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INTERNATIONAL JOURNAL OF PROGRESSIVE RESEARCH IN ENGINEERING MANAGEMENT AND SCIENCE (IJPREMS)
(Int Peer Reviewed Journal)
Vol. 04, Issue 12, December 2024, pp : 718-726

e-ISSN : 2583-1062
Impact Factor : 7.001

URBAN AREA CLASSIFICATION USING REMOTE SENSING AND DEEP LEARNING

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ABSTRACT

Rapid urban growth and land cover changes, driven by an expanding population, economic growth, or environmental challenges, require accurate and efficient monitoring methods. Remote sensing and deep learning (DL) are becoming important tools for monitoring land cover change, allowing us to monitor these changes more accurately. In this paper, High-resolution satellite imagery with DL algorithms used to classify urban areas which are important in urban planning and environmental management. There is additional spectral information in multi-spectral satellite imagery (including near-infrared (NIR) bands) that red-green-blue (RGB) images that cannot capture. NIR imagery is particularly useful for classification in fields like agriculture, forestry, and geology/natural resources. However, many DL methods are struggle to fully utilize spectral information. To overcome the drawback, this study presents an efficient model, Separated-Input U-Net (SiU-Net) which uses methods to independently process RGB and NIR data, which improves classification performance. The SiU-Net model was more accurate than DeepLabV3+ or U-Net particularly in scenarios with limited or imbalanced datasets. This suggests that SiU-Net may be an appropriate method to classify land cover in urban accretions even when the training data is limited or highly imbalanced.

Keywords: Remote Sensing Technology, Deep Learning Algorithms, U-Net model, DeepLabV3+ model , SiU-Net model, red, green, and blue (RGB), near-infrared (NIR).

1. INTRODUCTION

The unprecedented pace of urban expansion and land cover change worldwide brings forth significant environmental, social, and infrastructural challenges. Rapid urbanization affects ecosystems, alters hydrological cycles, and places immense pressure on resources, necessitating the development of effective monitoring systems. Accurate and timely classification of land cover is vital for urban planning, resource management, and sustainable development. Remote sensing, with its ability to capture extensive areas through high-resolution satellite imagery, has become an indispensable tool for such tasks. However, the complexities of urban landscapes, characterized by heterogeneous textures, varied spatial patterns, and overlapping land use types, demand sophisticated analytical methods capable of handling this spectral and spatial diversity.

Recent advances in deep learning (DL) offer promising solutions for land cover classification. Unlike traditional methods, which often rely on hand-crafted features and may lack adaptability to complex data, DL techniques especially convolutional neural networks (CNNs) can automatically extract relevant features from vast datasets. Models such as U-Net and DeepLabV3+ have demonstrated impressive accuracy in segmenting complex urban areas by leveraging CNNs for feature extraction. These models, however, encounter limitations when applied to noisy datasets or when handling highly imbalanced classes, as is often the case with remote sensing data. Furthermore, the rich spectral information available in multispectral and near-infrared (NIR) bands presents additional challenges in feature integration, as traditional DL models primarily process RGB imagery, potentially overlooking critical data embedded in other wavelengths.

To address these challenges, this survey focuses on advanced DL models and methodologies developed for land cover classification, particularly in urban contexts. Key contributions of this survey include the following:

1. **Exploring the Role of Novel Architectures in Urban Land Cover Classification**
   This paper provides an in-depth exploration of several DL models tailored to address urban land cover complexities, including U-Net, DeepLabV3+, and the newly proposed Separated-Input U-Net (SiU-Net). The SiU-Net architecture, with its unique dual encoder design, is particularly noteworthy for its independent processing of RGB and NIR channels. This separation allows SiU-Net to better capture and utilize spectral information, achieving improved classification accuracy over models that treat multispectral inputs as a unified data source. By comparing these models across varied urban datasets, this survey highlights SiU-Net's effectiveness, especially in scenarios with limited labeled data or highly imbalanced classes.
2. **Comprehensive Review of Techniques Addressing Data Imbalance and Noise**
   In remote sensing datasets, imbalanced classes and noisy labels are common issues due to the uneven distribution of urban features and the limitations of manual annotation. This paper examines dual-phase training and ensemble learning approaches that enhance model performance by prioritizing minority classes. Additionally, techniques like

pseudo-labeling—a method that refines labels by iteratively updating predictions—are discussed as effective strategies to mitigate the impact of noisy or low-resolution data. By surveying these approaches, this paper identifies methods that not only improve model performance but also increase generalizability across different urban landscapes.

3. **Analysis of Multi-Source and Multi-Scale Feature Fusion for Enhanced Classification**
   Urban environments exhibit complex spatial and spectral features that benefit from multi-source data integration. This survey covers models that leverage both spatial and spectral data, such as RGB and NIR bands, and techniques that fuse information across scales to enhance classification precision. Methods like multiscale context-aware feature fusion and dual encoder-decoder structures are reviewed for their effectiveness in integrating detailed local and broader contextual information, thereby capturing both fine-grained and large-scale patterns within urban scenes.
4. **Evaluation of Interpretability and Scalability in DL-based Remote Sensing Models**
   As DL models become increasingly complex, their interpretability and computational demands grow. This paper reviews methods, such as the Shapley additive explanations (SHAP) framework, that provide interpretability by quantifying the contribution of different spectral bands to model predictions. The survey also highlights scalable DL architectures, such as efficient encoder-decoder models, that maintain high accuracy while reducing computational costs. This focus on interpretability and scalability is essential for operational applications in urban planning and environmental monitoring, where models need to be both reliable and resource-efficient.
5. **Recommendations for Future Research Directions**
   In synthesizing the current advancements, this survey identifies key research gaps and proposes future directions. These include enhancing model robustness in highly noisy environments, exploring novel domain adaptation techniques to generalize models across diverse urban settings, and further developing real-time processing capabilities for timely decision-making in fast-evolving urban landscapes.

Contribution

This survey contributes to the field by providing a comprehensive overview of state-of-the-art DL techniques in land cover classification with a focus on urban applications. It synthesizes advancements in model architectures, training strategies, data augmentation, and feature fusion that collectively address the challenges posed by noisy, imbalanced, and multi-spectral urban datasets. By detailing the performance and limitations of these methods, this survey serves as a resource for researchers and practitioners seeking to apply DL for remote sensing in urban planning, environmental monitoring, and sustainable development.

In summary, this survey underscores the transformative potential of deep learning in land cover classification and paves the way for innovative solutions that are accurate, scalable, and adaptable to the demands of real-world urban monitoring applications.

Table 1: Comparison table

S.No	Title	Year	Objectives	Limitations	Advantages	Performance metrics	Gaps
Reference 1	A Dual Phase Approach for Addressing Class Imbalance in Land-Use and Land-Cover Mapping from Remotely Sensed Images.	2024	Improve class imbalance in LULC mapping using dual-phase training.	Limited to specific datasets. May overfit minority classes. Under sampling may lose information.	Enhanced overall performance metrics. Consistent results across datasets.	Overall Accuracy of 84.93%	Few studies on data-level techniques. Insufficient focus on pixel-level segmentation.
	Efficient Encoder-	2024	Improve building	Complexity in model	Effective use of LiDAR	89.09% of	Lack of real-time

Reference 2	Decoder Networks for Remote Sensing Based on Aerial RGB and LiDAR Data		segmentation accuracy by Integrate LiDAR and RGB data with Optimize deep learning models.	architecture. Dependence on quality of input data.	data. Enhanced model generalization.	IoU.	processing. Limited adaptability to diverse environments.
Reference 3	Semi-Supervised Multi-Label Classification of Land Cover in Remote Sensing Images with Predictive Clustering Trees and Ensembles	2024	Develop a semi-supervised framework for multi-label RSI classification.	Small dataset instability. Performance varies with labeled data. Limited generalization to unseen data.	Superior predictive performance. Effective with limited labeled data.	Overall Accuracy of 82.43%.	Integration strategies for unlabeled data. Real-time application challenges.
Reference 4	Land Cover Classification Using Deep Learning	2024	Global–Local Feature Fusion Module (GLFM) and fusion feature decoder to enhance classification accuracy and efficiency.	Performance degradation in high noise. Limited adaptability to complex scenes.	High classification accuracy. Robust to Gaussian noise. Effective feature extraction.	Mean Intersection over Union (MIoU): 63.58%	Lack of extensive real-world testing. Insufficient exploration of noise.
Reference 5	UFA Classification Using Integrated Features.	2023	Enhance classification accuracy by integrating spectral, spatial, and socio-economic features.	Limited data sources. Results may vary by location.	High classification accuracy, spatial, socio-economic data, Effective across different cities.	Overall Accuracy of 90%.	Limited data sources available, Model complexity increases training time.

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Reference 6	Interpretable Deep Learning Framework for LULC Classification.	2023	LULC Classification using CNN, SHAP models and also used Three-band combinations for data reduction to modules.	Limited Bands like Three-band combinations, similar class Vegetation categories.	High Accuracy: 94.72% Data Efficiency: Three-band combinations.	Accuracy: 92.72%	Limited Global Explanations, Features are Not fully explored.
Reference 7	Cross-Domain Land Cover Classification of Remote Sensing Images Based on Full-Level Domain Adaptation.	2023	Improve cross-domain classification using Full-Level Domain Adaptation Network (FLDA-NET)	Requires significant resources, Needs large datasets, Long training periods.	Improved classification accuracy, Reduces data collection difficulty.	OA: 86.9% F1 score: 85.2%	Limited to specific datasets. Not suitable for real-time. Limited to similar domains.
Reference 8	Pseudo-Labeling Approach for Land Cover Classification	2023	Improving land cover classification accuracy using CNNs and pseudo-labeling for noisy, low-resolution data.	Low-resolution data issues, Dependence on initial labels, Complexity in environmental variations.	Higher classification accuracy, Effective data sampling, Utilizes less data.	F1-score of 81.63%.	Limited high-resolution datasets, Need for better noise handling.
Reference 9	Multiscale Context-Aware Feature Fusion Network for Land-Cover Classification of Urban Scene Imagery.	2023	Improve urban land-cover classification accuracy using Multiscale feature fusion, attention mechanisms, pixel-shuffle decoder.	Interclass similarities. Scale-related inaccuracies. High computational complexity.	High accuracy. Efficient feature fusion. Reduced parameters. Robust to noise.	73.73% of mIoU.	Real-time processing, Diverse datasets, Robustness to noise.
	Land-Cover	2023	Semi-automatic	Insufficient practicality,	Efficient feature	IoU of 74.77%.	Dataset diversity,

Reference 10	Classification With High-Resolution Remote Sensing Images Using Interactive Segmentation		land cover classification using CNN and interactive segmentation.	High labeling costs, Limited generalization.	extraction, Reduced human participation, Large-scale sample library.		real-world applicability.
Reference 11	Deep Learning Models Performance Evaluations for Remote Sensed Image Classification	2022	The performance of deep learning models like convolutional neural networks (CNNs), transfer learning (TL).	Small dataset size. Longer training time for CNN. Limited comparison with other models.	Improved accuracy. Efficient training time. Robust feature extraction.	Overall accuracy of 88%.	Larger datasets needed. Advanced model exploration. GPU utilization.
Reference 12	Land Cover Classification of Resources Survey Remote Sensing Images Based on Segmentation Model	2022	Classify land cover using DL segmentation models	Low-resolution RS images, Manual labeling required, Limited training samples, Imbalanced data.	Effective for large-scale surveys, Suitable for low/medium resolution.	Overall Accuracy of 90.62%.	Detailed building classification, High-resolution data, Real-time processing.
Reference 13	Super-Resolution Mapping Techniques	2022	Improve land cover mapping using CNN models to address mixed pixel challenges.	Mixed pixel complexity, Spectral error impact, Spatial error influence.	Improved detail reconstruction, Geographically realistic outputs, Effective under various scales.	Overall Accuracy to 84.46%	Lack of real-time processing, Limited application scenarios, Need for larger datasets.

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Reference 14	Land-Cover Classification With Time-Series Remote Sensing Images	2022	High-accuracy land-cover classification using Informer network	Sensitive to imbalanced data, Requires extensive training data.	High classification accuracy, Effective multiscale feature extraction, Efficient memory usage.	F1-score of 90.11%	Handling imbalanced data, computational efficiency.
Reference 15	Attentive Spatial Temporal Graph CNN for Land Cover Mapping	2021	Integrate spatial and temporal data for SITS classification	Requires large memory, Complex model architecture, Limited to specific datasets.	Integrates spatial and temporal data. Scalable to large datasets.	84% of F1-score.	Scalability, computational efficiency, generalization to other datasets.

2. METHODOLOGIES

A. Dataset Preparation

The study utilized the 2020 satellite-derived land cover dataset, consisting of RGB and NIR bands obtained from Sentinel-2 images. Each input image had a spatial resolution of 10 meters and was segmented into 512×512 pixel tiles. The dataset covered six land cover classes: building, road, paddy field, upland field, forest, and unclassified areas. A total of 300 image patches were divided into training (64%, 192 patches), validation (16%, 48 patches), and testing (20%, 60 patches) sets, with no overlap. The dataset exhibited a significant class imbalance, with forest and unclassified areas dominating the distribution.

B. Model Architectures

The study compared three models: U-Net, DeepLabV3+, and a proposed Separated-Input-Based U-Net (SiU-Net). U-Net employed a symmetrical encoder-decoder architecture with skip connections to preserve edge information. DeepLabV3+ incorporated a ResNet-50 backbone and atrous spatial pyramid pooling (ASPP) for multi-scale feature extraction. The SiU-Net was designed to process RGB and NIR bands independently using dual encoders, enhancing the extraction of spectral features. Correlation coefficients between bands guided the decision to separate inputs, optimizing spectral differentiation while preserving edge details and improving class-specific performance, particularly for underrepresented classes.

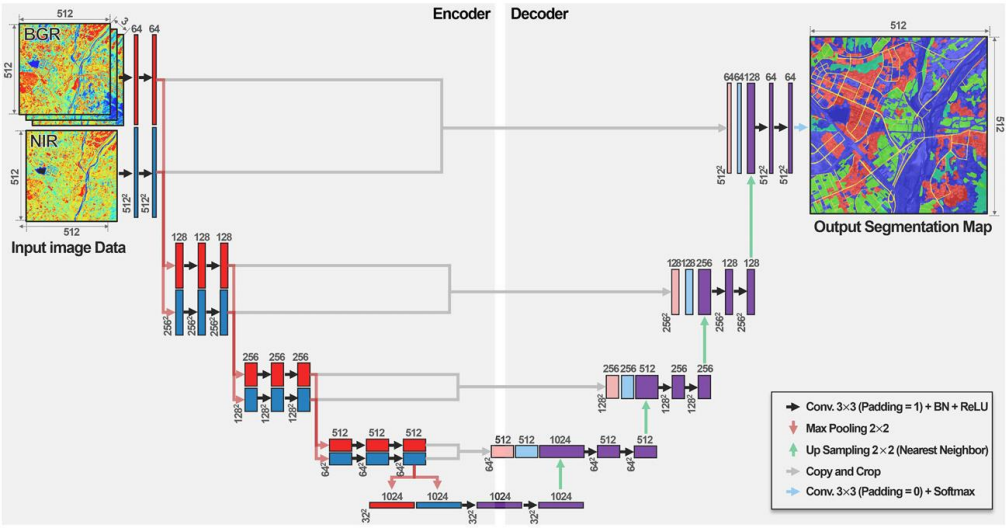

Fig 1: SiU-Net model Architecture

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C. Training and Optimization

The models were trained using hyperparameters optimized for their architectures. The Normal initialization was used for all models. Cross-entropy loss was adopted as the loss function, and different optimizers were employed: Adam with a learning rate of 0.0001 for U-Net and SiU-Net, and NAdam with a learning rate of 0.00001 for DeepLabV3+. All models were trained from scratch for 800 epochs, with the best-performing epoch selected based on validation accuracy. No additional data balancing or augmentation techniques were applied during training.

D. Performance Evaluation

To evaluate model performance, metrics such as pixel accuracy, precision, recall, and F1 score were calculated. The F1 score, a harmonic mean of precision and recall, was used to address class imbalance. Precision-recall curves and average precision (AP) scores were computed to assess the models' ability to classify each class and preserve boundaries. Both qualitative and quantitative comparisons were conducted to evaluate the baseline models and SiU-Net, with a particular focus on underrepresented classes such as upland fields.

E. Experimental Setup

The experiments were conducted in a GPU-enabled computational environment to manage the high computational demands of training deep learning models. The models' architectures were compared visually by examining semantic segmentation maps to assess their ability to preserve edges and recover class boundaries. Misclassifications and recovery of underrepresented classes were analyzed to determine the models' effectiveness.

F. Post-Processing and Analysis

Correlation coefficients between RGB and NIR bands were analyzed to validate the design of SiU-Net's dual encoder architecture. Statistical analyses were conducted to understand false positives and negatives, especially in misclassified classes. Trends in performance were evaluated to study the impact of class imbalance and the effectiveness of SiU-Net in improving classification for low-proportion classes. The study highlighted SiU-Net's ability to reduce data imbalance issues and achieve stable performance across classes.

3. RESULTS AND DISCUSSIONS

The literature on land cover classification using deep learning and remote sensing highlights advancements in model architectures to address data limitations, imbalance, and classification precision. Models like U-Net, DeepLabV3+, and SiU-Net have demonstrated improved accuracy in segmenting complex urban areas by leveraging high-resolution multi-spectral data, including near-infrared (NIR) bands, which capture details beyond standard RGB imagery. The SiU-Net model, with its dual encoder structure for processing RGB and NIR inputs independently, showed enhanced performance, especially with imbalanced data, outperforming more traditional architectures in scenarios with sparse labeled datasets.

Additional methodologies introduced in the literature employ approaches like dual-phase training to prioritize minority classes and feature fusion modules to balance local and global information for higher noise resilience. Techniques such as pseudo-labeling and multiscale feature fusion are also applied to improve label quality and model performance, even in noisy or low-resolution datasets. Overall, these approaches collectively enhance classification accuracy, model robustness, and scalability across varied urban landscapes, addressing both spectral complexity and data quality issues effectively.

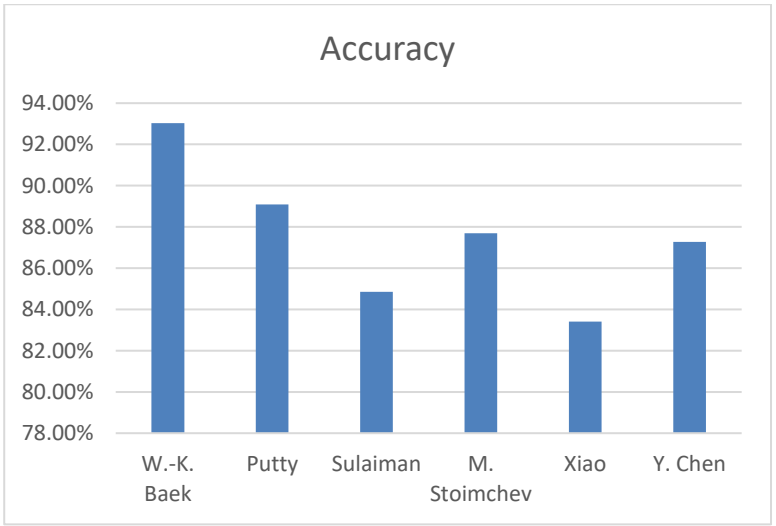

Fig 2: Result chart

4. CONCLUSION

The adoption of advanced deep learning models such as U-Net, DeepLabV3+, and the novel Separated-Input-Based U-Net (SiU-Net) has significantly enhanced land cover classification using multispectral satellite data. By leveraging the spectral richness of RGB and NIR bands, these models have overcome several limitations of traditional methods, particularly in handling class imbalance and low-resolution datasets. Among them, SiU-Net demonstrated superior performance by independently processing spectral bands, preserving spatial and spectral information, and achieving higher classification accuracy across diverse land cover types. These advancements underline the potential of deep learning to support critical applications in urban planning, environmental monitoring, and resource management.

Challenges: A significant challenge in land cover classification is the issue of data imbalance, where certain classes, such as forests, dominate the dataset while others, like urban structures or upland fields, are underrepresented. This imbalance often leads to biased models that perform well for majority classes but struggle with minority ones. Additionally, the computational cost of advanced models like SiU-Net is another concern, as its dual-encoder architecture requires extensive processing power, making it unsuitable for real-time applications or resource-constrained environments.

Another critical challenge lies in fully leveraging the spectral and spatial richness of multispectral data, including NIR bands. Traditional deep learning approaches often mix spectral features, leading to the loss of critical information required for precise classification. Moreover, noisy labels and low-resolution satellite data further exacerbate these issues, as inaccuracies in annotations and limitations in image quality make it harder for models to achieve consistent and accurate results. Finally, the generalizability of models remains a hurdle, as they may perform well on specific datasets but struggle when applied to different regions, seasons, or data sources due to variability in spectral and spatial characteristics.

Future Directions: Future advancements in land cover classification can address these challenges through several innovative approaches. Enhanced data augmentation techniques tailored specifically for multispectral imagery could mitigate class imbalance by enriching training datasets and improving model robustness. Lightweight architectures are also a promising direction, aiming to reduce computational overhead while maintaining high classification accuracy, which is crucial for real-time applications.

Domain adaptation and transfer learning methods could improve model generalizability by enabling them to perform effectively across diverse datasets and geographic regions. Additionally, the integration of explainable AI frameworks, such as SHAP (Shapley Additive Explanations), can enhance the transparency of model predictions, fostering trust and better decision-making.

Developing quantitative metrics for dynamically determining the separation of input bands in multi-spectral data could optimize encoder design, ensuring better utilization of spectral features. Incorporating ancillary data sources like LiDAR, socio-economic indicators, or temporal sequences could further enhance classification accuracy and provide richer contextual insights. Finally, automation in annotation processes and scalable cloud-based solutions can address the challenges of noisy labels and large-scale data processing, paving the way for broader and more effective applications of deep learning in remote sensing.

5. REFERENCES

[1] Putty, A., Annappa, B., Prajwal, R., & Perumal, S. P. (2024). A dual phase approach for addressing class imbalance in land-use and land-cover mapping from remotely sensed images. *IEEE Access*. https://doi.org/10.1109/ACCESS.2024.3425154.

[2] Sulaiman, M., Finnesand, E., Farmanbar, M., Belbach, A. N., & Rong, C. (2024). Building precision: Efficient encoder-decoder networks for remote sensing based on aerial RGB and LiDAR data. *IEEE Access*. https://doi.org/10.1109/ACCESS.2024.3391416.

[3] M. Stoimchev, J. Levatić, D. Kocev, and S. Džeroski, "Semi-Supervised Multi-Label Classification of Land Use/Land Cover in Remote Sensing Images With Predictive Clustering Trees and Ensembles," in IEEE Transactions on Geoscience and Remote Sensing, 2024, doi: https://doi.org/10.1109/TGRS.2024.3426981.

[4] Xiao, J., Cheng, T., Chen, D., Chen, H., Li, N., Lu, Y., & Cheng, L. (2024). Robust Land Cover Classification with Local-Global Information Decoupling to Address Remote Sensing Anomalous Data. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*.

[5] Y. Chen, C. He, S. Zheng, B. Wu, and W. Guo, "Shiqi Zheng was born in Zhengzhou, Henan, China, in 2002. He is currently working toward the undergraduate degree in geomatics engineering with the College of Geoscience and Surveying Engineering," in IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 2023,doi: https://doi.org/10.1109/JSTARS.2023.3308051.

[6] Temenos, A., Temenos, N., Kaselimi, M., Doulamis, A., & Doulamis, N. (2023). Interpretable deep learning framework for land use and land cover classification in remote sensing using SHAP. *IEEE Geoscience and Remote Sensing Letters*, *20*, 1-5.

[7] Meng, Y., Yuan, Z., Yang, J., Liu, P., Yan, J., Zhu, H., ... & Mi, X. (2023). Cross-domain Land Cover Classification of Remote Sensing Images based on Full-level Domain Adaptation. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*.

[8] I. Mirpulato, S. Illarionova, D. Shadrin, and E. Burnaev, "Pseudo-Labeling Approach for Land Cover Classification Through Remote Sensing Observations with Noisy Labels," in IEEE Access, 2023, doi: https://doi.org/10.1109/ACCESS.2023.3300967.

[9] Siddique, A., Li, Z., Azeem, A., Zhang, Y., & Xu, B. (2023). Multiscale Context-Aware Feature Fusion Network for Land Cover Classification of Urban Scene Imagery. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*.

[10] L. Xu, Y. Liu, S. Shi, H. Zhang, and D. Wang, "Land-Cover Classification with High-Resolution Remote Sensing Images Using Interactive Segmentation," in IEEE Access, vol. 11, pp. 6735-6746, 2023, doi: 10.1109/ACCESS.2022.3205327.

[11] A. Alem and S. Kumar, "Deep Learning Models Performance Evaluations for Remote Sensed Image Classification," in IEEE Access, vol. 10, pp. 111784-111793, 2022, doi: 10.1109/ACCESS.2022.3215264.

[12] Z. Fan, T. Zhan, Z. Gao, R. Li, Y. Liu, L. Zhang, Z. Jin, and S. Xu, "Land Cover Classification of Resources Survey Remote Sensing Images Based on Segmentation Model," in IEEE Access, vol. 10, pp. 56267-56278, 2022, doi: 10.1109/ACCESS.2022.3175978.

[13] Shang, C., Jiang, S., Ling, F., Li, X., Zhou, Y., & Du, Y. (2022). Spectral–spatial generative adversarial network for super-resolution land cover mapping with multispectral remotely sensed imagery. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, *16*, 522-537.

[14] J. Yan, J. Liu, L. Wang, D. Liang, and J. Peng, "Land-Cover Classification with Time-Series Remote Sensing Images by Complete Extraction of Multiscale Timing Dependence," in IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 15, pp. 1953-1962, 2022, doi: 10.1109/JSTARS.2022.3150430.

[15] M. Censi, D. Ienco, Y. J. E. Gbodjo, R. Pensa, R. Interdonato, and R. Gaetano, "Attentive Spatial Temporal Graph CNN for Land Cover Mapping from Multi Temporal Remote Sensing Data," in IEEE Access, vol. 9, pp. 23070-23079, 2021, doi: 10.1109/ACCESS.2021.3055554.