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Application of remote sensing data in digital transformation of land resource management in Kim Thanh commune, Hai Phong city

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Abstract:
In the context of digital transformation in public administration, especially in land resource management, remote sensing technology offers timely, objective and scalable solutions. This study investigates the integration of Sentinel-2 satellite imagery and object-based classification techniques to support digital land management in Kim Thanh commune, a newly established administrative unit in Hai Phong city, Vietnam. Sentinel-2 imagery acquired on 20 March 2025 was processed, atmospherically corrected and segmented using the SNIC algorithm. Land cover was classified into three main types: water body, agricultural land and non-agricultural land using the Random Forest algorithm on the Google Earth Engine platform. The classification achieved a high overall accuracy of 93.17% and a Kappa coefficient of 0.895, with User Accuracy ranging from 87.40% to 100%. The spatial distribution of land use types suggests reasonable zoning patterns that can be directly integrated into digital cadastral systems and spatial planning tools. The results of the study demonstrate the potential of combining remote sensing and cloud computing technologies to improve transparency, efficiency and decision-making in land governance, contributing to the broader goals of the national digital transformation strategy in Vietnam.
Keywords: *digital transformation, land resource management, Sentinel-2, classification.*

1. INTRODUCTION

In recent years, remote sensing has become a foundational technology in the broader digital transformation movement across many sectors, especially in environmental management and land management (Rogan & Chen, 2004; Dong et al., 2019). As countries prioritize the development of smart governance systems and e-government platforms, the integration of geospatial data collected, analyzed, and visualized through remote sensing technology has become important in improving transparency, efficiency, and responsiveness (Das et al., 2022; Sira & Kuzior, 2025).

Remote sensing provides a powerful means of acquiring up-to-date, multi-temporal, and large-scale spatial data without the need for extensive fieldwork (Dewan & Yamaguchi, 2009; Zhang et al., 2021; Metwaly et al., 2024). Among the most widely used sources of satellite data, the Sentinel-2 mission, operated by the European Space Agency (ESA), offers high-resolution multispectral imagery freely available to users worldwide (Phiri et al., 2020). Its short revisit time and 10-20 m spatial resolution makes it particularly valuable for monitoring land cover, crop patterns, water bodies, and urban expansion (Radočaj et al., 2020; Volpi et al., 2023).

In the context of digital transformation, remote sensing is not only a data provider but also a driver of change in how institutions manage land-related information (Reddy, 2018; Joannides, 2023). By integrating Earth observation data into cloud-based platforms such as Google Earth Engine (GEE), organizations can streamline data processing, automate analytical tasks, and generate real-time insights for decision-makers (Wu et al., 2020; Ghosh et al., 2022). The ability to overlay remote sensing products with cadastral boundaries, infrastructure maps, and administrative zones empowers stakeholders to make informed, data-driven decisions, which are essential in planning, zoning, and environmental protection (Attah et al., 2024; Nagavi et al., 2024).

Furthermore, the combination of remote sensing and artificial intelligence, particularly object-based image analysis (OBIA) and machine learning classifiers like the Random Forest (RF), Support Vector Machine (SVM), ANN algorithm, enhances the accuracy and interpretability of land cover classification (Jozdani et al., 2019; Kasahun & Legesse, 2024). This synergy supports the generation of reliable spatial databases that form the digital backbone of land resource governance. These tools also enable the identification of spatial trends and anomalies, contributing to better land use planning, agricultural monitoring, and disaster risk management (Rezvani et al., 2023).

This study explores the application of remote sensing in the digital transformation of land resource management, using Kim Thanh commune in Hai Phong City as a case study. By processing Sentinel-2 imagery through an object-based classification approach using the RF algorithm on GEE cloud computing platform, the research demonstrates the feasibility of building a spatial decision-support system that aligns with national goals for digital governance and sustainable land use.

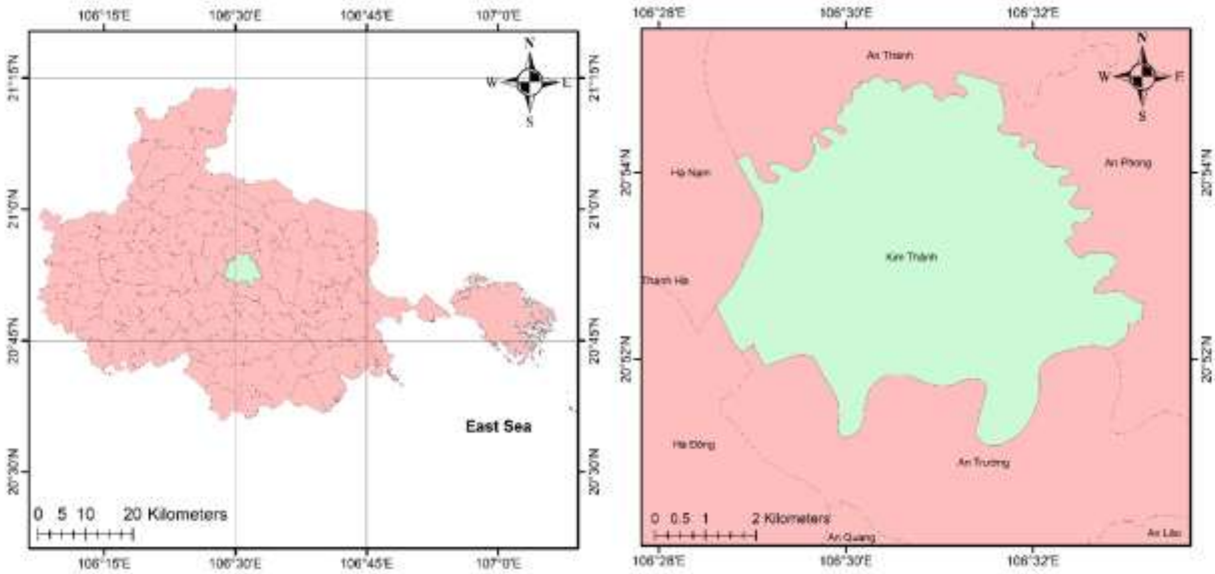
2. MATERIAL AND METHODOLOGY

2.1. Study area

Kim Thanh is a newly established administrative unit under Hai Phong City, located in the coastal plain region of northern Vietnam (Figure 1). The commune was officially established on July 1, 2025, under a resolution on the reorganization of commune-level administrative units, by merging several smaller former communes. With its geographical characteristics and regional connectivity role, Kim Thanh holds a strategic position as a transitional zone between traditional rural areas and rapidly developing urban and industrial zones of Hai Phong City.

In terms of topography and geography, Kim Thanh is a low-lying, relatively flat area, typical of the Red River Delta. The commune is situated in a transitional region between traditional agricultural land and suburban zones undergoing rapid urbanization. It borders communes such as An Phong and An Truong, which are home to several large industrial zones. The local landscape is characterized by rice paddy fields, aquaculture ponds, traditional rural settlements, and an expanding network of inter-commune rural roads.

Figure 1: Location of the study area



The selection of Kim Thanh as the study area is appropriate and practically significant for the following reasons:

First, the area is experiencing rapid land-use change, particularly the conversion of agricultural land to non-agricultural purposes (for example, industrial, residential, and infrastructure development), which poses major challenges for effective and sustainable land-use planning and management.

Second, the local government is actively implementing digital transformation policies in the land sector, such as digitizing cadastral maps, developing land information systems, and gradually deploying e-government platforms for public administration.

Third, Kim Thanh has a diverse land-use structure, including agricultural land, built-up areas, and unused land. This diversity creates favorable conditions for the application of remote sensing technologies, especially object-based image analysis combined with machine learning algorithms to accurately analyze and monitor land-use changes.

2.2. Material

In this study, the primary dataset used was Sentinel-2 satellite imagery, developed and operated by the European Space Agency (ESA) under the Copernicus program (ESA, 2025). Sentinel-2 consists of two satellites (Sentinel-2A and Sentinel-2B) capable of capturing high-resolution multispectral images with a short revisit cycle (every 5 days) and a wide swath width (290 km per scene). As an open-access data source, Sentinel-2 is highly suitable for land surface monitoring over time with high reliability (ESA, 2025).

The imagery was accessed via the Google Earth Engine (GEE) platform, which enables fast, cloud-based, and large-scale data processing. The spectral bands utilized included:

- Band 2 (blue), Band 3 (green), Band 4 (red) and Band 8 (near-infrared) at 10-meter resolution, ideal for detailed surface analysis.
- Band 11 and Band 12 (shortwave infrared) at 20-meter resolution, useful for distinguishing built-up materials and soil content.

With its appropriate spatial resolution, high temporal frequency, and consistent data quality, Sentinel-2 is an ideal data source for monitoring land use changes and supporting digital transformation in land resource management at the local level.

2.3. Methodology

To generate a land use map in support of digital transformation in land resource management, the study implemented a systematic sequence of remote sensing data processing steps, ranging from satellite image acquisition to classification and accuracy assessment. The entire data processing workflow is illustrated in Figure 2.

Step 1: Satellite data acquisition

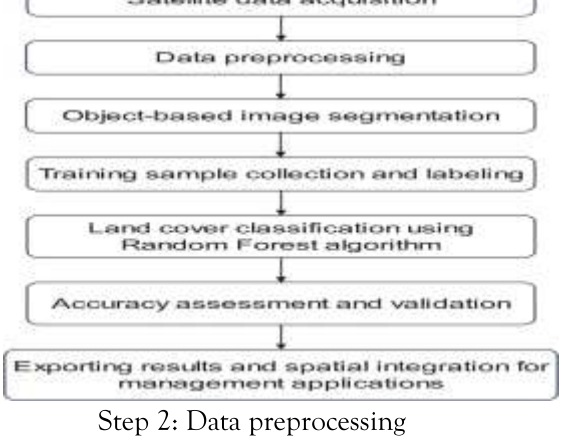
Satellite imagery was collected from the Sentinel-2 dataset using the GEE cloud computing platform. GEE is a powerful and widely used tool that provides free access to a global archive of satellite data along with built-in capabilities for large-scale spatial and temporal processing. By using GEE, the data retrieval process is not only convenient and efficient but also enables advanced operations such as cloud filtering, spectral index generation, and spatial clipping.

In this study, Sentinel-2 imagery was retrieved based on strict selection criteria to ensure the quality of the input data:

- Temporal filtering: Images were selected during the period corresponding to the dry season in the study area. This timeframe provides clearer observations of land surfaces and reduces the influence of rain, fog, or excessive vegetation growth.
- Cloud masking: GEE's built-in cloud filtering tools were applied, including the QA60 band and cloud probability functions to remove scenes with more than 10% cloud cover over the study area (Mateo-García et al., 2018).
- Spatial filtering: The imagery was clipped to the administrative boundary of Kim Thanh commune, ensuring that only relevant spatial data were processed, which improved computational efficiency and analysis precision.

The output of this step is a clean, temporally-filtered, and spatially-focused Sentinel-2 image collection, ready for preprocessing and analysis in the following phases.

Figure 2: Flowchart of the data processing



Step 2: Data preprocessing

After acquiring satellite imagery via the GEE platform, the next step involved preprocessing to ensure the quality and reliability of the input data for further analysis. In this study, the preprocessing phase focused on two primary components: geometric correction and atmospheric correction.

Geometric correction ensures the spatial accuracy of each pixel in the satellite image. The Sentinel-2 images used in this study were provided at Level-1C and Level-2A processing levels by the European Space Agency (ESA). Level-1C products are already orthorectified and projected to a standard coordinate reference system (WGS 84 / UTM zone 48N). For a local-scale study such as Kim Thanh commune, the geometric accuracy of Sentinel-2 imagery at this level is fully adequate for land cover analysis.

Atmospheric correction was applied to minimize the influence of atmospheric conditions such as water vapor, aerosols, and other atmospheric particles on surface reflectance values. Within Google Earth Engine, Level-2A Sentinel-2 products were prioritized, as these images have already undergone atmospheric correction using the Sen2Cor algorithm (Main-Knorn et al., 2017). This correction ensures that the spectral information more accurately represents the true surface conditions, which improves the performance and reliability of the subsequent classification

In addition to these corrections, the imagery was clipped to the administrative boundary of Kim Thanh commune, which helps reduce data volume and focus the analysis on the target area. As a result, this step produced geometrically and radiometrically corrected Sentinel-2 imagery, ready for higher-level processing such as object-based segmentation and classification.

Step 3: Object-based image segmentation

In this step, the preprocessed satellite imagery was segmented into homogeneous regions using the SNIC (Simple Non-Iterative Clustering) algorithm available in Google Earth Engine (Tassi & Vizzari, 2020). Object-based segmentation groups pixels with similar spectral and spatial characteristics into meaningful units (objects), reducing the “salt-and-pepper” noise commonly found in pixel-based classification. The resulting segments serve as the foundational input for the subsequent land use classification process.

Step 4: Training sample collection and labeling

Training samples were manually collected for three primary land cover types: water bodies, agricultural land, and non-agricultural land. High-resolution imagery from Google Earth and auxiliary data such as administrative boundaries were used to guide visual interpretation. Each segmented object was assigned a corresponding class label. The labeled dataset was divided into two parts: 70% for model training and 30% for accuracy assessment in later stages.

Step 5: Land cover classification using random forest

After segmenting the images and preparing the training data, the next important step in the workflow is to classify the land cover types. In this study, the Random Forest (RF) algorithm was chosen to perform supervised classification, assigning each segmented object to one of the three main land cover types: water body, agricultural land, and non-agricultural land.

Random Forest is an ensemble learning algorithm introduced by Breiman (2001), which is widely used in remote sensing due to its robustness, high classification accuracy, and ability to handle large datasets with many input features (Breiman, 2001). The RF algorithm works by building a large number of decision trees during training, each using a randomly selected subset of training samples and features. The final class assigned to an input object is determined by majority voting among the individual trees. This process reduces the risk of overfitting and improves generalization performance compared to a single decision tree.

In this study, the RF classifier was deployed in the GEE environment, leveraging cloud computing capabilities and built-in machine learning functions. The labeled training dataset from Step 4 was used to fit the RF model. The number of trees selected, and other parameters were kept at default values as specified by the GEE API, due to its proven stability in classification tasks (Avcı et al., 2023). The model was trained to distinguish samples corresponding to three land cover classes based on both spectral and spatial information.

After training, the model was applied to the entire image segmentation to generate a classified land cover map. Each segment (or object) in the study area was assigned a unique class label based on the RF prediction. The resulting map effectively delineates water, agricultural and non-agricultural land areas (including built-up and residential areas), serving as a foundational dataset for land use monitoring and digital land management.

Step 6: Accuracy assessment and validation

The classification results were evaluated using a confusion matrix based on 30% of the labeled data reserved for validation. Key metrics, including Overall Accuracy, Kappa Coefficient, User's Accuracy, and Producer's Accuracy, were calculated to assess model performance. Additionally, a visual comparison with high-resolution imagery helped verify the spatial accuracy of the classified land cover map.

Step 7: Exporting results and integration into digital land management

The final classified land cover map was exported in GeoTIFF format and integrated into a digital land management system. By aligning the output with cadastral boundaries and administrative data, the results support e-governance initiatives, spatial planning, land monitoring, and resource allocation. This step contributes directly to the digital transformation of land resource management by providing standardized, up-to-date spatial data for data-driven decision-making at the local level.

3. RESULTS AND DISCUSSION

The Sentinel-2 image used in this study was acquired on March 20, 2025, covering the entire study area. The data was processed using a Natural Color Composite, combining three spectral bands: B4 (Red), B3 (Green), and B2 (Blue), in order to represent ground landscapes in a way that closely resembles natural human vision (Figure 3).

Figure 3: Sentinel-2 image of the study area collected on March 20, 2025

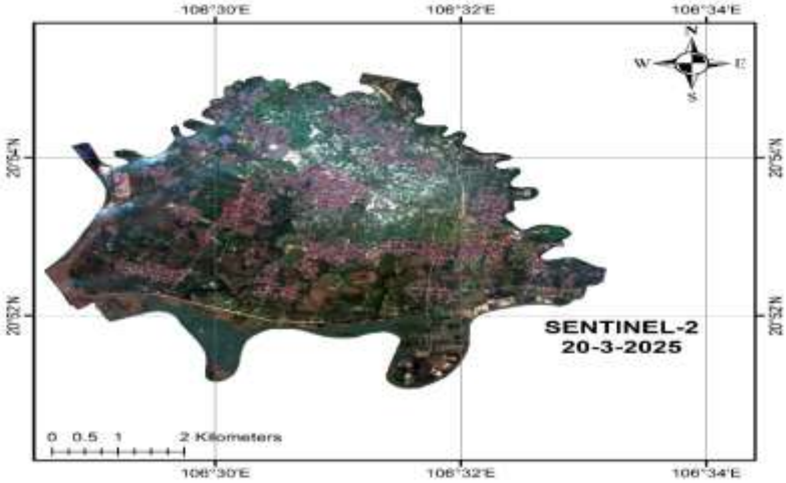


Table 1. Accuracy assessment results of the land cover classification

Class	Producer's Accuracy (PA)	User's Accuracy (UA)
Water bodies	99.08%	87.40%
Agricultural land	87.40%	95.56%
Non-agricultural land	94.16%	100.00%
Other accuracy evaluation parameters		
Overall Accuracy (OA):	93.17%	
Kappa Coefficient (κ):	0.895	

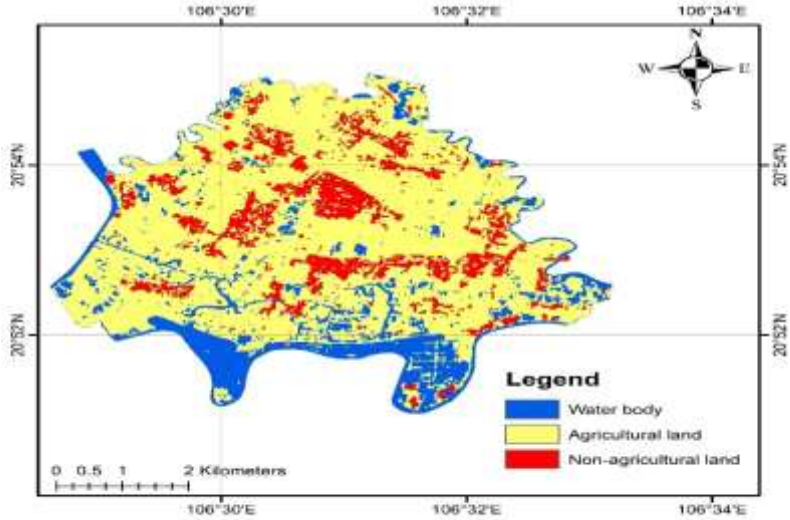
The accuracy of the classification results was evaluated using a confusion matrix derived from 30% of the labeled validation samples. As shown in Table 1, the overall accuracy (OA) reached 93.17%, indicating a high level of agreement between the classified and reference data. The Kappa coefficient was 0.895, reflecting substantial agreement beyond chance. Among the three classes, water bodies achieved the highest producer's accuracy (99.08%), while non-agricultural land attained perfect user's accuracy (100%). These results confirm the reliability of the classification and its suitability for supporting digital land management applications.

In addition, Figure 4 presents the land cover classification results for the study area using an object-based classification method combined with the Random Forest algorithm. Figure 4 shows the spatial distribution of land cover classes across the entire Kim Thanh commune.

Firstly, water body in the study area are unevenly distributed, primarily concentrated in the eastern and central parts. In the east, a large river stretches in a north-south direction and occupies a significant portion of the area. The central region contains smaller hydrological features, such as ponds or artificial canals, which are mainly used for irrigation. In contrast, the northwest and southwest areas have almost no water body, indicating higher elevation or a lack of natural water sources. Notably, most water body are adjacent to agricultural land, highlighting a strong relationship between water availability and farming activities.

Next, agricultural land occupies the largest area, widely distributed across the commune but most concentrated in the western and southwestern regions. In the west, an agricultural belt stretches from 20°52'N to 20°54'N, closely linked to the eastern water bodies, taking advantage of irrigation sources. The southwestern area contains a large, contiguous zone of agricultural land adjacent to non-agricultural land, suggesting the presence of specialized cultivation zones. Meanwhile, although the eastern fringe is near water sources, agricultural land there is limited in size, possibly due to sloping terrain or land reserved for other uses. This spatial distribution reflects a strategic approach to land use, aimed at ensuring efficient resource utilization and food security.

Figure 4: Land cover classification map of the study area from satellite images



Additionally, non-agricultural land is primarily concentrated in the northern part of the commune, where the terrain is higher and more suitable for infrastructure development. This area likely includes residential zones, urban spaces, or public facilities, strategically positioned to avoid flooding risks from the eastern water bodies. A few small patches are scattered within agricultural zones, possibly representing housing or transportation infrastructure supporting production activities. Notably, non-agricultural land is rarely found near water bodies, except in some central areas that may be associated with aquaculture services. This distribution pattern reflects rational land-use planning, separating residential areas from agricultural zones and water resources.

Moreover, there is a clear spatial relationship among the three land use types: water bodies are closely associated with agricultural land to ensure irrigation supply, while non-agricultural land is located away from low-lying areas to minimize flood risk. The boundary between agricultural and non-agricultural zones is relatively distinct, reflecting a rational functional zoning. However, urbanization pressure may lead to the shrinkage of agricultural land, emphasizing the need for balanced and forward-looking spatial planning in the future.

The results of this study not only provide an accurate spatial distribution of land cover in Kim Thanh commune but also demonstrate the practical potential of remote sensing in the digital transformation of land resource management. Traditionally, land use monitoring has relied heavily on manual surveys and fragmented cadastral data, which are time-consuming, costly, and often outdated. In contrast, satellite-based data, particularly from Sentinel-2, offer timely, repeatable, and large-scale observations that are essential for dynamic land governance.

By integrating object-based image analysis and machine learning algorithms such as Random Forest within platforms like Google Earth Engine (GEE), this study showcases an efficient and scalable approach to automate land classification processes. The outputs can be directly incorporated into digital land management systems, serving as input layers for cadastral updates, spatial planning, and environmental monitoring.

Furthermore, the high accuracy of the classification results supports the feasibility of applying remote sensing to build standardized geospatial databases, which are crucial for e-governance initiatives. For local authorities, such tools enable data-driven decision-making, transparency in land allocation, and early detection of land-use changes, particularly under urbanization pressure.

In the context of Kim Thanh commune, a newly established administrative unit undergoing rapid development, these digital tools provide a foundation for establishing modern land management practices. They also align with national strategies on digital government and smart city development, where land information systems play a central role in infrastructure planning, agricultural zoning, and climate resilience.

Ultimately, this approach contributes to shifting land management from a reactive, paper-based system to a proactive, data-driven model, reinforcing the importance of remote sensing as a core component in Vietnam's broader digital transformation agenda.

4. CONCLUSION

The research demonstrates that combining Sentinel-2 imagery with object-based image analysis and machine learning techniques provides an effective and scalable approach for land cover classification. With an overall accuracy of 93.17% and a strong Kappa value (0.895), the classification results are highly reliable and suitable for integration into digital land management platforms. Spatial patterns observed in Kim Thanh commune such as the concentration of agricultural land in the west and the clustering of non-agricultural land in higher northern areas reflect rational land-use planning that can be better managed and monitored through digital tools. The successful deployment of Google Earth Engine in this study also illustrates the feasibility of low-cost, cloud-based solutions for local authorities. In the context of rapid urbanization and administrative restructuring, this approach can significantly support real-time decision-making, cadastral updates, and the broader goals of e-government and sustainable development.

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