KG-MS-ResNet: A Knowledge-Guided Multi-Scale Attention Residual Network for Cultivated Land Change Monitoring

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Abstract

Cultivated land conversion to built-up area is the core form of farmland non-agriculturalization and the main threat to farmland protection. China has strict requirements for safeguarding farmland security and holding the 1.8-billion-mu farmland red line. However, current remote sensing monitoring methods for cultivated land non-agriculturalization have two limitations: insufficient integration of domain prior knowledge, and the inability of purely data-driven models to achieve high Precision and Recall. To tackle these challenges, this study proposes a knowledge graph-enhanced method for cultivated land–built-up area change detection. First, a multi-scale knowledge analysis framework with feature, scene, and business knowledge layers is constructed, which integrates topographic factors, ecological indicators, and land surface indices, to form the semantic representation of domain knowledge. On this basis, KG-MS-ResNet, a knowledge fusion residual network is designed. It adopts ResNet-18 as the backbone and modifies the first convolutional layer to accommodate bi-temporal image inputs. TransE is employed to embed geographic indicators knowledge into multi-scale semantic vectors. A semantic–feature dual-path fusion strategy and a knowledge-guided attention mechanism are further proposed, enabling deep coupling and collaborative optimization between image features and domain prior knowledge. Experiments conducted in Pei County, Jiangsu Province, demonstrate that the proposed method outperforms the baseline ResNet across all evaluation metrics, with 4.84% higher Recall and 0.0752 higher F1-score. The proposed method effectively enhances the detection capability of true change regions. The results demonstrate that deeply integrating domain knowledge graphs with deep learning models can improve the performance of cultivated land–built-up area change detection.

1. Introduction

Scene image classification is a very important and challenging subject in the field of robotics and computer vision. Scene image classification refers to observing the content of a given image, and then judging the category of the scene. There are four main categories of common scenes: natural scenes, event scenes, urban scenes and indoor scenes. At present, most studies focus on natural scenes, such as farmland, airport, baseball field, bare land, beach, bridge and so on (Fang and Yan, 2023; Ge, et al., 2022; Meng, et al., 2024; Li, et al., 2025). The process of natural scene classification is mainly as follows: first of all, scene images are selected as samples, and which are then combined with deep-learning algorithms to extract and learn the features of the samples, and then a model is built for recognition of scene types (Chen, et al., 2023; Li, et al., 2022; Xu, et al., 2023; Li , et al., 2024;)

In the field of farmland scene monitoring, the conversion of cultivated land to built-up area is the core representative form of the cultivated land non-agriculturalization. It is also the primary threat to cultivated land protection. There are two more points to be noted. On the one hand, in terms of national demand, the state pays great attention to the security of cultivated land resources (General Office of the State Council, 2020a). The Party Central Committee issued the requests that we should ensure that 1.8 billion mu red line for protecting farmland is not crossed and implement hard measures to protect farmland with "teeth", which requires timely mastering of changes in cultivated land, especially the transition between cultivated land and built-up area. (General Office of the State Council, 2020b). On the other hand, the methods of cultivated land change monitoring mainly focus on the spectral texture characteristics, phenological change characteristics, spatial semantic structure and other aspects of cultivated land, and mainly regard cultivated land as a natural scene for change monitoring.

However, the cultivated land presents different spectral characteristics and texture characteristics with time change (temporal phase/phenology change). These characteristics are affected by the diversity of cultivated land types, the phenological changes of cultivated land cover growth, and the unstable imaging conditions. Moreover, due to its lack of utilization of prior knowledge and rules of cultivated land change, it is difficult for cultivated land change monitoring methods to achieve high "precision" and "recall" at the same time. In addition, the change of cultivated land itself is an event, and has its specific event scenes knowledge and characteristics. For example, the "non-agricultural" of cultivated land is characterized by changes in the structure aspect, such as illegal construction, whose monitoring focuses on the early detection of the event. And the "non-grain" of cultivated land shows the change in the land function aspect, and its monitoring focuses on identifying the transformation relationship between " cultivated land, garden land, forest land, grassland and wetland ".

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Therefore, to address the challenges of existing methods, this study proposes a multi-scale knowledge graph-enhanced method for detecting cultivated land-to-built-up area changes. The method integrates domain prior knowledge into a deep learning framework to improve both precision and recall. First, a multi-scale knowledge analysis framework is constructed, including feature, scene, and business knowledge layers. This framework is used to model the semantic relationships underlying cultivated land ‑ built-up area conversion. Second, a knowledge-enhanced cultivated land-built-up area change detection network named KG-MS-ResNet (Knowledge-Guided Multi-Scale Attention Residual Network) is developed. The network is based on ResNet-18, with a modified first convolution layer to process bi-temporal images. And it employs TransE to embed eight categories of geographic indicators as semantic vectors. During the feature fusion stage, a dual-path strategy combining semantic information and image feature is adopted, where knowledge vectors are spliced and compressed with image feature maps to achieve deep integration. And a knowledge-guided attention mechanism is introduced to adaptively adjust feature weights. In addition, a change reasoning branch is designed to perform semantic consistency verification and filter false detections. This closed-loop framework combines data-driven learning and knowledge-guided reasoning, effectively improves the accuracy of cultivated land-to-built-up area change detection.

2. Methodology

The proposed method consists of two main components: (1) the construction of a multi-scale knowledge analysis framework for cultivated land–built-up area change events, and (2) the design of a knowledge-guided attention residual network, named KG-MS-ResNet.

First, a three-layer multi-scale knowledge analysis framework is constructed, including the feature layer, the scene layer, and the business knowledge layer. The feature layer integrates eight types of auxiliary indicators, such as DEM, slope, and NDVI. These indicators are discretized and modeled as attribute nodes. The scene layer captures the association patterns among multiple indicators under typical scenarios, such as urban–rural fringe and pure agricultural areas. These patterns are further abstracted as scene entities. The business knowledge layer organizes indicators according to application requirements. It assigns priority levels to different indicators and constructs a structured knowledge representation, namely “task objective–indicator priority–decision rules”. These three layers together form the core entities and multi-scale semantic relationships of the knowledge graph. Next, the TransE graph embedding method is used to map entities and relationships in the knowledge graph into low-dimensional multi-scale dense semantic vectors, while preserving their semantic associations. Finally, the knowledge embedding vectors are concatenated and fused with image feature vectors extracted by ResNet-18. The fused features are then fed into a classification network to perform knowledge-guided cultivated land–built-up area change detection. By introducing semantic constraints from the knowledge graph, the proposed framework effectively guides the learning process of the neural network and improves detection accuracy. The overall workflow is illustrated in Figure 1.

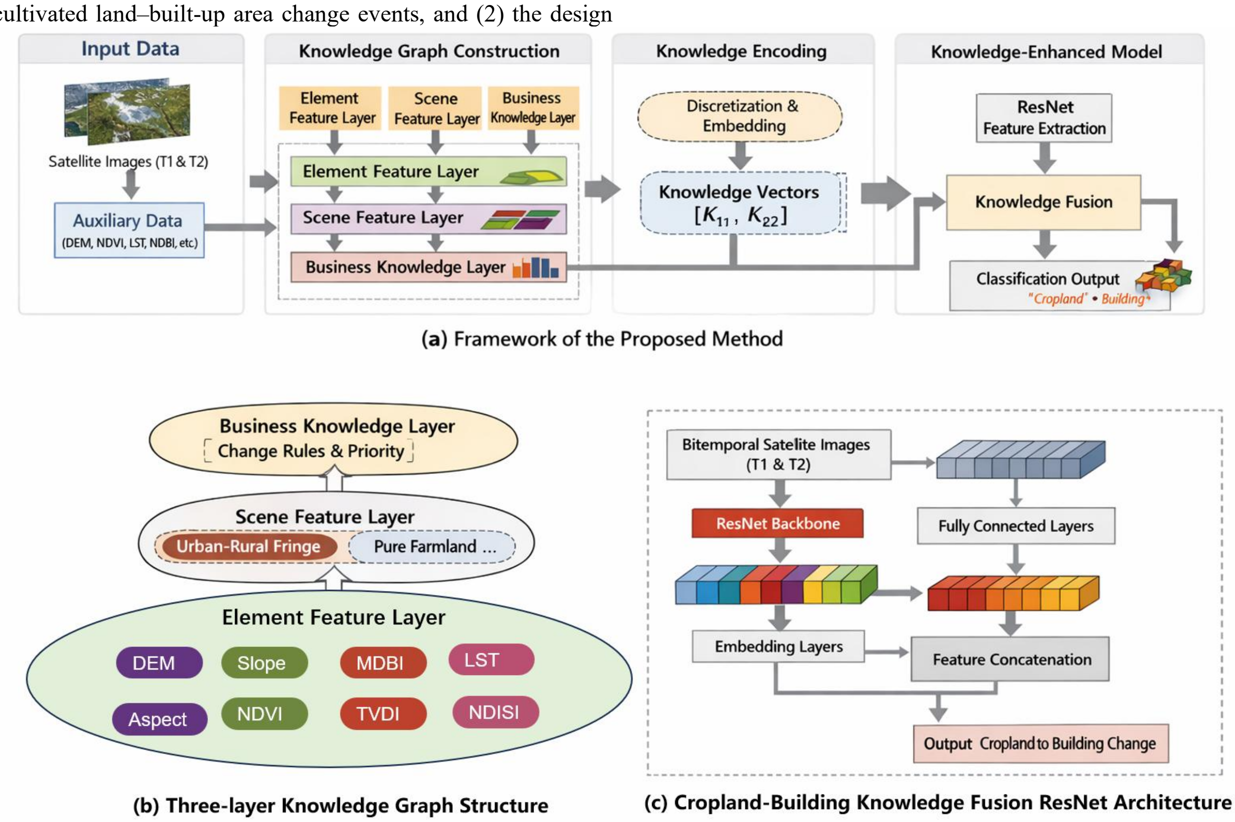

Figure 1. Overview of the proposed KG-MS-ResNet change detection workflow

2.1 Knowledge Analysis Framework for Cultivated Land–Built-up Area Change Events

The proposed multi-scale knowledge analysis framework for cultivated land–built-up area change events serves as the core foundation for domain knowledge graph construction. These three layers jointly provide comprehensive semantic constraints and knowledge support for cultivated land–built-up area change detection. The framework consists of three levels: the feature layer, the scene layer, and the business knowledge layer.

2.1.1 Feature Layer

The feature layer is the core component of the knowledge graph. It systematically integrates eight key data features that are highly relevant to cultivated land and built-up area. These features are grouped into three categories: topographic factors, ecological indicators, and land surface indices.

- Topographic factors: elevation (DEM), slope, and aspect, which describe the topographic characteristics of the study area.
- Ecological indicators: the Normalized Difference Vegetation Index (NDVI), Land Surface Temperature (LST), and the Temperature Vegetation Drought Index (TVDI).
- Land surface indices: the Normalized Difference Build-up Index (NDBI) and the Normalized Difference Impervious Surface Index (NDISI).

2.1.2 Scene Layer

The scene layer acts as a macro-level constraint for cultivated land–built-up area change. It represents the interrelationship among multiple indicators. Scene features are formed through the combination of different indicators, enabling the abstraction from individual indicators to high-level scene representations .

Typical scenes include urban–rural fringe and pure agricultural areas. Urban–rural fringe are usually characterized by high built-up index values, moderate to high vegetation coverage, and relatively flat terrain. These areas are the most active regions for the conversion of cultivated land to built-up area. In contrast, pure agricultural areas are characterized by high vegetation coverage and low built-up index values, where the probability of change is relatively low.

The introduction of the scene layer enables the model to identify typical patterns in a multi-dimensional feature space, thereby improving its discrimination capability in complex regions.

Table 1 illustrates the typical scenarios of changes in cultivated land and built-up area.

Typical Scenarios	Scenario Definition	Metric Characteristics
Urban-rural fringe	Adjacent distribution of cultivated land and built-up areas. It is the most active region for non-agricultural use of cultivated land. Characterized by high NDBI, moderate-to-high NDVI, and gentle slope	1. Slope: Over 90% consists of gently sloping cultivated land (0–2°); 2. NDBI/NDISI: Medium-high to high values (built-up expansion signal); 3. NDVI: Medium-high vegetation cover (mixture of cultivated land and built-up area); 4. DEM: Low to medium-low elevations; 5. LST: Medium-high to high temperatures (early signs of the urban heat island effect); 6. TVDI: Medium to medium-high drought (declining soil moisture); 7. Slope aspect: No clear preference (limited influence of microtopography in plain areas)
Purely agricultural area	Continuous cultivated land far from built-up areas. Characterized by high NDVI, low NDBI, and gentle slope.	1. Slope: Over 95% consists of gently sloping cultivated land (0–2°); 2. NDBI/NDISI: Low to medium-low values (no signs of building); 3. NDVI: High coverage (healthy vegetation growth); 4. DEM: Low elevation (core area of the plain); 5. LST: Low to moderate temperatures (no heat island effect); 6. TVDI: Low to medium-low drought (high soil moisture, high productivity on cultivated land); 7. Slope aspect: NDVI on south-facing slopes is significantly higher than on north-facing slopes (marked differences in productivity)

Table 1. Typical scenarios of changes in cultivated land and built-up area

2.1.3 Business Knowledge Layer

The business knowledge layer further integrates domain knowledge with practical monitoring requirements. Centred on the core business objective (detection of cultivated land converted to built-up area), it establishes the monitoring priorities for eight indicators and the decision rules for identifying changes in cultivated land. Thereby it constructs a structured knowledge representation of "business objective–indicator priority–decision rules". Based on the business analysis of cultivated land–built-up area change, NDVI, NDBI, slope, and NDISI are defined as core indicators. LST and TVDI are regarded as important indicators, while DEM and aspect are treated as auxiliary indicators. This hierarchical prioritization scheme is used to guide the weight allocation of different indicators in the model.

The knowledge graph of cultivated land–built-up area changes is shown in Figure 2.

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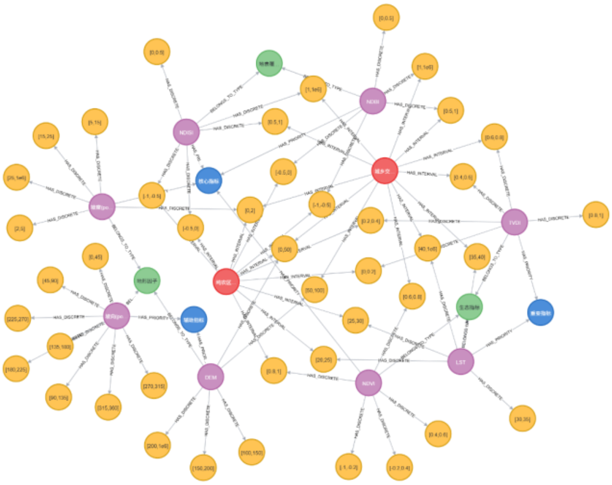

Figure 2. Knowledge graph of cultivated land-built-up area changes

2.2 KG-MS-ResNet

To achieve deep coupling between domain prior knowledge of cultivated land–built-up area change and deep features from bi-temporal remote sensing images, this study proposes a KG-MS-ResNet, based on the ResNet-18 architecture. The network introduces a dual-path fusion strategy that integrates multi-scale semantic and feature information, as well as a knowledge-guided attention mechanism.

The proposed network adopts ResNet-18 as the backbone. Its residual connections structure effectively alleviate the gradient vanishing problem in deep networks and enhance the propagation and preservation of deep features from bi-temporal images. Considering the 6-channel input formed by concatenating bi-temporal RGB images (2018 and 2021), the first convolutional layer of the backbone is modified. The number of input channels is expanded from 3 to 6. The weights of the new channels are initialized by averaging and replicating the pretrained weights of the original 3-channel convolution. This strategy enables adaptation to bi-temporal inputs while preserving the effectiveness of pretrained weight transfer.

Meanwhile, based on the constructed knowledge graph of cultivated land-built-up area change, eight types of geographic indicators (for both 2018 and 2021), such as DEM, LST, and NDBI, can be mapped to knowledge entities through discretization. Specifically, for the discrete value range of each indicator, the corresponding entity and its description are available in the knowledge graph. The TransE graph embedding method is then applied to jointly learn entity and relationship representations related to the image, producing low-dimensional multi-scale dense vectors. This ensures that semantically similar entities are adjacent in the vector space, thereby encoding domain-specific association rules(e.g., strong correlation between “urban–rural fringe” and “high NDBI”). The embedding dimension for each indicator is set to 16. The embeddings of all indicators (8 types $\times$ 2 temporal phases) are concatenated to form a 256-dimensional knowledge representation. This representation encodes semantic constraints between indicators and scene-level contextual information, providing knowledge guidance for subsequent fusion modules and enhancing the model’s ability to distinguish cultivated land change patterns.

During the fusion stage, a semantic–feature dual-path fusion strategy is proposed. The image feature maps and knowledge semantic vectors are first upsampled via 1×1 convolutions and duplicated. They are then concatenated and compressed along the channel dimension to obtain joint features. Furthermore, a knowledge-guided attention module is introduced to adaptively refine the joint features. This module is based on the three-layer knowledge framework of “feature–scene–business”. The semantic vectors generated by TransE serve as guidance weights. Two fully connected layers are used to generate an attention weight matrix corresponding to the joint feature channels. The weight allocation strictly follows the prior rules defined in the knowledge graph. For feature channels corresponding to core indicators (NDVI, NDBI, slope, and NDISI), the weights are automatically increased to emphasize the most core feature signals for change detection. For channels corresponding to auxiliary indicators, such as DEM and aspect, the weights are adaptively adjusted based on scene semantics. This design preserves useful complementary information while suppressing redundant noise. Through this attention mechanism, the model can focus on the most relevant features for cultivated land–built-up area change detection under the guidance of domain-specific prior knowledge.

Finally, the proposed network follows a complete pipeline of “feature extraction–knowledge embedding–dual-path fusion–knowledge-guided attention refinement–result output”. It retains the strong generalization capability of data-driven models while introducing interpretability through knowledge-guided constraints. The method effectively improves detection performance in challenging scenarios, such as blurred boundaries between cultivated land and built-up area and fragmented illegal construction areas. It provides reliable technical support for precise monitoring of non-agricultural use of cultivated land.

3. Experiment

3.1 Study Area and Data

This study selects Pei County, Xuzhou City, Jiangsu Province, as the study area. The region is located in the central part of the Huang–Huai-Hai Plain and is dominated by flat terrain. It is a core component of the Huang–Huai commodity grain production base, with highly concentrated cultivated land resources. The dominant cropping system is a rice–wheat rotation. Furthermore, situated at the heart of the Huaihai Economic Zone, Paixian County has rapid urbanisation in recent years. The non-agricultural use of cultivated land in urban–rural fringe has become increasingly prominent. This includes various activities such as housing construction, road development, greenhouse construction, and artificial lake excavation. Cultivated land change scenarios in this region are complex and diverse. Therefore, the study area is highly representative for research on cultivated land protection and urban expansion in the Huang–Huai-Hai Plain.

The PX-CLCD high-resolution remote sensing dataset constructed for cultivated land change detection is shown in Figure 3. It covers the study area with 1 m spatial resolution GF-2 satellite images from 2018 to 2021. In addition, eight auxiliary indicator datasets matched to the imagery were processed and generated, including DEM, slope, aspect, NDVI, LST, TVDI, NDBI, and NDISI. The processing results of these indicators are shown in Figure 4. All data are divided into training, validation, and test sets with a ratio of 6:2:2.

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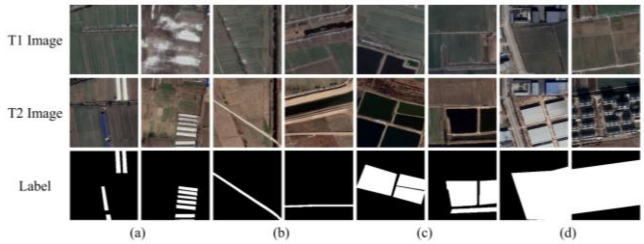

Figure 3. Example sample (256×256) from the PX-CLCD high-resolution remote sensing dataset

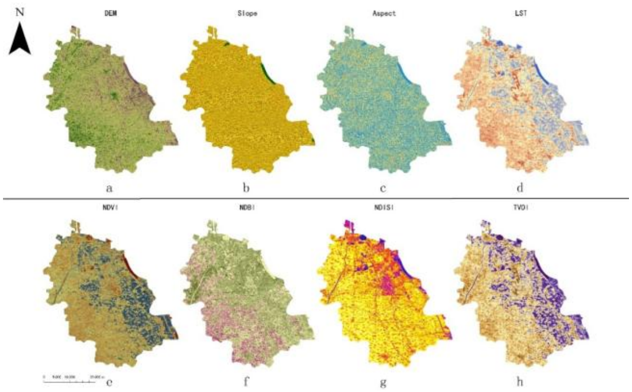

Figure 4. Example of a feature diagram for eight categories

3.2 Experimental Results and Analysis

To evaluate the effectiveness of the proposed KG-MS-ResNet for cultivated land–built-up area change detection, ResNet-18 is adopted as the baseline model. Precision (P), Recall (R), F1-score, Overall Accuracy (OA), and the Kappa coefficient are used as evaluation metrics. The definitions, formulations, and parameter descriptions of these metrics are given in Eqs. (3.1)–(3.6). A quantitative comparison between the two methods is conducted, and the results are shown in Table 2.

(1)Precision
Precision measures the proportion of correctly predicted change samples among all samples predicted as change. It reflects the accuracy of the detection results. The formulation is given as:

$$\text{Precision} = \frac{TP}{TP + FP} \tag{3.1}$$

Where:
TP (True Positives) denotes the number of samples that are actually change and correctly predicted as change; FP (False Positives) denotes the number of samples that are actually non-change but incorrectly predicted as change.

(2)Recall
Recall measures the proportion of actual change samples that are correctly detected by the model. It reflects the model’s ability to identify change regions. It is calculated as follows:

$$\text{Recall} = \frac{TP}{TP + FN} \tag{3.2}$$

Where:
FN (False Negatives) denotes the number of samples that are actually change but not detected by the model.

(3)F1-score
The F1-score is the harmonic mean of Precision and Recall. It provides a comprehensive evaluation of detection performance. It is particularly useful when there is an imbalance between positive and negative samples. It is calculated as follows:

$$F1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{3.3}$$

(4)Overall Accuracy
Overall Accuracy represents the proportion of correctly classified samples among all samples. It reflects the overall classification performance of the model. It is calculated as follows:

$$OA = \frac{TP + TN}{TP + TN + FP + FN} \tag{3.4}$$

Where:
TN (True Negatives) denotes the number of samples that are actually non-change and correctly predicted as non-change.

(5)Kappa Coefficient
The Kappa coefficient measures the agreement between the predicted results and the ground truth, while excluding agreement caused by chance. It is a more robust evaluation metric. It is calculated as follows:

$$\text{Kappa} = \frac{OA - P_e}{1 - P_e} \tag{3.5}$$

Where:
P_e denotes the probability of random agreement. It is calculated as follows:

$$P_e = \frac{(TP + FP) \times (TP + FN) + (FN + TN) \times (FP + TN)}{(TP{+}TN{+}FP{+}FN)^2} \tag{3.6}$$

These five metrics evaluate the model from multiple dimensions, including accuracy, completeness, overall performance, consistency, and chance-corrected agreement. They provide a comprehensive assessment of KG-MS-ResNet for cultivated land–built-up area change detection.

Evaluation Criteria	ResNet	KG-MS-ResNet
Precision(P/%)	92.71	92.35
Recall(R/%)	71.77	76.61
F1-Score	0.7623	0.8375
OA/%	94.87	96.03
Kappa	0.7868	0.8003

Table 2. Comparison of the accuracy of cultivated land change detection across different methods

As shown in Table 2, it can be observed that the proposed KG-MS-ResNet outperforms the baseline ResNet across most evaluation metrics. Specifically, in terms of Precision, KG-MS-ResNet achieves 92.35%, which is comparable to ResNet (92.71%), with only a slight decrease. This indicates that the introduction of knowledge fusion does not compromise the model’s ability to accurately identify positive samples. In terms of Recall, KG-MS-ResNet achieves a significant improvement, reaching 76.61%, compared to 71.77% for ResNet, with an increase of 4.84 percentage points. This demonstrates that the incorporation of domain knowledge effectively enhances the detection of true cultivated land–built-up area change regions and reduces missed detections. Benefiting from the joint improvement of Precision and Recall, the F1-score of KG-MS-ResNet reaches 0.8375, which is substantially higher than that of ResNet (0.7623), with an improvement of 0.0752. This confirms that the proposed method achieves a better balance between accuracy and recall.

In addition, for global evaluation metrics, KG-MS-ResNet achieves an Overall Accuracy of 96.03%, outperforming ResNet (94.87%). The Kappa coefficient also increases from 0.7868 to 0.80

03, further indicating improved overall classification consistenc y. These results demonstrate that by deeply integrating semantic information from the cultivated land change knowledge graph with image features, and introducing a knowledge-guided attent ion mechanism to dynamically focus on critical regions, KG-M S-ResNet effectively addresses the issue of feature ambiguity in cultivated land–built-up area change detection. The model sho ws enhanced capability in identifying true change regions.

In summary, the proposed KG-MS-ResNet significantly improv es Recall and overall performance while maintaining high Preci sion. This verifies the superiority of domain knowledge embedd ing for cultivated land–built-up area change detection..

4. Conclusions

To address the limitation that domain prior knowledge is insuffi ciently integrated into purely data-driven deep learning models f or remote sensing monitoring of non-agricultural use of cultivat ed land, this study proposes a knowledge graph-enhanced metho d for cultivated land–built-up area change detection. A three-lay er knowledge analysis framework, consisting of feature, scene, and business knowledge layers, is constructed to model cultivat ed land–built-up area change knowledge. This framework comp letes structured and semantic representation of domain knowled ge and provides comprehensive prior semantic constraints for th e model. Then based on ResNet-18, a knowledge fusion residual network KG-MS-ResNet is developed. The input layer is modif ied to accommodate bi-temporal images. TransE is employed to embed geographical feature knowledge. A semantic–feature du al-path fusion strategy and a knowledge-guided attention mecha nism are further designed. These components together form a ch ange detection model with both strong generalization capability and interpretability. Experiments conducted in Pei County, Jian gsu Province, demonstrate that the proposed model outperforms the ResNet baseline across all major evaluation metrics. It achi eves superior Precision, Recall, and F1-score. The results verify that the knowledge-guided mechanism is effective in suppressin g false changes and enhancing the expression of key features. In summary, this study provides a technically effective and seman tically interpretable solution for precise monitoring of non-agric ultural use of cultivated land. It also offers a practical paradigm for integrating knowledge-driven and data-driven approaches in intelligent remote sensing interpretation.

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