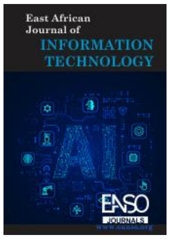

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Original Article

Leveraging Artificial Intelligence for Land Use/Land Cover Change Detection to Improve Monitoring of the National Land Use Development Master Plan (NLUDMP) in the City of Kigali (CoK), Rwanda

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Agricultural Encroachment, AI-driven Framework, ConvSegNet, LULCCD, NLUDMP.

ABSTRACT

This research introduces a novel AI-driven framework, the Convolution Sequential Segmentation Network (ConvSegNet), which integrates Convolutional Long Short-Term Memory (ConvLSTM) networks for sequential multi-scale feature extraction from multispectral airborne and satellite imagery. ConvSegNet enhances high-resolution Land Use and Land Cover Change Detection (LULCCD), particularly for monitoring urban expansion and agricultural encroachment in Kigali, Rwanda. Using multi-temporal satellite imagery from 2009, 2020, and 2024, this study offers a detailed analysis of spatial and temporal LULC dynamics, capturing subtle changes that conventional methods often miss. ConvSegNet's integration of spatial and temporal dependencies improves the detection of land cover transformations, such as urban sprawl and agricultural encroachment into forested areas. A key innovation is its ability to distinguish previously undifferentiated land cover classes, such as built-up areas and road networks, which traditional models have struggled to classify. The model demonstrated high accuracy, achieving 92% for urban areas, 85% for agricultural land, and 75% for forested regions. The results show significant LULC changes: agricultural land decreased from 70.68% (1,419.52 km²) in 2009 to 60.92% (1,213.49 km²) in 2024, while built-up areas grew by 32.71%, means from 0.81% (16.09 km²) in 2009 to 3.46% (69.38 km²) in 2024. Forest cover declined by 202.23 km², from 16.42% (327.27 km²) in 2009 to 11.15% (222.92 km²) in 2024, indicating significant environmental degradation in the city of Kigali. Despite high classification accuracy, ConvSegNet showed limitations in detecting gradual land cover transitions, especially in forests affected by agricultural encroachment. This highlights the need for further model improvements, including higher temporal resolution data and additional spectral features. Overall, the study provides valuable insights for sustainable land management in Rwanda, supporting the National Land Use Development Master Plan (NLUDMP) with advanced AI tools for monitoring LULC changes, mitigating urban sprawl, and enhancing environmental conservation efforts.

APA CITATION

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INTRODUCTION

Autonomous, high-resolution monitoring of land use and land cover (LULC) is critical for conducting detailed spatial-temporal analyses that advance our understanding of Earth's ecosystems and their dynamics (Yu et al., 2014, Mugiraneza et al., 2020;). Precise and current LULC datasets are indispensable for monitoring environmental transformations, informing policy frameworks, and facilitating sustainable development initiatives, particularly in regions like Rwanda, where land resources play a vital role in economic development and urban planning strategies. The health and prosperity of human societies are closely linked to a robust natural environment, which delivers essential resources and ecosystem services(United Nations, "World Population Prospects 2019). However, the path to sustainable development is obstructed by two significant challenges that undermine ecological balance and human well-being both locally and globally (Mugiraneza et al., 2020; Winkler et al., 2021, Chen et al., 2022; Shih et al., 2022a;).

The first challenge is the rapid global population growth, which drives an increasing demand for essential resources such as food and raw materials (Müller & Robertson, 2014; Winkler et al., 2021, Neugarten et al., 2024;). This surge in demand, coupled with the finite availability of arable land, intensifies land use changes, thereby exerting substantial pressure on environmental systems. The second challenge is the urgent need to conserve natural ecosystems and services, as these are critical in mitigating climate change and preserving biodiversity issues that pose significant threats to human livelihoods(Díaz et al., 2006; Lenczner et al., 2022; Thangamani et al., 2024). In response to these global challenges, the United Nations has established the 2030 Agenda for Sustainable Development, which encompasses a comprehensive set of Sustainable Development Goals (SDGs). This framework leverages advanced Earth observation technologies, such as remote sensing and open-access satellite missions, to provide governments and researchers with essential data for addressing diverse development objectives, including poverty reduction and climate resilience(van Dijk et al., 2021).

AI-driven approaches in LULC change detection offer promising solutions by automating high-resolution monitoring(Khan et al., 2024), enabling timely detection of land cover changes and facilitating efficient monitoring of land use. As Rwanda moves forward with its National Land Use

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Development Master Plan, advanced AI methods for LULC monitoring are valuable for informed decision-making and the sustainable management of land resources. Rwanda has made significant strides towards becoming a low-income economy by 2025 with zero carbon emissions by pursuing comprehensive land use and land cover (LULC) management initiatives(Mugiraneza et al., 2019, 2020). Since 2009, Rwanda has employed a master plan as a primary tool to monitor and regulate land use, which has played an instrumental role in environmental management, aligning with zero-emission goals, and supporting a transition from an agriculture-based to a service-oriented economy(Nduwayezu et al., 2017). Although Rwanda has made notable progress in tracking land use allocation, challenges remain in achieving effective LULC change detection for improving monitoring of NLUDM, which ranges from innovative to autonomous models, therefore, problematic issues include: The need for autonomous high-resolution land cover maps is evident, as existing datasets often lack the high spatial and spectral detail necessary for comprehensive monitoring of land resources (Brown et al., 2022). With the increasing reliance on high-frequency and high-resolution datasets for Land Use and Land Cover (LULC) monitoring, managing large volumes of data has become a significant challenge. Data storage, processing, and management are substantial obstacles in effectively utilizing these datasets for monitoring (Li, et al., 2022a). Furthermore, the development of innovative AI architectures for processing spatiotemporal data is crucial for agricultural land management. Advanced AI models capable of processing large-scale, multitemporal datasets are essential for accurately detecting LULC changes, particularly in monitoring agricultural encroachment into protected ecosystems or urban planning zones. These models must integrate multimodal data sources, address regional heterogeneity, and support predictive analytics to anticipate future encroachment patterns. Such innovations will enhance the effectiveness of the National Land Use and Development Management Plan (NLUDMP), aligning land management practices with sustainable agricultural and environmental policies (Campos-Taberner et al., 2020).

Despite significant progress in land use planning and monitoring in Rwanda, particularly with the land registration initiative launched in 2009 (Bayisenge, 2018), current LULC datasets still fall short in terms of autonomous systems for the usage of spatial and spectral resolution information. This limits their ability to support detailed land use monitoring and analysis. Traditional methods of LULC mapping face challenges due to the massive data volumes needed for comprehensive national-scale monitoring, and the lack of autonomous systems that can effectively integrate spatial and temporal data (Li et al., 2024). Furthermore, there is a pressing need for more accurate, high-resolution LULC data to better capture the dynamic and complex nature of land cover changes, especially to improve land use monitoring. One of the most pressing issues is agricultural encroachment, which exacerbates land resource conflicts and threatens protected ecosystems in Rwanda. Current LULC datasets and monitoring approaches struggle to detect and address this encroachment due to their limited resolution and lack of predictive capabilities to identify high-risk areas. To address this challenge, there is a clear need for innovative AI-based architectures that can process large-scale, high-resolution, and multitemporal datasets, enabling more precise detection of LULC dynamics, including agricultural expansion into sensitive zones. This research aimed to (1) introduce ConvSegNet for enhancing the spatial and temporal accuracy of land cover change detection, (2) develop a very High-Resolution Spatiotemporal Dataset for AI-driven monitoring of NLUDMP, (3) evaluate the effectiveness of ConvSegNet for LULC change detection in improving monitoring of NLUDMP**.**

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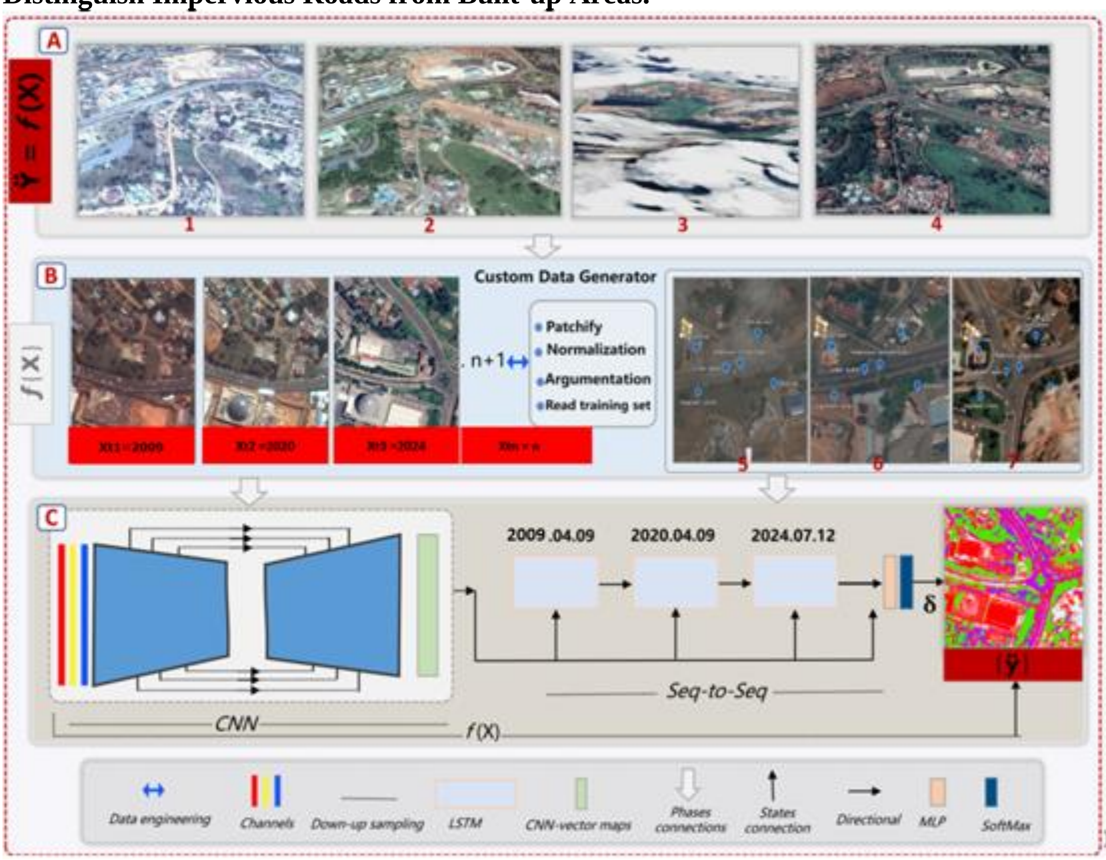
MATERIALS AND METHODS

Research Design

For the network architecture learning development, given the complexity of land cover changes in Rwanda, the research employed a sophisticated hybrid deep learning model known as ConvSegNet (Convolutional Long Short-Term Memory Segmentation Nework). The model architecture in Figure 1, is specifically chosen to capture both spatial and temporal patterns within multi-temporal high-resolution imagery. ConvLSTM combines the spatial feature extraction capabilities of convolutional neural networks (CNNs) with the temporal sequence modelling strengths of LSTMs.

Figure 1 highlights the Comprehensive Workflow for Land Cover Classification and Validation which demonstrates the entire workflow, from data acquisition using multisource and multimodal sensors to data engineering, model development, evaluation, and final land cover validation. The final prediction image highlights novel cases, where road networks were classified as impervious surfaces and distinguished from built-up areas. Figure 1 presents data collection workflows (A), data engineering (B), and the proposed sequential learning framework (C). Sentinel-2 satellite images were acquired on 2009-04-09, 2020-04-09, and 2024-07-12. The convolutional layers focus on extracting spatial features from each high-resolution image, while the LSTM units are designed to capture temporal dependencies, enabling the model to detect changes over time. This dual approach is critical for analyzing Rwanda's dynamic land use, where shifts can occur due to agricultural cycles, urban expansion, and conservation efforts.

Figure 1: Comprehensive Land Cover Workflow Using Multisource Data and Sentinel-2 Imagery to Distinguish Impervious Roads from Built-up Areas.



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Experimental Setup

The experimental setup for high-resolution Land Use and Land Cover (LULC) mapping in Rwanda incorporates advanced deep learning techniques to address the challenges posed by large-scale geospatial data. A core feature of the model is the multi-scale feature extraction module, which utilizes dilated convolutions and pyramid pooling to capture land cover details at varying spatial scales. This allows the model to effectively analyze both urban and rural landscapes. Additionally, an attention mechanism is integrated to focus on areas with rapid land use changes or mixed land cover types, improving the model's ability to prioritize critical regions and enhance detection accuracy. The data preprocessing pipeline includes atmospheric correction using the Dark Object Subtraction (DOS) method, geometric alignment through histogram matching, and noise reduction via Non-Local Means filtering to ensure high-quality input data.

To enhance model robustness and mitigate overfitting, various data augmentation techniques were used as random rotations, flips, translations, and spectral variations like contrast and brightness adjustments. For efficient data handling, Xarray was used to manage multi-dimensional satellite image arrays, enabling memory-efficient data processing through lazy loading and parallelization. Additionally, JAX was utilized to optimize computational performance, leveraging just-in-time (JIT) compilation and automatic differentiation to accelerate model training. These combined techniques, along with the system's optimization for a 12GB GPU, ensured rapid processing and efficient training, making the setup ideal for large-scale LULC mapping from high-resolution satellite imagery without encountering memory or performance limitations.

Source of Data

The effectiveness of Land Use Land Cover Dynamics (LULCD) models is critically dependent on the quality, diversity, and spatial resolution of the input data. This study aimed to capitalize on a comprehensive multi-temporal archive of airborne high-resolution imagery. These datasets are fundamental for broad-scale land cover mapping and temporal analysis due to their extensive historical coverage and reliable temporal frequency.

To improve spatial resolution and capture finer details of land use, high-resolution cloudless imagery of Kigali City with a spatial resolution of 50 cm was utilized as the model was validated. This enhanced resolution is particularly effective for accurately identifying medium-to-large-scale structures, agricultural areas, and other land use features, providing a clearer and more detailed understanding of urban and rural dynamics in the area. For achieving even finer-scale land cover detection, this study integrated high-resolution airborne, from 2009 and 2020 alongside the recent of 2024, respectively.

These high-resolution datasets are crucial for capturing minute features such as individual buildings, narrow roadways, and specific vegetation types, which are vital for accurately differentiating between closely related land cover categories in dense urban, peri-urban and rural landscapes. The integration of these diverse datasets was designed to enhance the model's capacity to detect subtle land cover transformations, thereby improving the granularity and accuracy of LULCCD models. This approach not only supports the precise monitoring of NLUDMP and land use changes but also contributes to informed decision-making in sustainable land management specifically in the agriculture sector.

In addition to satellite data, ground truth information is to be collected through field surveys and local data sources. This ground-truth dataset includes annotated polygons representing key land cover classes such as water bodies, agricultural lands, wetlands, forests, and built-up areas. This blend of high-resolution imagery and precise ground truth data formed a robust foundation for

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training and validating the deep learning model, ensuring accurate classification across Rwanda's diverse landscapes.

Data Collection Techniques

The training process began with data preparation, where high-resolution imagery with a 50cm was pre-processed to address variations in spectral properties. These images were patchified into tiles of 512×512 pixels, ensuring compatibility with the ConvLSTM model's input requirements. Data augmentation techniques, such as temporal shifting, random rotations, and spectral jittering, were applied to increase the diversity of training samples and mitigate overfitting. Given the noisy labels associated with high-resolution LULC datasets, a self-supervised loss function was introduced to improve the model's robustness. This loss function leverages both labelled and pseudo-labelled data, employing a combination of cross-entropy loss for supervised classification and a consistency regularization loss to reduce the impact of label noise. This dual approach not only enhances the model's ability to learn from imperfect data but also promotes better generalization across different land cover types.

Table 1: Details of Ground Truth for Critical Areas Showing Dramatic Changes in the City of Kigali

	Area 1		Area 2		Area 3	
LC Classes	**Train**	**Test**	**Train**	**Test**	**Train**	**Test**
Water	140	60	120	50	100	40
Agriculture	200	80	180	70	150	60
Wetland	100	40	90	30	80	30
Forest	180	70	160	60	140	50
Built-up	150	60	130	50	120	40

In addition to satellite data, ground truth information is to be collected through field surveys and local data sources. This ground-truth dataset includes annotated polygons representing key land cover classes such as water bodies, agricultural lands, wetlands, forests, and built-up areas. This blend of high-resolution imagery and precise ground truth data forms a robust foundation for training and validating the deep learning model, ensuring accurate classification across Rwanda's diverse landscapes.

To optimise the ConvLSTM Model with Advanced Techniques, during training, the ConvLSTM model's architecture captured complex spatiotemporal patterns by stacking convolutional layers with increasing filter sizes, followed by LSTM layers to model temporal dependencies. The convolutional layers are to be configured with 3×3 kernels to extract local spatial features, while deeper layers utilize dilated convolutions to capture broader contextual information without increasing computational costs. The LSTM layers processed these extracted features across multiple time steps, allowing the model to learn temporal correlations critical for detecting gradual land cover transitions and the model employed a stratified sampling strategy during mini-batch training, ensuring a balanced representation of all land cover classes, particularly those with limited training samples.

For optimization, the Adam optimizer is utilized with a cyclical learning rate schedule to dynamically adjust the learning rate, improving convergence speed and model accuracy. To further enhance the model's resilience to overfitting, techniques such as dropout, batch normalization, and early stopping were integrated into the training pipeline. The proposed self-supervised loss function is complemented by a Dice coefficient loss, which prioritizes boundary accuracy, ensuring finer segmentation results and k-fold cross-validation to assess performance metrics like F1-score, IoU, and Kappa coefficient, thereby validating the model's effectiveness in high-resolution LULC mapping. The ConvLSTM results are expected to deliver

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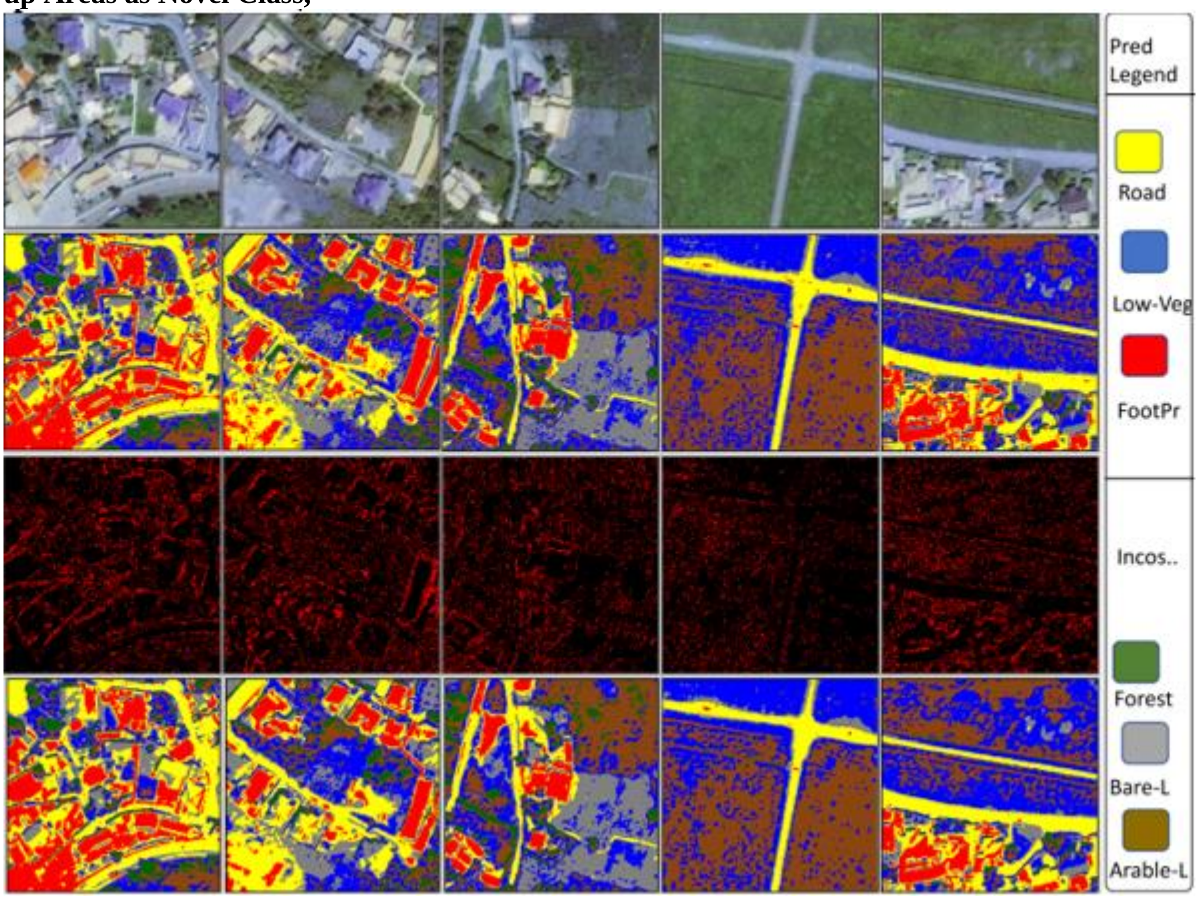
precise, high-resolution LULC outputs that align with Rwanda's NLUDMP, supporting sustainable land and environmental management initiatives.

RESULTS AND DISCUSSIONS

One of the core objectives of this study was to generate high-resolution land use and land cover (LULC) maps that facilitate continuous monitoring under Rwanda's National Land Use and Development Master Plan (NLUDMP). By integrating ConvSeqNet with multi-temporal airborne multispectral datasets (2009, 2020, and 2024), we achieved an advanced spatiotemporal mapping framework capable of discerning fine-scale land transitions with unprecedented precision. The 2024 dataset presented new challenges, such as increased spectral heterogeneity and variations in atmospheric distortions. Despite these complexities, ConvSeqNet retained an accuracy of 85% outperforming traditional methodologies in delineating urban expansion and agricultural encroachment. The weighted F1-score remained stable across all temporal benchmarks, with the built-up class maintaining near-perfect classification (94.36% accuracy). However, forested areas exhibited a notable decline in classification performance (76.33% accuracy), attributed to seasonal phenological variations and sensor discrepancies across the multi-year dataset. Such findings emphasize the necessity for domain adaptation techniques and multi-source data fusion to improve temporal generalization in AI-driven LULC monitoring.

Figure 2: Illustration of ConvSegNet Capabilities in Distinguishing Road Network from Other Built-up Areas as Novel Class,



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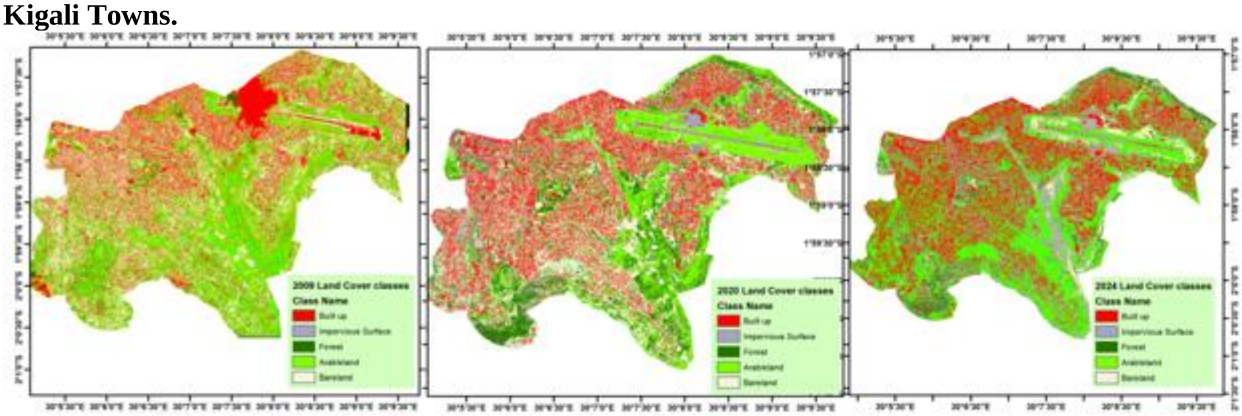
Further evaluation of ConvSeqNet's performance against conventional models reveals its superior capability in learning spatial dependencies and capturing complex temporal patterns. Traditional convolutional networks, constrained by static spatial kernels, often struggle to model long-term dependencies in dynamic landscapes. In contrast, ConvSeqNet's recurrent structure enables the propagation of spatial-temporal contextual information, reducing classification ambiguity for transitional land classes such as bare land and arable land. Comparing the model's performance over the years, the study observed a gradual decline in classification accuracy from 2009 (81%) to 2024 (85%). The trend highlights the increasing complexity of LULC dynamics in Kigali, likely driven by rapid urbanization and shifting agricultural practices. ConvSeqNet's precision-recall trade-offs indicate a strong ability to generalize across temporal datasets, but lower recall scores for background (57.30% in 2024) suggest room for improvement in spectral signature discrimination. Further, the model's misclassification patterns emphasize the importance of incorporating additional modalities such as synthetic aperture radar (SAR) and LiDAR to enhance feature representation for complex land cover types. Future refinements could also involve integrating attention mechanisms to optimize feature selection and reduce redundancy in spatial-temporal embeddings.

Figure 2 illustrates the ConvSegNet capabilities in distinguishing road networks from other built-up areas as a novel class, where we reduce insistence in multi-scale feature detections along the first phase filters as they convolve over. The figure demonstrates ConvSegNet's capability to effectively distinguish road networks (yellow in the illustration) from other built-up areas, a common challenge for many convolutional networks. This is achieved through a novel architectural approach that better differentiates between global and small-scale features often confused during initial filtering, enabling successful segmentation of roads even within complex urban environments where traditional networks might struggle.

Figure 3 illustrates class distributions in three sample towns of Kigali, mapped using ConvSegNet, highlighting its ability to distinguish land cover types with high precision.

Figure 3: An illustration of Class Distributions from ConvSegNet Mapping in Three Samples of Kigali Towns.



The ConvSeqNet model was able to distinguish subtle transitions between agricultural land and urban sprawl, even in complex zones where land-use conflicts often arise. The distribution of LULC classes in these areas aligns with the known urbanization trends in Rwanda, demonstrating that the model's predictions are consistent with observed changes. The evaluation also compared ConvSeqNet's performance to other deep learning models and traditional methods. The statistical

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results from the F1-score and recall metrics show that ConvSeqNet outperforms other CNN-based models and traditional classifiers in both precision and recall, highlighting its superior ability to capture dynamic land cover transitions. The comparison with SegFormer (Segmentation transformer) and U-Net models illustrates that ConvSeqNet provides more accurate regional information retention, with results closely matching the ground truth. Therefore, the ConvSeqNet framework proves highly effective in mapping fine-scale LULC changes and can be leveraged for policy evaluation, land use planning, and environmental monitoring. Future work could focus on integrating additional data sources, such as SAR and LiDAR, to further enhance classification accuracy and provide even finer insights into land cover dynamics.

The research successfully met its objectives, providing detailed insights into the temporal changes in land cover in Rwanda. The ConvSegNet model demonstrated high accuracy in detecting urban expansion, with an overall accuracy of 92% for urban areas. The model also achieved a good level of accuracy in detecting agricultural changes (85%) and forest transitions (75%). However, while ConvSegNet performed well in general, challenges remain, particularly in detecting subtle transitions such as gradual deforestation or shifts in agricultural land use. These transitions often lead to misclassifications, especially when there is insufficient temporal data or when land cover changes are subtle.

CONCLUSION

The research demonstrated the utility of AI-based deep learning models, specifically ConvSegNet, in improving land cover and land use change detection in Rwanda. The study successfully achieved its objectives by developing an effective framework that utilizes multi-temporal satellite imagery to detect urbanization, agricultural encroachment, and deforestation. The results obtained from the ConvSegNet model specifically its high accuracy in urban areas and agricultural zones affirm the potential of deep learning techniques in addressing land management challenges in Rwanda. By leveraging spatial and temporal features, ConvSegNet has proven to be a powerful tool for analyzing the dynamic changes occurring in the country's land use patterns. The model's ability to capture the subtle shifts in land cover makes it an ideal tool for monitoring the impact of urbanization and agricultural expansion, both of which are critical issues in Rwanda's development planning. Moreover, the ability to identify these changes on a large scale provides valuable data for policymakers and environmental planners to make informed decisions regarding land use management and conservation efforts.

RECOMMENDATIONS

Building upon the promising results of this study, several avenues for improvement exist to further enhance the ConvSegNet model's effectiveness and applicability for key public institutions in Rwanda responsible for land use and satellite imagery, such as the National Land Authority, Rwanda Housing Authority and the Rwanda Space Agency. The following subsequent recommendations aim to refine the model to better support these institutions in their crucial work of monitoring and managing land uses and satellite imagery through the application of artificial intelligence: (1) improving Temporal Resolution; (2) incorporating Additional Data Sources; (3) enhancing Model Sensitivity to Forested Areas; (4) scalability and Generalization, (5) Real-Time Monitoring Systems.

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