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Evaluation of Advanced LULC Classification of Satellite Imagery with Convolutional Neural Networks

Peter T. Adetoro[1]; Adedayo, T. Adeboye[2]; Paul T. Elufisan[3]; & Kolawole S. Ilesanmi[4]

[1,3&4]Department of Surveying and Geoinformatics, Ajayi Crowther University Oyo, Nigeria. [2]Department of Geomatics, Abiola Ajimobi Technical University, Ibadan, Nigeria

Corresponding Author: ks.ilesanmi@acu.edu.ng

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Abstract

Accurate Land Use/Land Cover (LULC) classification plays a crucial role in sustainable environmental management, urban planning, and agricultural monitoring. Traditional classification techniques often struggle with the complexity of heterogeneous landscapes, particularly in rural areas like Ekiti West Local Government Area, Nigeria. This study employs a Convolutional Neural Network (CNN) framework for LULC classification using Sentinel-2 multispectral satellite imagery combined with ground-truth data. The methodology includes comprehensive data pre-processing, image augmentation, CNN model development, and hyper-parameter optimization. The CNN architecture was specifically designed to handle multispectral inputs and spatial variability. Results show that farmland dominates the landscape, followed by forest, bare land/rock, and built-up areas. The CNN model achieved high classification performance with an overall accuracy of 96.86%, demonstrating strong precision, recall, and F1-scores across all classes. This study confirms the potential of CNN-based approaches for reliable and scalable LULC mapping in data-scarce rural environments and contributes to the growing body of geospatial Artificial Intelligence applications in Africa.

Keywords: Artificial Intelligence, Convolutional Neural Network, Land Use/Land Cover, Sentinel

Introduction

Remote sensing technology has revolutionized LULC classification by providing consistent, large-scale, and multi-temporal observations of the Earth's surface (Saeed & Al-Ghamdi, 2024). Among the many earth observation missions, the Sentinel-2 Multispectral Instrument (MSI) has emerged as a leading platform due to its high spatial resolution (10–20 meters), multispectral capabilities, and frequent revisit time (Phiri, 2020). It provides an excellent basis for land cover mapping in rural and semi-urban areas like Ekiti West Local Government Area (Alegbeleye *et al.,* 2024; European Space Agency, 2023).

The temporal and spatial dynamics of LULC are critical indicators of environmental change, urbanization processes, and ecosystem health. In Nigeria, rapid population growth and economic development have led to significant LULC changes, particularly in rural areas where agricultural expansion, urbanization, and infrastructure development are driving landscape transformation (Piao *et al.,* 2023; Alegbeleye *et al.,* 2024; Olorunfemi et al., 2020). Understanding these changes is essential for sustainable land management and environmental policy formulation.

However, traditional classification techniques such as Maximum Likelihood Classifiers, Support Vector Machines, and Decision Trees, though widely used, are often inadequate for complex landscapes (Foody & Mathur 2004). These pixel-based methods are limited in their ability to handle spectral overlap, high intra-class variability, and spatial heterogeneity, resulting in misclassifications especially in areas with mixed or transitional land cover (Belgiu & Drăguţ, 2016).

The rise of artificial intelligence (AI) and machine learning (particularly deep learning) has brought significant advancements in image classification tasks (LeCun, 2015; Ma, 2019). Convolutional Neural Networks (CNNs) have shown remarkable success in extracting hierarchical spatial features from remotely sensed images, making them highly effective for LULC classification (Zhu et al., 2017). CNNs learn both low-level and high-level representations of land features and can generalize across different scenes with minimal need for manual feature engineering.

Recent advances in machine learning have introduced ensemble methods and deep learning approaches that can capture complex, non-linear relationships in spectral data Zhu *et al.,* (2017). These methods often outperform traditional classifiers by automatically learning optimal feature representations and handling high-dimensional data more effectively.

Satellite imagery represents a critical data source for LULC mapping, providing consistent, repeatable observations of the Earth's surface (Gong *et al.*, 2013). The European Space Agency's Sentinel-2 mission, launched as part of the Copernicus program, has become particularly significant for LULC applications due to its optimal balance of spatial, spectral, and temporal resolution (Drusch *et al.*, 2012).

The Sentinel-2 mission provides high resolution satellite data for land cover/use monitoring, carrying onboard multispectral scanners with 13 spectral bands ranging from

visible to shortwave infrared wavelengths (Li *et al.*, 2020; European Space Agency, 2023). The system consists of two identical satellites (Sentinel-2A and 2B) that together provide a global revisit time of 5 days, enabling frequent monitoring of land surface dynamics. With spatial resolutions of 10m for visible and near-infrared bands, 20m for red-edge and shortwave infrared bands, and 60m for atmospheric correction bands, Sentinel-2 offers unprecedented detail for regional and local LULC mapping.

The 13-band multispectral capabilities of Sentinel-2 are particularly valuable for distinguishing between different land cover types, with the red-edge bands being especially useful for vegetation mapping and crop discrimination. The freely available data policy and consistent global coverage make Sentinel-2 an ideal platform for LULC studies in developing countries, where access to commercial high-resolution imagery may be limited (Immitzer, *et al.*, 2016).

Accurate land cover classification is essential for effective land use planning and sustainable environmental management. However, conventional classification methods often fall short when applied to heterogeneous landscapes like Ekiti West. These techniques typically rely on hand-crafted features and pixel-level statistics that do not capture spatial dependencies or complex patterns present in high-resolution imagery (Liu *et al.*, 2018). Consequently, they are prone to misclassification, especially in areas with similar spectral characteristics such as urban-rural fringes or interspersed vegetation and bare land.

In addition, the fragmented land use patterns in Ekiti West pose a classification challenge due to the fine-scale transitions between agricultural, residential, and forested zones. The presence of cloud cover, sensor noise, and seasonal variation further complicates image interpretation, reducing the reliability of traditional techniques.

The need for a more robust, automated, and accurate classification framework has motivated the adoption of deep learning approaches. CNNs, in particular, offer a scalable and data-driven method that can capture spatial hierarchies, reduce manual bias, and improve classification accuracy (Ma et al., 2019). Despite their success in urban and well-mapped regions, CNNs are yet to be widely tested in rural Nigerian settings where reliable LULC data is scarce. This study fills that gap by applying a CNN model for LULC classification in Ekiti West LGA. This research aims to apply a Convolutional Neural Network (CNN) model for accurate classification of Land Use/Land Cover (LULC) in Ekiti West Local Government Area using satellite imagery and field-verified data.

Study Area

Ekiti West Local Government Area is a region in Ekiti State, Nigeria, known for its distinct geographical features and coordinates.The local government area is situated in the western part of Ekiti State. Its geographical location lies approximately between 7° 30' N and 8° 00' N approximately between 4° 30' E and 5° 00' E for Latitude and longitude respectively.

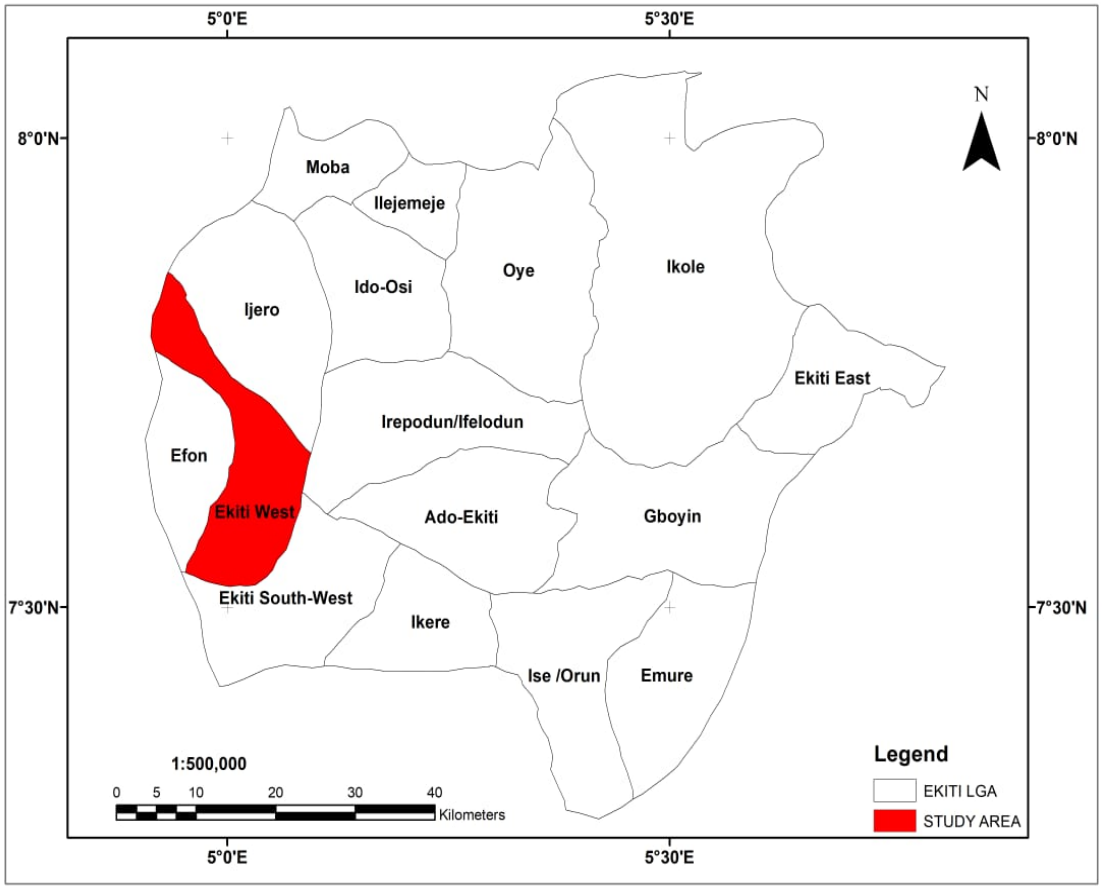


Figure 1: Study Area

Data Collection

Data acquisition is a critical phase in Land Use/Land Cover (LULC) classification, as the quality and diversity of data directly influence the accuracy of the model. For this study, Field surveys were conducted using high-precision GPS devices to collect reference points for different LULC classes (e.g., urban areas, vegetation, water bodies) while Sentinel-2 MSI Imagery was obtained from the Copernicus Open Access Hub as it offers higher spatial resolution (10–20 m) and additional spectral bands enhancing feature discrimination in complex landscapes.

Table1: Data acquired and Sources

Data Source	Sensor	Spatial Resolution	Data Type	Acquisition Year
Copernicus	Open Hub	Sentinel-2 MSI 10 m	Raster	2025
Field Survey	GPS	N/A	Vector	2025

Data Preprocessing

The following procedures were undertaken:

a. Cloud and Shadow Masking: Pixels contaminated by clouds or shadows were masked out using quality assessment (QA) bands or machine learning-based filters to prevent misclassification.
b. Noise Reduction: A Gaussian smoothing filter was applied to minimize salt-and-pepper noise in the imagery.
c. Band Stacking: Multispectral bands (e.g., visible, near-infrared, shortwave infrared) were stacked into a single composite image to provide the CNN with comprehensive spectral information for classification.
d. Image Clipping: Clipping was performed using geospatial software such as QGIS and ArcGIS Pro, ensuring that only the target area was retained for further analysis.
e. Radiometric Correction: To account for atmospheric interference—such as scattering, absorption, and sensor noise—radiometric correction was applied to the satellite imagery.
f. Normalization: The normalization formula as shown in equation 1 was applied. Pixel values from the satellite bands were normalized to a common scale of [0, 1] to facilitate efficient model training. Normalization prevents bias toward bands with higher numerical ranges (e.g., near-infrared vs. visible bands) and accelerates the convergence of the CNN during gradient descent optimization.

$$\text{Normalized Value} = \frac{\text{Pixel Value-Min Band Value}}{\text{Max Band Value-Min Band Value}} \quad [1]$$

g. Data Augmentation: Augmentation was implemented using Python libraries such as TensorFlow and Keras, dynamically generating new training samples during each epoch. This approach reduces overfitting and improves the robustness of the CNN when classifying unseen data.

Model Development

The development of the Convolutional Neural Network (CNN) model represents the core analytical component of this LULC classification study. This section details the architectural design and optimization strategies employed to create an efficient and accurate deep learning model for satellite image classification.

Training and Validation

The training and validation phase represents a critical stage in developing a robust CNN model for LULC classification. This involves the methodological approach to model training, validation strategies, and comprehensive accuracy assessment protocols employed in the study.

Raster Composite of Ekiti West

The raster composite of Ekiti West provides a visual representation of the land cover distribution in the region. The image highlights distinct areas such as built-up zones, farmland, forests, and bare land, offering a foundational understanding of the terrain. This composite

serves as a baseline for further classification and analysis, enabling the identification of spatial patterns and variations. The clarity of the raster image underscores its utility in mapping and land use planning, providing stakeholders with actionable insights for environmental and urban management.

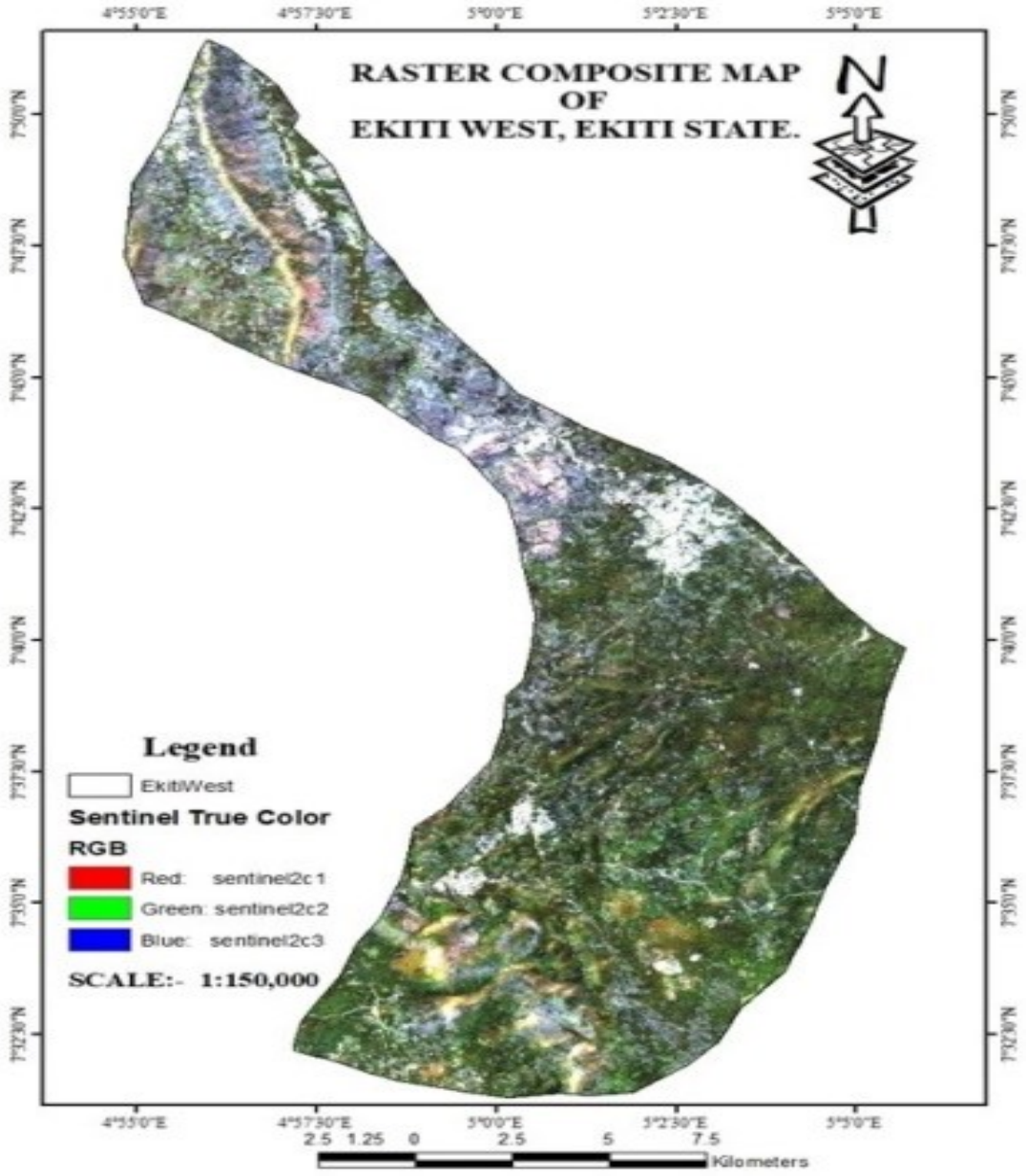


Figure.2: Raster Composite Map of Ekiti West

Classification Analysis of Ekiti West

The classification analysis as shown in Table 2 reveals the dominance of farmland, covering 23,582.51 hectares, followed by bare land-rock (1,702.52 ha), forest (1,458.23 ha), and built-

up areas (852.9 ha). This distribution reflects the region's agricultural prominence and limited urban development. The results align with Ekiti West's rural characteristics, where farming is a primary livelihood. The classification accuracy is critical for resource allocation and policy formulation, ensuring sustainable land use practices are prioritized.

Table. 2: Classification Analysis

VALUE	NAME	AREA(Ha)
1	Built-up	852.9
2	Bare land-Rock	1702.52
3	Farmland	23582.51
4	Forest	1458.23

Convolutional Neural Network

The CNN process involved locating raster data and training samples, followed by model sequencing and training (Figure 3). The images depict the systematic workflow, from data input to model optimization. The CNN's ability to process large datasets efficiently underscores its suitability for land cover classification. The training phase highlights the model's learning progression, ensuring robust performance in subsequent classification tasks. This step is pivotal for achieving high accuracy in automated land use mapping.

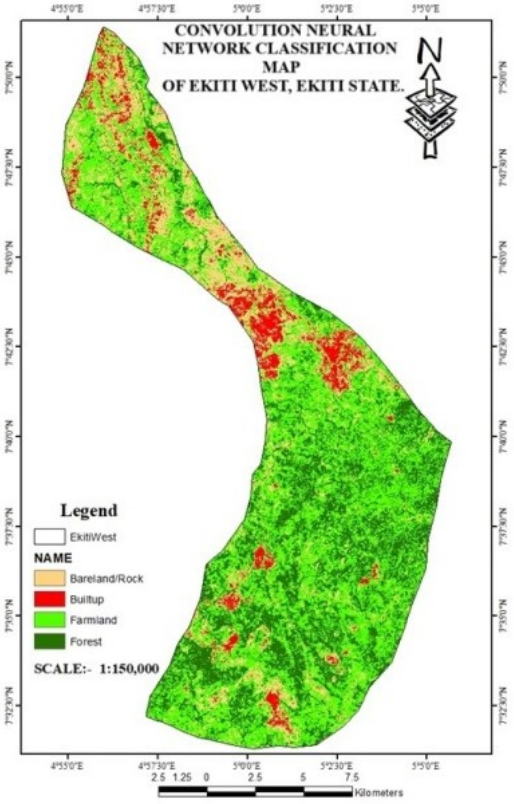


Figure 3: Convolution Neural Network Classification

The CNN classification results show significant changes in land cover areas compared to the initial analysis, with built-up areas increasing to 1,766.03 hectares and farmland decreasing to 13,561.1 hectares (Table 3). The accuracy assessment demonstrates high precision, recall, and F1-scores (all above 0.94), with an overall accuracy of 0.9686. These metrics validate the CNN's effectiveness in distinguishing land cover classes, making it a reliable tool for environmental monitoring and decision-making. The weighted and macro averages further confirm the model's consistency across all categories.

Table. 3: CNN Classification

VALUE	NAME	AREA
1	Built-up	1766.03
2	Bare land/Rock	4885.33
3	Farmland	13561.1
4	Forest	7383.7

Accuracy Assessment

The accuracy assessment of the Convolution Neural Network (CNN) classification demonstrates high performance, with precision, recall, and F1-scores exceeding 0.94 for all land cover classes (Built-up, Bare land/Rock, Farmland, and Forest). The model achieves an overall accuracy of 96.86%, indicating strong reliability in distinguishing between different land use categories.

Precision values (0.944–0.968) reflect the model's ability to correctly classify each class without significant false positives. Meanwhile, recall scores (consistently 0.9686) confirm that the CNN effectively identifies true instances of each class with minimal omissions. The F1-scores (0.9561–0.9683) further validate the balance between precision and recall, ensuring robust classification performance.

The macro average and weighted average (both 0.9613 precision, 0.9686 recall, and 0.9649 F1-score) highlight the model's consistency across all classes, regardless of their size or prevalence in the dataset. This high accuracy underscores the CNN's suitability for automated land cover mapping, providing reliable data for environmental monitoring, urban planning, and agricultural management in Ekiti West.

Conclusions

This study concludes that Convolutional Neural Networks offer a powerful and efficient approach to automated land cover classification, particularly in rural areas with fragmented and diverse land cover types. By integrating Sentinel-2 imagery and ground truth data, the developed CNN model effectively classified LULC categories with a high level of precision and spatial consistency.

The research demonstrated that deep learning models are not only scalable but also adaptable to diverse geographic contexts. The CNN's hierarchical feature extraction capability enabled better discrimination between similar spectral signatures and subtle landscape variations—an area where conventional classification methods often fail (Zhu et al., 2017).

Based on the findings of this research, it is recommended that Remote Sensing and GIS experts should combine Sentinel-2 data with higher-resolution datasets (e.g., PlanetScope, WorldView) for more granular analysis.

References

Alegbeleye, O.M., Rotimi, Y.O., Shomide, P. *et al.* (2024). Land use land cover (LULC) analysis in Nigeria: a systematic review of data, methods, and platforms with future prospects. *Bull Natl Res Cent*, *48*, 127. https://doi.org/10.1186/s42269-024-01286-z

Belgiu, M., & Drăguţ, L. (2016). Random forest in remote sensing: A review of applications and future directions. ISPRS Journal of Photogrammetry and Remote Sensing, 114, 24–31. https://doi.org/10.1016/j.isprsjprs.2016.01.011

Drusch, M., Del Bello, U., Keitel, K., Konaduzi, M., Nittel, B., Odate, M., ... &Bonsii, M. (2012). SENTINEL-2: ESA's optical hig-resolution mission for GMES operational services. Remote Sensing of Environment, 120, 25-36.

European Space Agency (ESA). (2023). Sentinel-2 User Guide. https://sentinel.esa.int/web/sentinel/user-guides/sentinel-2-msi

Foody, G. M., & Mathur, A. (2004). A relative evaluation of multiclass image classification by support vector machines. *IEEE Transactions on Geoscience and Remote Sensing, 42*(6), 1335–1343. https://doi.org/10.1109/TGRS.2004.827257

Gong, P., Wang, J., Yu, L., Zhao, Y., Zhao, Y., Liang, L., Niu, Z., Huang, X., Fu, H., Liu, S., Li, C., Li, X., Fu, W., Liu, C., Xu, Y., Wang, X., Cheng, Q., Hu, L., Yao, W., ... & Chen, J. (2013). Finer resolution observation and monitoring of global land cover: First mapping results with Landsat TM and ETM+ data. *International Journal of Remote Sensing, 34*(7), 2607–2654. https://doi.org/10.1080/01431161.2012.748992

Immitzer, M., Vuolo, F., & Atzberger, C. (2016). First experience with Sentinel-2 data for crop and tree species classifications in Central Europe. *Remote Sensing, 8*(3), 166. https://doi.org/10.3390/rs8030166

LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature, 521*(7553), 436–444. https://doi.org/10.1038/nature14539

Li, Q., Qiu, C., Ma, L., Schmitt, M., & Zhu, X. X. (2020). Mapping the Land Cover of Africa at 10 m Resolution from Multi-Source Remote Sensing Data with Google Earth Engine. *Remote Sensing*, *12*(4), 602. https://doi.org/10.3390/rs12040602

Liu, Y., Wu, H., Wang, C., Du, Q., & Zhu, X. X. (2018). Deep learning for pixel-level image fusion: Recent advances and future prospects. Information Fusion, 42, 158–173. https://doi.org/10.1016/j.inffus.2017.10.007

Ma, L., Liu, Y., Zhang, X., Ye, Y., Yin, G., & Johnson, B. A. (2019). Deep learning in remote sensing applications: A meta-analysis and review. ISPRS Journal of Photogrammetry and Remote Sensing, 152, 166–177. https://doi.org/10.1016/j.isprsjprs.2019.04.015

Olorunfemi, J. F., Kolayžny, K., &Kolayžý, M. (2020). Urban sprawl, land use and land cover change in Lagos, Nigeria. International Journal of Environmental Research and Public Health, 17(18), 6539.

Phiri, D., Simwanda, M., Salekin, S., Nyirenda, V. R., Murayama, Y., & Ranagalage, M. (2020). Sentinel-2 Data for Land Cover/Use Mapping: A Review. *Remote Sensing*, *12*(14), 2291. https://doi.org/10.3390/rs12142291

Piao, Y., Xiao, Y., Ma, F., Park, S., Lee, D., Mo, Y., Jeong, S., Hwang, I., & Kim, Y. (2023). Monitoring Land Use/Land Cover and Landscape Pattern Changes at a Local Scale: A Case Study of Pyongyang, North Korea. *Remote Sensing*, *15*(6), 1592. https://doi.org/10.3390/rs15061592

Saeed, M.A., Al-Ghamdi, A.M. (2024). Improving land cover classification accuracy of Sentinel-2 images: a systematic review of articles between 2015 and 2021. *Arab J Geosci* 17, 136. https://doi.org/10.1007/s12517-024-11945-0

Zhu, X. X., Tuia, D., Mou, L., Xia, G. S., Zhang, L., Xu, F., & Fraundorfer, F. (2017). Deep learning in remote sensing: A comprehensive review and list of resources. *IEEE Geoscience and Remote Sensing Magazine, 5*(4), 8–36. https://doi.org/10.1109/MGRS.2017.2762307