efficiency, and practical implementation remain insufficiently investigated, particularly for heterogeneous agricultural and urban landscapes. Addressing these challenges is essential for identifying robust and efficient classification techniques that can be readily applied in operational remote sensing applications.

Motivated by these research gaps, this study presents a comprehensive comparative evaluation of three widely used supervised classification algorithms— MLC, MDC, and NNs—for LULC classification using Sentinel-2 multispectral imagery acquired over the Villupuram district of Tamil Nadu, India. Prior to classification, atmospheric correction, radiometric calibration, and cloud masking were performed to improve image quality and enhance classification reliability. The performance of each classifier was quantitatively evaluated using OA, producer's accuracy (PA), user's accuracy (UA), and the Kappa coefficient. The results provide practical insights into the trade-offs between classification accuracy and computational efficiency while demonstrating the effectiveness of Sentinel-2 multispectral imagery for reliable LULC mapping. The findings contribute to the development of robust remote sensing methodologies that support precision agriculture, environmental monitoring, land resource management, and sustainable regional planning.

2. METHOD

2.1. Study area

The research is focused on the Villupuram district in Tamil Nadu, India, located at approximately 11°57'17" N latitude and 79°31'40" E longitude. Villupuram has various land cover types such as agriculture, forest, water body, and urban [18]. This region is important for agricultural activities in Tamil Nadu, where rice, sugarcane, and other fruits and vegetable crops are widely grown. The district also has vast dry deciduous and dry dense forests, facilitating important ecological variables that promote environmental conservation. The monitoring of LULC has proved helpful for agricultural-driven decision-support systems in precision agriculture to optimize water resource utilization and sustainable farming practices, as it highlights the significance of LULC over this region, influencing both the local environment and climate. Figure 1 shows a graphical representation of the study area used in this research. Figure 1(a) shows the map of India, while Figure 1(b) represents the geographical boundary of the study area. Sentinel-2 satellite imagery in natural color band combination is represented in Figure 1(c).



(a) (b) (c)

Figure 1. Representation of study area; (a) map of India, (b) study area (Villupuram District) highlighted, and (c) Sentinel-2 satellite imagery of the study area taken on October 7, 2023

2.2. Satellite dataset

Data used in this study was collected using the ESA Sentinel-2 satellite, which is part of the Copernicus program. The dataset was captured on October 7, 2023, and consisted of high-resolution optical images with 13 spectral bands spanning from visible to SWIR wavelengths [19]. Due to its spatial resolution of 10 meters, Sentinel-2 is well-suited for land cover classification that requires the highest level of detail in distinguishing vegetation, water bodies, and urban areas [20]. The short revisit times of a few days enabled by the high temporal resolution are one of the main benefits of monitoring changes in agricultural areas, forests, or water bodies. Sentinel-2's spectral and spatial characteristics have synergistic benefits that further improve the accuracy of land classification, supporting better sustainable land use planning to increase agricultural productivity in the region.

2.3. Preprocessing

The pre-processing stage of the methodology started with Sentinel-2 satellite images. It included correcting atmospheric effects like haze and cloud cover before addressing radiometric distortions from the sensor images to maintain data in its true form [21]. Radiometric calibration was done using ERDAS imagine V.15 in the current research. The goal of this calibration is to standardize the pixel values of each image for the different dates and locations at which images were taken [22]. Here, resampling was performed on the satellite imagery to reference actual geographic coordinate systems and ensure correct spatial measures for land use classification. Cloud masking and noise reduction techniques were also applied to eliminate undesired background interference or clouds. Preprocessing is essential to ensure the satellite images are clean, well-aligned, and suitable for detailed classification. Figure 2 shows the methodology of performing land cover classification of the study area using the three different algorithms, visually depicting various land cover types, including vegetation, water bodies, and urban areas. Sentinel-2 satellite imagery is initially downloaded from the ESA's Copernicus programme (https://browser.dataspace.copernicus.eu/). The satellite imagery comes in different bands, as shown in Figure 2(a), which need to be stacked to make them ready for preprocessing. Figure 2(b) shows the stacked satellite imagery, representing the study area in a natural color band combination. After preprocessing the satellite imagery, thematic maps were generated using various classification algorithms.

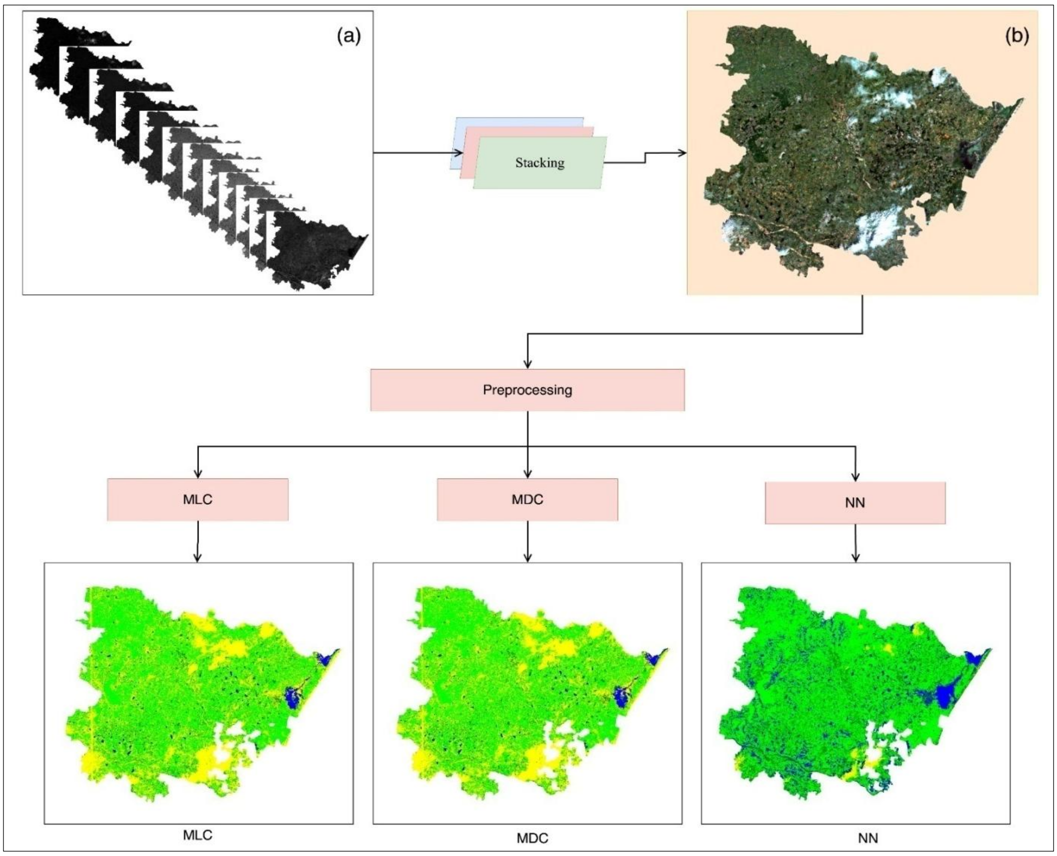


Figure 2. Methodology to implement classifiers in the study area (a) the satellite imagery comes in different bands and (b) the stacked satellite imagery

2.4. Stacking

The images were processed and atmospherically corrected using ERDAS Imagine software, in which all bands of the Sentinel-2 satellite data were stacked to derive a single composite image. Stacking is required to put visible, NIR, and shortwave infrared data in one image for a complete land cover picture. This process enhances the effectiveness of discriminating between land types (vegetation, water bodies, urban areas) because it exposes spectral signatures that are not visible in any of the isolated bands but only when we overlap multiple bands [23]. The resulting image enhances classification accuracy because different machine-learning algorithms can effectively learn from various spectral information. Combining multiple bands makes the analysis more detailed and reliable, enabling precise identification of subtle differences in land cover. This is especially beneficial in regions with diverse landscapes that require fine-grained analysis. Combining the spectral bands is a crucial step in remote sensing because it allows us to obtain higher classification accuracies and improve indexing for superior utilization in land management.

2.5. Classification

Classification is an important task that classifies satellite imagery into various land categories. Thematic maps can be generated to understand the land's diversity further, which is essential for decision-makers and stakeholders to make informed decisions. Three different classifiers were applied to the preprocessed data acquired using the Sentinel-2 satellite. By leveraging the spectral and spatial information captured by Sentinel-2, these methods facilitate precise monitoring of land-use changes over time.

2.5.1. Maximum likelihood classifier (MLC)

MLC is widely used in remote sensing, where the spectral data must be separated based on a broad assumption. This assumes that the data among the classes follow a normal distribution. According to this assumption, probability is calculated for each pixel, introducing itself as belonging to a particular class and then categorizing it into that category with maximum likelihood [24]. It considers the variance and covariance of the spectral signatures, making it effective for complex data distributions. MLC requires substantial training data to estimate these parameters accurately.

2.5.2. Minimum distance classifier (MDC)

Each pixel in the feature space is assigned to a land cover class using the MDC based on the closest spectral signature, or centroid [25]. The Euclidean distance between the spectral values of each pixel and the mean values (centroids) of known classes such as water, vegetation, and urban areas is computed for each pixel. After that, the pixel is categorized into the class with the shortest distance. It performs well for discrete land cover types but may have trouble with overlapping or mixed classes. MDC is computationally efficient, making it suitable for large datasets, but its simplicity may lead to reduced accuracy in heterogeneous landscapes.

2.5.3. Neural network (NN)

NNs are computational models that mimic the human brain. They are mainly used for pattern recognition and classification tasks. NNs are highly effective in classifying satellite imagery, as the interconnected neurons can learn intricate patterns and relationships within the complex image data. Every neuron takes an input, processes it, and passes the information forward [26]. In land cover classification, several non-linear relationships exist that are complex to handle, and NNs are great at handling this problem. NN can incorporate both spectral and spatial information, enhancing classification accuracy. However, they require significant computational resources and careful tuning of hyperparameters to prevent overfitting.

3. RESULTS AND DISCUSSION

The study area was categorized by three algorithms: MLC, MDC, and NN. This allows us to evaluate identification by focusing on the thematic images created by those algorithms. It was observed through visual analysis that MLC techniques offer more accurate classification for vegetation. MDC algorithms easily separate built-up areas. A quantitative assessment was performed to evaluate the classification accuracy using several metrics, such as producer accuracy (PA), user accuracy (UA), and Kappa coefficient, which are mandatory for determining the reliability and efficacy of an algorithm. The results show that the MLC algorithm attained 94.81% accuracy, with an overall classification Kappa coefficient of 0.9308, signaling the robustness and reliability of this classification for discriminating between different land-cover types. The MDC algorithm achieved 90.65% accuracy, with a Kappa coefficient of 0.8753, although it was less efficient in classifying urban sites. The NN algorithm's total accuracy was 84.38% and a Kappa coefficient of 0.7917.

The MLC method is considered an efficient technique for identifying different land types in the region compared to MDC and NN algorithms. MLC algorithms are applied to separate vegetation from built-up areas. The performance of the NN algorithm, while showing potential, suggests significant room for optimization to improve generalization. These results underscore the importance of selecting a suitable land cover classification algorithm for sustainable agricultural production and land management practices. Table 2 shows the performance metrics of land classification algorithms for MLC, MDC, and NN across land cover classes. Figure 3 shows how three land classification algorithms calculated the accuracy and Kappa coefficients. A visual comparison of accuracy for every algorithm in the classification of different land cover types over the study area with Sentinel-2 satellite images is shown in Figure 3. It confirms the highest accuracy of ML and largest Kappa among the three models in terms of overall accuracies by MLC, MDC, and NN, as well as their strengths and weaknesses for land cover classification.

Table 2. Quantitative analysis of classification techniques

Algorithm	Class	TR	TC	CC	PA	UA	Kappa
MLC	Deciduous vegetation	34	34	32	94.12%	94.12%	0.9214
	Dense vegetation	34	35	33	97.06%	94.29%	0.9236
	Water	36	35	34	94.44%	97.14%	0.961
	Urban	31	31	29	93.55%	93.55%	0.9163
	Total	**135.00**	**135.00**	**128.00**	-	-	-
MDC	Deciduous vegetation	39	36	33	84.62%	91.67%	0.8842
	Dense vegetation	36	33	31	86.11%	93.94%	0.9182
	Water	35	35	33	94.29%	94.29%	0.9236
	Urban	29	35	29	100.00%	82.86%	0.7834
	Total	**139.00**	**139.00**	**126.00**	-	-	-
NN	Deciduous vegetation	44	40	34	77.27%	85.00%	0.7931
	Dense vegetation	41	40	33	80.49%	82.50%	0.7647
	Water	33	40	31	93.94%	77.50%	0.7165
	Urban	42	40	37	88.10%	92.50%	0.8983
	Total	160.00	160.00	135.00	-	-	-

Note: TR (total reference), TC (total classified), CC (correctly classified), PA (producer's accuracy), UA (user's accuracy)

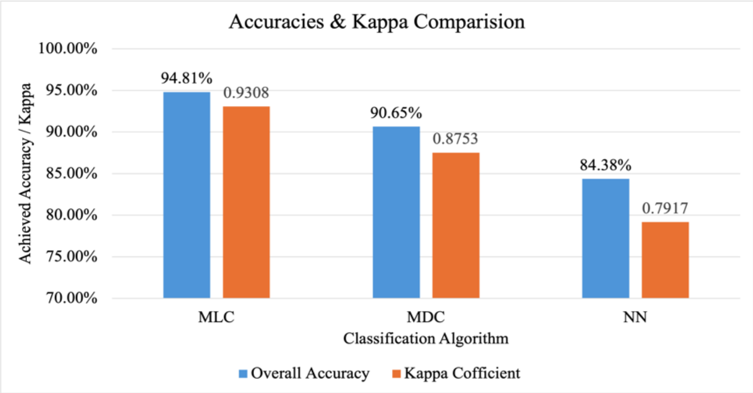


Figure 3. Accuracy and Kappa comparison of the classification algorithms

This research demonstrates the feasibility of applying satellite imagery, especially Sentinel-2, to LULC classification with this significantly high accuracy. Among all algorithms tested in this study, MLC produced the highest OA of 94.81%, with Kappa of 0.9308, followed by the MDC and NN. MLC performs better because it considers variance and covariance in spectral data transformation. Hence, MLC can be applied to problems with complex data distribution. The lower performance of MDC and NN classifiers indicates that improvements in their generalization ability (optimized for the whole training set) are still needed to deal with mixed land cover classes and complex spatial patterns. The variety of land cover types in the study area (agricultural, urban, and forest) also confirms the suitability of these algorithms for heterogeneous landscapes.

When analyzing these results in comparison with past studies, MLC performs similarly to previous findings that revealed its strength with remote sensing data classification, particularly with heterogeneous land cover types [27]. Conversely, the relatively poor performance of NN as compared to MLC is not uncommon and can be due to the issue of parameter tuning and data scarcity, which are well-known bottlenecks of deep learning-based approaches. The main novelty of this research is that it uses high-resolution multispectral data from Sentinel-2 to improve classification accuracy. MDC also performs well, which indicates that it could be a computationally cheaper option for simpler land cover classifications.

In conclusion, the present study shows the potential of MLC, which produced a high OA of LULC mapping from Sentinel-2 imagery, which may be adopted as a timely solution to efficient LULC mapping for sustainable agricultural practice and sound decision-making for land management in the future. Future research can focus on multi-sensor fusion and hybrid systems modeling to capitalize on the strengths of different classifiers and increase performance and computational efficiency. Furthermore, exploring time-series analysis and automated classification frameworks can also strengthen the reliability of LULC change detection, which can be even more useful for precision agriculture and environmental conservation.

4. CONCLUSION

This study demonstrated the effectiveness of Sentinel-2 multispectral imagery for accurate LULC classification through a comparative evaluation of three supervised classification algorithms: MLC, MDC, and NNs. Experimental results revealed that the MLC achieved the highest classification performance, with an OA of 94.81% and a Kappa coefficient of 0.9308, outperforming the MDC and NN models in distinguishing diverse land cover classes. These findings indicate that the MLC remains a robust and computationally efficient approach for LULC mapping using high-resolution multispectral satellite imagery. The comparative analysis further demonstrates that although MDC and NN produced satisfactory classification results, their performance was comparatively lower, suggesting the need for further optimization when applied to complex and heterogeneous landscapes. The results highlight the importance of selecting an appropriate classification algorithm to improve mapping accuracy and support reliable geospatial analysis for environmental monitoring and sustainable land management. The proposed approach provides valuable geospatial information that can support precision agriculture by enabling informed decision-making related to crop management, irrigation planning, land resource utilization, and environmental conservation. Future research should investigate the integration of multi-temporal and multi-sensor satellite data, advanced machine learning and deep learning techniques, automated hyperparameter optimization, and near real-time LULC monitoring frameworks to further improve classification accuracy, scalability, and operational applicability in large-scale remote sensing applications.

ACKNOWLEDGEMENTS

The authors gratefully acknowledge the Copernicus Programme of the European Space Agency (ESA) for providing the Sentinel-2 multispectral satellite imagery used in this study. The availability of these open-access Earth observation datasets has significantly contributed to the successful completion of this research.

REFERENCES

[1] E. M. B. M. Karunathilake, A. T. Le, S. Heo, Y. S. Chung, and S. Mansoor, "The path to smart farming: innovations and opportunities in precision agriculture," *Agriculture (Switzerland)*, vol. 13, no. 8, p. 1593, Aug. 2023, doi: 10.3390/agriculture13081593.

[2] A. Kamilaris and F. X. Prenafeta-Boldú, "Deep learning in agriculture: A survey," *Computers and Electronics in Agriculture*, vol. 147, pp. 70–90, Apr. 2018, doi: 10.1016/j.compag.2018.02.016.

[3] M. Belgiu and L. Drăgu, "Random forest in remote sensing: a review of applications and future directions," *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 114, pp. 24–31, Apr. 2016, doi: 10.1016/j.isprsjprs.2016.01.011.

[4] D. Phiri, M. Simwanda, S. Salekin, V. R. Nyirenda, Y. Murayama, and M. Ranagalage, "Sentinel-2 data for land cover/use mapping: A review," *Remote Sensing*, vol. 12, no. 14, p. 2291, Jul. 2020, doi: 10.3390/rs12142291.

[5] S. Reinermann, U. Gessner, S. Asam, T. Ullmann, A. Schucknecht, and C. Kuenzer, "Detection of grassland mowing events for Germany by combining Sentinel-1 and Sentinel-2 Time Series," *Remote Sensing*, vol. 14, no. 7, p. 1647, Mar. 2022, doi: 10.3390/rs14071647.

[6] R. Abiri, N. Rizan, S. K. Balasundram, A. B. Shahbazi, and H. Abdul-Hamid, "Application of digital technologies for ensuring agricultural productivity," *Heliyon*, vol. 9, no. 12, p. e22601, Dec. 2023, doi: 10.1016/j.heliyon.2023.e22601.

[7] K. M. Panduranga and R. H. Ranganathasharma, "Sustainability insights on learning-based approaches in precision agriculture in internet-of-things," *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 14, no. 3, pp. 3495–3511, Jun. 2024, doi: 10.11591/ijece.v14i3.pp3495-3511.

[8] J. Segarra, M. L. Buchaillot, J. L. Araus, and S. C. Kefauver, "Remote sensing for precision agriculture: Sentinel-2 improved features and applications," *Agronomy*, vol. 10, no. 5, p. 641, May 2020, doi: 10.3390/agronomy10050641.

[9] P. H. Verburg *et al.*, "Land system science and sustainable development of the earth system: a global land project perspective," *Anthropocene*, vol. 12, pp. 29–41, Dec. 2015, doi: 10.1016/j.ancene.2015.09.004.

[10] N. S. Rengma and M. Yadav, "Generation and classification of patch-based land use and land cover dataset in diverse Indian landscapes: a comparative study of machine learning and deep learning models," 2024. doi: 10.1007/s10661-024-12719-7.

[11] S. Dhakal, S. Kandel, L. Puri, and S. Shrestha, "Assessment on land use land cover mapping: Sentinel-2 Versus Landsat-9," *Forestry: Journal of Institute of Forestry, Nepal*, vol. 19, no. 01, pp. 56–63, Dec. 2022, doi: 10.3126/forestry.v19i01.55704.

[12] J. Jagannathan, M. T. Vadivel, and C. Divya, "Land use classification using multi-year Sentinel-2 images with deep learning ensemble network," *Sci Rep*, vol. 15, no. 1, Aug. 2025, doi: 10.1038/s41598-025-12512-7.

[13] M. Z. Hasan, R. S. Leya, and K. S. Islam, "Comparative assessment of machine learning algorithms for land use and land cover classification using multispectral remote sensing image," *Khulna Univ. Stud.*, pp. 33–46, Oct. 2022, doi: 10.53808/kus.2022.icstem4ir.0124-se.

[14] S. Talukdar *et al.*, "Land-use land-cover classification by machine learning classifiers for satellite observations-A review," *Remote Sensing*, vol. 12, no. 7, p. 1135, Apr. 2020, doi: 10.3390/rs12071135.

[15] J. Sun and S. Ongsomwang, "Optimal parameters of random forest for land cover classification with suitable data type and dataset on Google Earth Engine," *Front. Earth Sci.*, vol. 11, Oct. 2023, doi: 10.3389/feart.2023.1188093.

[16] C. Luo et al., "Using time series sentinel-1 images for object-oriented crop classification in Google Earth Engine," *Remote Sensing*, vol. 13, no. 4, p. 561, Feb. 2021, doi: 10.3390/rs13040561.

[17] A. Rodríguez-Dorna, L. Alonso, F. Costas, J. Picos, and J. Armesto, "Very high resolution Worldview-3 images for land cover mapping on a large scale: strengths and remaining challenges," *Geocarto International*, vol. 40, no. 1, Jul. 2025, doi: 10.1080/10106049.2025.2538802.

[18] D. Abijith and S. Saravanan, "Assessment of land use and land cover change detection and prediction using remote sensing and CA Markov in the northern coastal districts of Tamil Nadu, India," Jun. 11, 2022. doi: 10.1007/s11356-021-15782-6.

[19] A. Revill, A. Florence, A. MacArthur, S. P. Hoad, R. M. Rees, and M. Williams, "The value of Sentinel-2 spectral bands for the assessment of winter wheat growth and development," *Remote Sensing*, vol. 11, no. 17, p. 2050, Aug. 2019, doi: 10.3390/rs11172050.

[20] J. Zhai, C. Xiao, X. Liu, and Y. Liu, "Analysis of 10-m Sentinel-2 imagery and a re-normalization approach reveals a declining trend in the latest rubber plantations in Xishuangbanna," *Advances in Space Research*, vol. 73, no. 12, pp. 5910–5924, Jun. 2024, doi: 10.1016/j.asr.2024.03.032.

[21] L. Ranghetti, M. Boschetti, F. Nutini, and L. Busetto, "'sen2r': An R toolbox for automatically downloading and preprocessing Sentinel-2 satellite data," *Computers and Geosciences*, vol. 139, p. 104473, Jun. 2020, doi: 10.1016/j.cageo.2020.104473.

[22] G. Misra, F. Cawkwell, and A. Wingler, "Status of phenological research using sentinel-2 data: a review," *Remote Sensing*, vol. 12, no. 17, p. 2760, Aug. 2020, doi: 10.3390/RS12172760.

[23] F. Vuolo *et al.*, "Data service platform for Sentinel-2 surface reflectance and value-added products: system use and examples," *Remote Sensing*, vol. 8, no. 11, p. 938, Nov. 2016, doi: 10.3390/rs8110938.

[24] P. S. Sisodia, V. Tiwari, and A. Kumar, "Analysis of supervised maximum likelihood classification for remote sensing image," in *International Conference on Recent Advances and Innovations in Engineering, ICRAIE 2014*, IEEE, May 2014, pp. 1–4. doi: 10.1109/ICRAIE.2014.6909319.

[25] V. Sharma, A. A. Mir, and D. A. Sarwr, "Detection of rice disease using bayes' classifier and minimum distance classifier," *Journal of Multimedia Information System*, vol. 7, no. 1, pp. 17–24, Mar. 2020, doi: 10.33851/jmis.2020.7.1.17.

[26] Z. H. Khalil and S. M. Abdullaev, "Neural network for grain yield predicting based multispectral satellite imagery: comparative study," *Procedia Computer Science*, vol. 186, pp. 269–278, 2021, doi: 10.1016/j.procs.2021.04.146.

[27] N. Vyas, S. Singh, and G. K. Sethi, "A novel image fusion-based post classification framework for agricultural variations detection using Sentinel-1 and Sentinel-2 data," *Earth Science Informatics*, vol. 18, no. 1, p. 40, Jan. 2025, doi: 10.1007/s12145-024-01506-0.

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