Cropland De-Agriculturalization and De-Fooding Monitoring Based on Multi-Source Remote Sensing Data

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Abstract. With economic development and scientific and technological progress, China's agriculture has made remarkable achievements, and its agricultural production capacity has increased significantly, guaranteeing national food security. However, agricultural development is also faced with the challenge of non-farming and non-food cultivation of arable land. Industrialization and population reduction have led to the conversion of a large amount of arable land to non-farm use or non-food crop cultivation, affecting food production capacity and the balance of agricultural structure. In particular, "non-food" cultivation—i.e., the conversion of arable land to forest land, garden land, or other uses not associated with basic food crops—has become a prominent trend, threatening food security. In order to obtain farmland information and monitor the changes of farmland in a timely manner, this paper takes Suixian County in Hubei as the study area, and utilizes 2020 and 2023 Jilin-1 remote sensing images, combines the cloud GPU platform to train a deep learning model, adopts Yolov5 for non-agriculturalization target detection, and analyzes the fine-grained changes of farmland with the MSCANet network. The results show that Yolov5 can basically recognize photovoltaic land, wasteland and new buildings, and MSCANet is more advantageous than traditional methods in terms of accuracy and computational efficiency. The study shows that remote sensing technology has an important value in farmland monitoring, and multi-source remote sensing combined with deep learning provides a scientific basis for monitoring the non-agriculturalization of arable land and supports policy-making in areas such as land use planning, food security management, and ecological protection.

Keywords: Farmland; De-agrarianization; Non-food; Target detection; Change detection; Deep learning.

1 Introduction

With the rapid development of China's economy and the acceleration of urbanization, the pattern of land use has changed significantly, and the phenomenon of "non-agriculturalization" and "non-food" of arable land has become increasingly prominent. The traditional agricultural structure centered on arable land is gradually shifting to a non-agricultural structure dominated by construction land and ecological land, which not

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only affects the production and living styles of farmers, but also puts forward higher requirements for the sustainable development of agriculture, food security and management of arable land resources. In recent years, the area of arable land has continued to decrease in most provinces across the country, especially in Sichuan Province, where the area of arable land has decreased by a total of 22.39 million mu in ten years [1]. In this context, it is particularly urgent to carry out the dynamic monitoring and assessment of the non-agriculturalization and non-foodization of arable land.

The development of remote sensing technology provides strong support for large-scale and high-efficiency land use monitoring. Multi-source remote sensing images have been widely used in the field of land cover classification and change detection due to their multi-temporal, multi-angle and multi-resolution characteristics [2]. In image classification, traditional algorithms such as support vector machines, decision trees, and random forests have been gradually replaced by deep learning methods such as convolutional neural networks (CNN), which have significantly improved the classification accuracy [3][4].

As for cropland change detection, classical methods such as change vector analysis (CVA) [6] and principal component analysis [7] were widely used in the early stage [5], but in the face of high-precision and fine-grained cropland dynamics detection tasks, the research focus has gradually shifted to deep learning-based change detection models, such as UNet, DeepLab, MSCANet, etc [8] [9]. In addition, the introduction of emerging models such as Transformer [10] has also shown good long-distance modeling and contextual expression ability, which has become a new direction for change detection research.

This study aims to target typical problems of non-agriculturalization and non-foodification such as occupation of photovoltaic projects, abandonment of arable land, illegal encroachment of water bodies and buildings in the experimental area, and constructs a deep learning model to carry out target detection and change detection experiments of non-agriculturalization of arable land based on multi-source remote sensing data. On the one hand, the mainstream target detection algorithms, such as YOLOv5 and Faster R-CNN, are trained and compared to achieve accurate identification of non-agriculturalization targets; on the other hand, the change detection model of MSCANet is combined to extract the changing areas of arable land in the dual-time-phase remote sensing images, focusing on the trend changes of the conversion of agricultural land to construction land and abandonment of land. This study not only helps to improve the intelligence and automation level of monitoring non-agriculturalization of cropland, but also provides technical support for the construction of efficient and scalable cropland protection technology system, which is of great practical significance for guaranteeing

2 Cultivated Land Non-agriculturalization and Non-food Monitoring Based on Target Detection

2.1 Study Area and Data

This study takes Suixian County in Hubei Province as the study area, and Dunziwan Village and Yaomiao Village, where the phenomenon of non-agriculturalization is more prominent, are selected as the typical sample areas. In recent years, the urbanization process in Suixian County has accelerated, the demand for construction land has risen, and the arable land is at risk of diversion, which is representative of remote sensing monitoring of changes in the use of arable land. The data used in the study are multi-temporal high-resolution remote sensing images acquired by the Jilin-1 satellite (operated by Chang Guang Satellite Technology Co., Ltd.). The images were captured in April 2020 and June 2023, with a spatial resolution of 0.75 meters, covering Dunziwan and Yaomiao villages in Suixian County. Each image spans approximately 10 km × 10 km and was delivered in GeoTIFF format.

In order to ensure the quality of the analysis, the image data were preprocessed as follows: first, the data needed to be corrected and enhanced to eliminate or reduce these effects and improve the availability and interpretation accuracy of the data. Multi-source remote sensing data need to be aligned to ensure that they are interpreted in the same coordinate system. If a single remote sensing image cannot cover the entire study area, data need to be mosaicked or spliced to stitch multiple images into a complete image. For images with different data formats, they are uniformly converted to TIFF format and homogenized for subsequent processing and analysis.

2.2 Definition of Non-agriculturalisation of Non-foodstuffs and Testing Indicators

The Ministry of Natural Resources, the Ministry of Agriculture and Rural Development, and the State Forestry and Grassland Administration's Circular on Issues Related to the Strict Control of the Use of Arable Land makes it clear that: general arable land is mainly used for the production of food, agricultural products such as cotton, oil, sugar and vegetables, as well as forage and fodder; on the premise of not destroying the arable land's arable layer and not changing the arable land's land use category, other crops can be planted to an appropriate extent. In addition, the Circular of the General Office of the State Council on resolutely stopping the ‘non-agriculturalisation’ of arable land stipulates that: Firstly, it is strictly prohibited to illegally occupy arable land for greening and afforestation. Secondly, it is strictly prohibited to build green corridors in excess of the standard. Third, it is strictly prohibited to illegally occupy arable land to dig lakes and create scenery. Fourth, it is strictly prohibited to occupy permanent basic farmland to expand the nature reserve. Fifth, it is strictly prohibited to illegally occupy arable land for non-agricultural construction. Sixth, it is strictly prohibited to grant land in violation of the law. According to the requirements of the above policies and regulations, this study defines non-farming and non-food as follows: ‘non-farming’ of arable land refers to the illegal use of arable land for non-farming construction activities;

'non-food' refers to the use of arable land as forest land, garden land, etc., main types of changes labelled in CLCD include buildings, roads, lakes, and bare soil which is detached from the use of basic agricultural crops, such as food. through the analysis In this study, the following typical feature types were extracted as the detection targets for non-agriculturalisation and non-foodification based on the policy requirements and the actual situation in the study area. Table 1 shows the key indicators for monitoring non-agriculturalisation of non-food products (NTFPs), including land-use changes such as conversion to photovoltaic (PV) land, buildings, water bodies, and wasteland. And these numerical codes (01–04) are used as label identifiers during the training and annotation process in the target detection model. Each code corresponds to a specific land-use change type to facilitate model classification and result interpretation.

Table 1. Indicators for monitoring non-agriculturalisation of NTFPs

Type of monitoring	Code	Characteristics
New PV land 01	01	Cultivated land in the pre-temporal image, the post-temporal image generally appears as long strips and arrays
New buildings	02	Cultivated land in the pre-temporal image, the post-temporal image generally appears as a regular polygonal shape
New water bodies	03	Cultivated land in the pre-temporal image, the post-temporal image generally appears as a dark-coloured irregular block
Cultivated land to wasteland	04	Cultivated land in the pre-temporal image, the post-temporal image generally appears as a Granular, post-temporal images generally appear as earthy colours

2.3 Typical Target Detection Model Selection and Brief Principles

To detect the non-agricultural non-food targets of arable land, this paper selects several typical target detection models for experiments, namely Yolov5, Faster-RCNN, and SSD models. The following is an overview and basic principles of these typical models: YOLOv5 is a lightweight detection model released by Ultralytics in 2020, which adopts an end-to-end structure with strong real-time detection capability. Its key features include Mosaic data augmentation, adaptive anchor frames, CSPNet backbone network, FPN+PAN feature fusion architecture, and redundant frames removed by non-maximum suppression (NMS). The model is compact and suitable for deployment in resource-constrained environments. Faster-RCNN is a two-stage detection model, which performs classification and bounding box regression after generating candidate regions through RPN (Region Proposal Network). Despite its high accuracy, it suffers from the problem of multiple detection overlaps and slow inference when dealing with small and dense targets. The SSD model is based on multi-scale feature maps and performs detection at different levels, taking into account both semantic and detailed information.

Its structure is lighter than Faster-RCNN, but it has limited ability to recognise small targets in complex scenes and relatively low recall.

2.4 Model Training and Evaluation Metrics

In this study, three models were trained and tested on a unified hardware environment and dataset based on the Pytorch framework. The image input is uniformly 2048×2048, the optimiser is SGD, and the training is performed using the cosine annealing learning rate strategy and migration learning using VOC pre-trained weights. Evaluation is done using metrics such as average precision (AP), recall with model size, and **inference speed (frames/s)**. The results are shown in Table 2:

Table 2. Comparison of training model effect accuracy

Model	P./%	R/%	Model size
Faster-RCNN	82.87	84.64	546MB
SSD	86.79	76.84	95.7MB
Yolov5	91.37	94.09	23.9MB

From the comparison, it can be seen that YOLOv5 outperforms the other two models in terms of precision, recall and model size, and has the strongest overall performance. Although Faster-RCNN is close in precision, it consumes a lot of computational resources and has a slow inference speed. And although SSD model is lightweight, it has insufficient recall and is prone to miss detecting small targets. Therefore, YOLOv5 is most suitable as the backbone detection model in this study, which can identify non-agriculturalised targets more efficiently.

2.5 Test of Detection Results

As the targets of non-agriculturalisation are unevenly distributed in the study area, in order to improve the validity of the detection results, areas with concentrated and typical non-agriculturalisation phenomena were selected for testing in this study, and the accuracy of the detection results was determined by manual visual interpretation. Specifically, part of the areas in Dunziwan Village and Yaomiao Village in Suixian County were selected, mainly because of the large area of arable land, the richness of the type of non-agriculturalisation (e.g. water bodies and buildings occupying arable land, and the obvious phenomenon of non-food phenomenon), and the conformity with the non-agriculturalisation/non-food indicator settings mentioned above in the article. The target detection results of the typical non-agriculturalisation area selected in Dunziwan Village are shown in Figure 1:

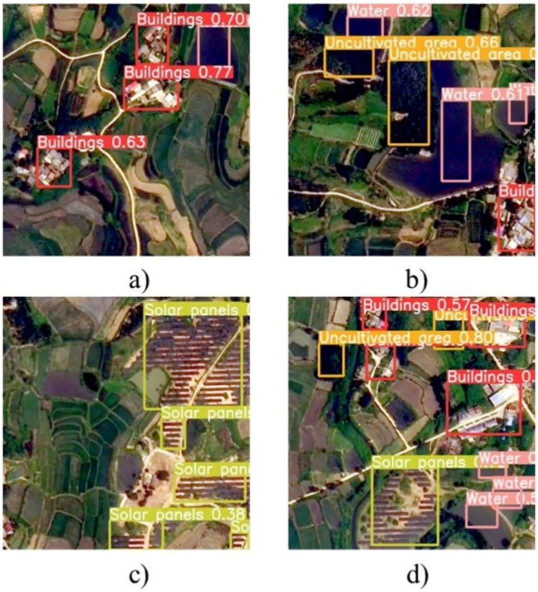

Fig. 1. Detection results in Dunziwan Village

The target detection results of the typical non-agriculturalisation zone selected in Yao Miao Village are shown in Figure 2:

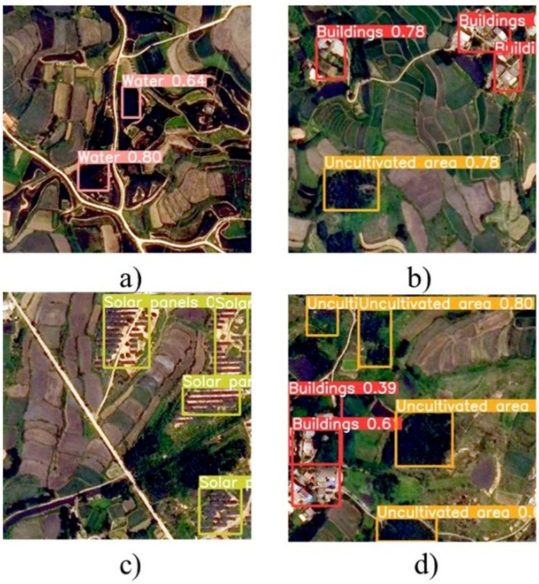

Fig. 2. Detection results in Yao Miao Village

From some of the detection results, it can be seen that the model trained in this study can basically complete the identification of arable land and abandoned land, and can detect new non-agricultural facilities in arable land areas, such as houses, photovoltaic panels, etc., but there are some cases of misjudgmethere is a small part of misinterpretationnt in some of the characteristics of the plots of land is not clearly distinguishable, the misclassification is mainly caused by the model's inability to effectively distinguish the spectral similarity between barren land and certain buildings, so there is also a need to improve the model to improve the model, so that the model is not in place. Therefore, the model needs to be improved, but it can basically meet the detection of non-agricultural and non-food targets.

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3.1 Overview of the Technical Process

The overall technical process is shown in Figure 3, and the main processes include: image acquisition and pre-processing, sample set production, model training, change detection, and result validation. Among them, in terms of image data and pre-processing, the multi-temporal images used in the study are the remote sensing image data of Jilin 1 in April 2020 and June 2023 in the two areas of Dunziwan Village and Yaomiao Village in Suixian County. Considering factors such as cloudiness and incomplete coverage of single-phase images, the original image of April 2020 was pre-processed as the pre-temporal image of arable land for monitoring of non-farming non-food cultivation; the original image of June 2023 was pre-processed and used as the pre-temporal image of monitoring of non-farming non-food cultivation. The raw images of April 2020 will be pre-processed as pre-temporal images for monitoring non-agriculturalisation of arable land; the raw images of June 2023 will be pre-processed as post-temporal images for monitoring. The pre-processing includes quality checking, removing invalid areas with cloudiness greater than 10 per cent, and levelling the light and colour.

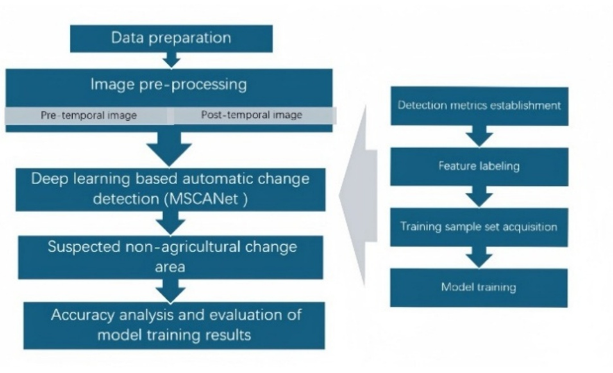

Fig. 3. Overall Technology Flow

3.2 Model Selection and Dataset Training Configuration

In this study, the MSCANet network [9] proposed in the article Multiscale Context Aggregation of CNN-Transformer Networks for Fine-Grained Farmland Change Detection is used as a deep learning model for experiments. MSCANet firstly adopts a CNN backbone to capture multiscale features from bi-stochastic images; then, a multi-scale context aggregator (MSCA) is used to model and aggregate the rich contextual information; finally, a multi-branch prediction head (MBPH) is applied to obtain the change map to further enhance the hidden layer feature extraction and learning. MSCANet firstly uses the CNN backbone to capture multi-scale features from bistatic images; then, it uses the Multi-scale Context Aggregator (MSCA) to model and aggregate the rich contextual information; finally, it applies the Multi-branch Prediction Head (MBPH) to obtain the change map to further enhance the feature extraction and learning in the hidden layer. MSCANet is constructed based on the CNN-Transformer structure, which can fully combine the advantages of both CNN and Transformer to meet the urgent need of fast and accurate farmland change monitoring.

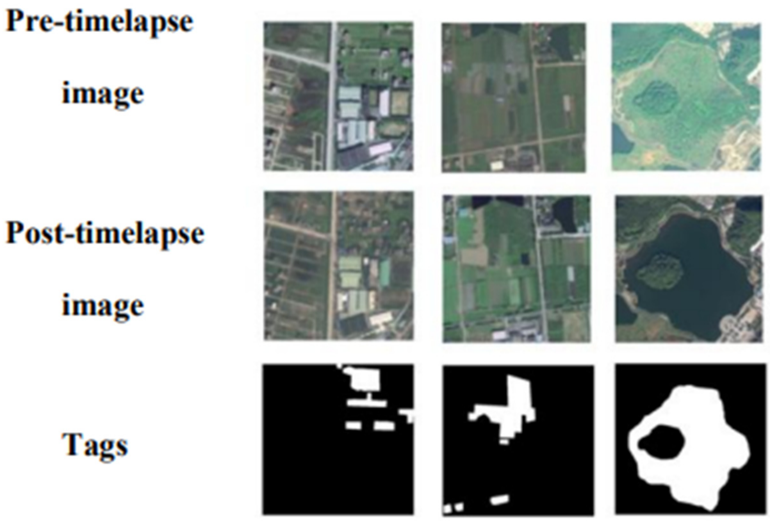

Fig. 4. Example of CLCD dataset with size of 512×512

This experiment mainly uses the CLCD dataset to train the MSCANet deep learning model, the CLCD dataset contains 600 pairs of sample images of changes in agricultural land (resolution of 0.5-2 m), as shown in Fig. 4, the main types of changes labelled in CLCD include buildings, roads, lakes, and bare soil. Here, feature labeling refers to the annotation of these change types in the images, which are used as ground truth for training and evaluating the change detection model. The models used and all experiments involved were implemented in PyTorch. All model training using the Adam optimiser was done in batch size.8 The training process lasted 100 epochs while data enhancement strategies were randomly applied to the training set to avoid overfitting, including vertical and horizontal flipping, and random rotation. In this paper, four commonly used metrics are chosen for accuracy assessment: precision (Pre), recall (Rec), F1 score and IoU. They can be defined as follows:

$$F1 = \frac{2Pre*Rec}{\mathrm{P}re+Rec}$$

$$IoU = \frac{\mathrm{T}P}{\mathrm{F}P+TP+FN}$$

where TP is the number of correctly detected non-agricultural change regions, FP denotes the number of misclassified non-agricultural change regions, i.e., the number of false detections, and FN is the number of missed targets in the image.

3.3 Detection Results and Analysis

According to the non-agriculturalisation and non-food monitoring indicators in the above article, there are a total of four types of changes that need to be detected, namely: new photovoltaic land, new buildings, new water bodies, and changes of arable land to wasteland. Due to the limited number of areas in the whole experimental area where the above changes have occurred, the areas where the above changes have occurred and where the changes are more obvious have been selected after manual visual interpretation, and the distribution of these areas in the whole experimental area is shown in Figure 5.

Fig. 5. Selection of typical non-agricultural and non-food areas in the experimental area

After selecting the test areas, the trained model was applied to monitor cultivated land changes between temporal images, with the following results:

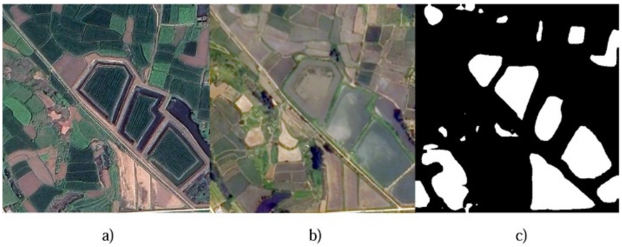

Fig. 6. Change detection result map (cropland changed to water body)

Figure 6 presents the change detection results for cropland converted to water bodies. As can be seen from the first area, the trained model correctly interpreted the change of arable land to water in the central area, but misjudged the change of arable land to wasteland in a small part of the area.

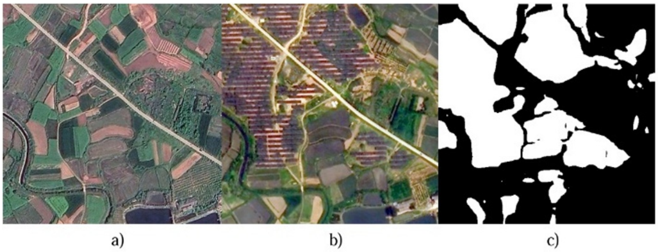

Fig. 7. Map of change detection results (arable land changed to PV land)

Figure 7 displays the detection outcomes for cropland-to-PV land conversion., it can be seen that the training model correctly identified that the cultivated land in the northwestern area has been turned into PV land, but there is a slight misclassification in the northwestern area.

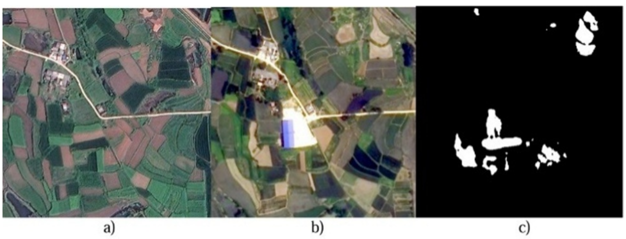

Fig. 8. Graph of change detection results (arable land changed to buildings)

Figure 8 illustrates building construction detection on former cropland. it can be seen that the training model correctly identified the location of the newly built greenhouses and the abandoned land in the northeast and southwest, but the interpretation of the entire area of the greenhouses is incomplete, andsome areas were misinterpreted, particularly where image quality or land cover features were ambiguous.

By analysing the change detection results of the above three selected areas, it can be preliminarily judged that the model can basically meet the change detection requirements of the four types of monitoring indicators of non-agriculturalisation and non-foodstuffs in this paper. However, the reasons for the misjudgement in some small areas are analysed as follows: 1) the spectral characteristics of some wasteland are different due to the change of lighting conditions in the before and after time-phase images, which leads to the failure of detecting the changes in non-foodification; 2) the CLCD dataset lacks of annotation of special features, which leads to the misdetection of changes in non-foodification.

In accordance with the above approach, several test areas were selected for this experiment, and the accuracy indexes of the experiment, i.e., Pre, Rec, F1 scores and IoU, based on the interpretation of the change areas by manual visual interpretation and the change areas predicted by the model, were calculated by comparing manual visual interpretations with model predictions, with the quantitative results presented in Table 3:

Table 3. Accuracy indexes of the change detection model.

model	***Pre(%)***	***Rec(%)***	***F1(%)***	***IoU(%)***
MSCANet	73.14	65.24	70.21	54.32

According to the accuracy results, the model can basically meet the needs of monitoring non-agriculturalisation and non-foodstuffs in the experimental area.

4 Conclusion

In response to the existing research background and progress of monitoring non-agricultural NTFPs on arable land based on multivariate remote sensing data, in order to achieve rapid and accurate perception of non-agricultural NTFP targets and change areas, this paper, based on multi-source optical remote sensing data and using a target detection and change detection model based on deep learning, carries out experiments in the experimental areas of Dunziwan and Yaomiao villages in Suizhou City, Suixian County, Hubei Province, with the aim of comparing and analysing and validating the effectiveness of the methodology of this paper. The effectiveness of the method of this paper was verified. On the one hand, for the detection of non-farming and non-food targets, this paper selects Yolov5, FasterR-CNN and other deep learning-based target detection models. Experiments show that the Yolov5 model can achieve basic recognition of photovoltaic land, abandoned land, new buildings, etc. in the experimental area, but there are misjudgments in a few areas, and the overall accuracy meets the requirements of this paper. On the other hand, for the change detection of non-agricultural and non-food areas, this paper refers to a multi-scale context-aggregated CNN-Transformer network in the latest research progress, and carries out change detection in the experimental area of Suixian County. Compared with traditional methods, the method used in this paper can obtain higher F1 scores and has certain advantages in terms of space and computational complexity. It can be preliminarily judged that the photovoltaic land in the southwestern region of the site has seriously occupied the arable land, some of the newly built ponds in the eastern region have occupied the original arable land, and the new greenhouses and other buildings in the central region have seriously occupied the arable land. In the future, with the development of remote sensing technology and artificial intelligence, the monitoring of non-agricultural and non-food cultivation of arable land based on multi-source remote sensing data will further evolve in the direction of intelligence and dynamics.

References

1. TAN Yong-zhong, HE Ju, YUE Wen-ze, ZHANG Liang, WANG Qing-ri. Spatial Pattern Change of the Cultivated Land before and after the Second National Land Survey in China[J]. Journal of Natural Resources, 2017,32(2): 186-197
2. Zhang, X., Liu, L., Liu, X., & Chen, Y. Multi-source remote sensing data fusion for land cover classification and change detection: A comprehensive review. Remote Sensing of Environment, 2023, 285, 113370.
3. Alzubaidi, L., Zhang, J., Humaidi, A. J., Al-Dujaili, A., Duan, Y., Al-Shamma, O., ... & Farhan, L. Review of deep learning: Concepts, CNN architectures, challenges, applications, future directions. Journal of Big Data, 2021, 8(1), 1-74.
4. Krizhevsky A, Sutskever I, Hinton G E. ImageNet classification with deep convolutional neural net works[J]. Communications of the ACM, 2017, 60(6): 84-90.
5. Liu Mengxi, Chai Zhuoqun, Deng Haojun, et al. A CNN-Transformer Network With Multiscale Co ntext Aggregation for Fine-Grained Cropland Change Detection[J]. IEEE Journal of Selected Topic s in Applied Earth Observations and Remote Sensing. 2022,15:4297-4306.
6. Johnson R D , Kasischke E S .Change vector analysis: A technique for the multispectral monitoring of land cover and condition[J].International Journal of Remote Sensing, 1998, 19(3):411-426.
7. Byrne G F , Crapper P F , Mayo K K .Monitoring land-cover change by principal component analys is of multitemporal landsat data[J].Remote Sensing of Environment, 1980, 10(3):175-184.
8. Lv Z , Liu T ,Jón Atli Benediktsson,et al.Land Cover Change Detection Techniques: Very-high-reso lution optical images: A review[J].Geoscience and remote sensing, 2022(1):10.
9. Tan K , Jin X , Plaza A ,et al.Automatic Change Detection in High-Resolution Remote Sensing Ima ges by Using a Multiple Classifier System and Spectral–Spatial Features[J].IEEE Journal of Selecte d Topics in Applied Earth Observations & Remote Sensing, 2016, 9(8):3439-3451.
10. Bazi Y , Bashmal L , Rahhal M M A ,et al.Vision Transformers for Remote Sensing Image Classific ation[J].Remote Sensing, 2021, 13(3):516.