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Identification Method of Diseased trees in Forest Areas Based on UAV Multispectral Remote Sensing and SCANet Model

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Abstract To address the problems of low efficiency and poor precision in traditional forest disease monitoring, an automatic identification method for diseased trees was proposed by combining UAV multispectral remote sensing with deep learning. A vertical take-off fixed-wing UAV equipped with a Rededge-MX multispectral camera was used to acquire high-resolution multispectral images of forest areas. After preprocessing steps including radiometric calibration and aerial triangulation, the SCANet semantic segmentation model was introduced to achieve automated extraction of discolored diseased trees. The results showed that the proposed method achieved a precision of 0.909 3, a recall of 0.808 2, and a miss rate of only 0.191 8 for diseased tree identification, significantly outperforming traditional methods such as support vector machine (SVM) and BP neural network, as well as mainstream deep learning models including ResNet and DenseNet. This method enables efficient, high-precision, and automated monitoring of diseased trees in forest areas, providing technical support for the prevention and control of forest pests and diseases.

Keywords Multispectral remote sensing, UAV, Deep learning, Diseased tree identification, Semantic segmentation

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Pine wilt disease and other wood diseases pose a major threat to forestry ecological security. Traditional manual survey methods suffer from low efficiency, limited coverage, and heavy reliance on human expertise, making it difficult to meet the demands of large-scale forest disease monitoring. UAV-based low-altitude remote sensing has become an important tool for forestry monitoring with its advantages of high resolution, high timeliness, and operational flexibility. However, visible-light remote sensing faces challenges such as spectral similarity among different objects and difficulty in identifying early-stage diseases. Therefore, multispectral remote sensing is adopted, which can enhance disease identification capability through differences in vegetation spectral characteristics[1-2].

In recent years, numerous studies have been conducted both domestically and internationally on remote sensing monitoring of forest pests and diseases. In early studies, spectral index methods and traditional machine learning approaches were commonly used for disease monitoring. However, these methods suffered from issues such as salt-and-pepper noise and reliance on manually selected features[3-4]. Deep learning technology has shown remarkable advantages in target recognition of high-resolution remote sensing images, with its automatic feature extraction capability. Nevertheless, existing semantic segmentation models are prone to losing spatial details when extracting small-target infected wood, and their identification accuracy still requires improvement[5-8].

To address the need for monitoring discolored diseased trees, this paper proposes a diseased tree identification method based on UAV multispectral remote sensing and the SCANet model. Based on the combination of multispectral features with deep learning semantic segmentation, the method achieves high-precision automated extraction of diseased trees, providing an efficient technical solution for the prevention and control of forest diseases.

1 Research Methods

1.1 UAV multispectral data acquisition and preprocessing

A Zongheng CW-007A vertical take-off fixed-wing UAV equipped with a Rededge-MX multispectral camera was used to acquire image data in five bands: blue (475 nm), green (560 nm), red (668 nm), red edge (717 nm), and near-infrared (840 nm), with a ground resolution of 15 cm.

The data preprocessing workflow included four steps. Specfically, (1) Radiometric calibration: Standard diffuse reflectance panels were photographed before take-off to establish the conversion relationship between image DN values and surface reflectance. (2) Post-processing differential calculation: PPK technology was applied to obtain high-precision POS data for high-precision positioning without ground control points. (3) Aerial triangulation: Band registration and aerial triangulation were completed using Pix4D software to generate multispectral orthophoto images. (4) Image enhancement: Band combination and histogram equalization stretching were applied to highlight the spectral characteristics of dead trees and extract forest land boundaries. The technical workflow is shown in Fig.1.

1.2 Infected wood semantic segmentation model based on SCANet

The SCANet semantic segmentation model was introduced to address the problem of detail loss in small-target diseased tree extraction. The core structure of the model includes three parts. (1) Context information module: Multi-scale down-sampling and an attention optimization module were used to extract semantic features at different scales, enhancing the model's ability to perceive infected wood of various sizes. (2) Spatial information retention module: Dense connection blocks and transition layers were combined to reduce spatial information loss during convolution, preserving the boundary details of diseased trees. (3) Atrous spatial pyramid pooling (ASPP): Atrous convolutions with different dilation rates were employed to expand the receptive field while avoiding

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checkerboard artifacts, balancing local details and global semantic information of diseased trees. The technical workflow is shown in Fig.2.

The model was optimized using the Adam optimizer with an initial learning rate of 10^{-2} and a batch size of 15, and trained for 60 epochs. Multi-scale sample augmentation was applied to prevent overfitting.

2 Experimental Results and Analysis

2.1 Experimental data and sample construction

The experimental area was a pine wilt disease-prone forest region in the Huangshan area. Multispectral image data were collected in September 2020, accompanied by simultaneous ground survey validation. A total of 558 discolored infected trees were delineated by visual interpretation to construct vector boundaries, and a sample library was established (Fig.3). The images and labels were segmented into two scales, 128×128 and 256×256, and divided into a training set (4,862 images) and a validation set (1,712 images) at a ratio of 3:1.

2.2 Evaluation indicators

Precision, recall, and miss rate were used as evaluation indicators. Precision is the proportion of correctly identified diseased trees out of the total number of detections, reflecting the reliability of the identification results. Recall is the proportion of correctly identified diseased trees out of the total number of actual diseased trees, reflecting the detection capability. Miss rate is the proportion of missed diseased trees out of the total number of actual diseased trees, reflecting the situation of missing inspection of diseases.

2.3 Experimental results and comparative analysis

For the SCANet+m model, the number of visual interpretation targets was 558, the number of detections was 496, and the number of correct detections was 451, achieving a precision of 0.909 3, a recall of 0.808 2, and a miss rate of 0.191 8. The model effectively extracted discolored diseased trees in the forest area (Table 1, Fig.4), with complete boundary extraction and no significant salt-and-pepper noise.

The proposed method was compared with traditional machine learning methods and mainstream deep learning models. Compared with traditional methods, support vector machine (SVM) and BP neural network exhibited severe issues of missed classification or misclassification. The maximum likelihood method achieved a relatively high recall but an extremely low precision (0.098 9), with extremely severe misclassification (Fig.5). Compared with deep learning models, HRNet, DenseNet, and ResNet all showed varying degrees of missed classification. The proposed method significantly outperformed other models in both precision

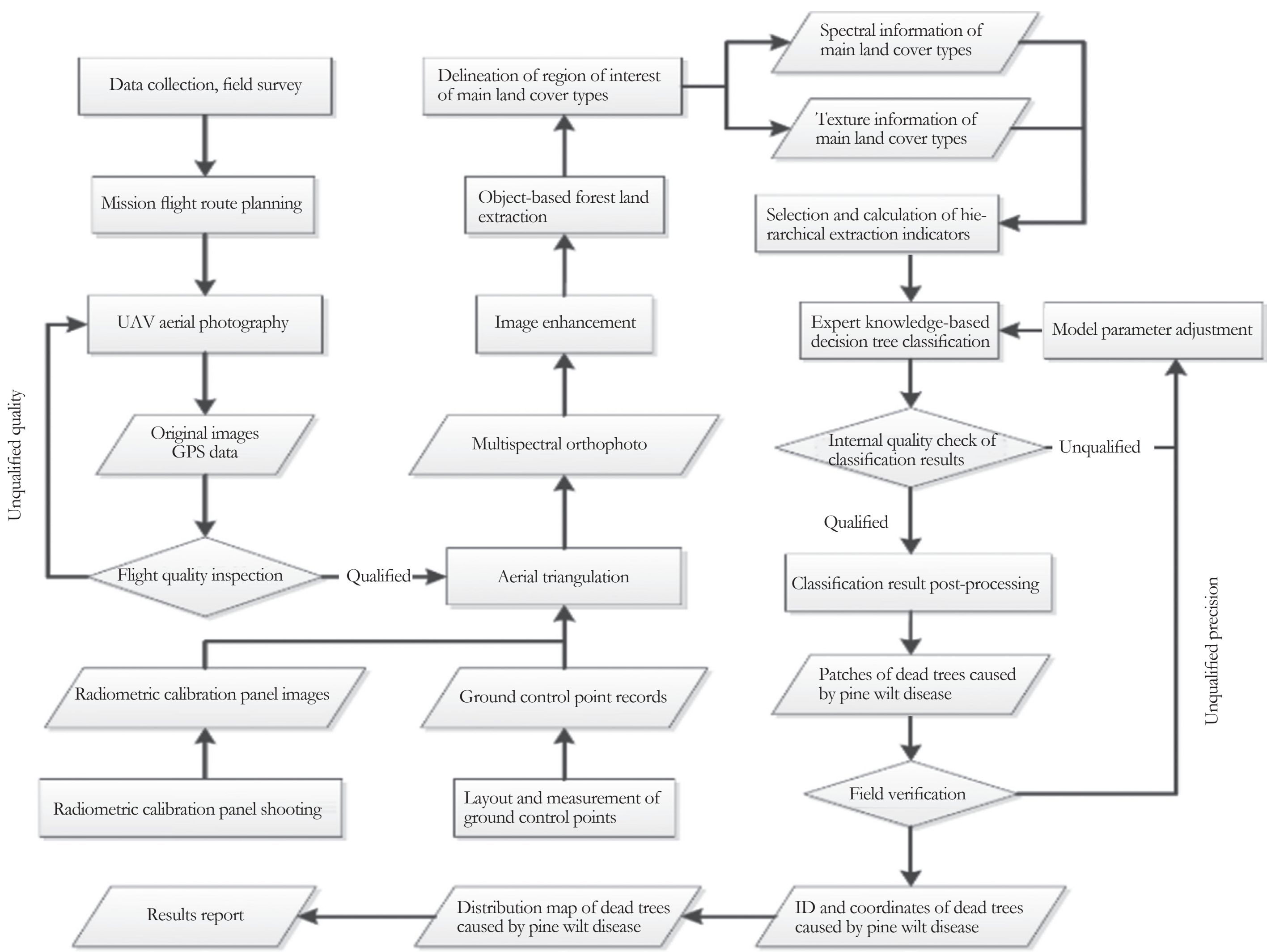

Fig.1 Technical workflow

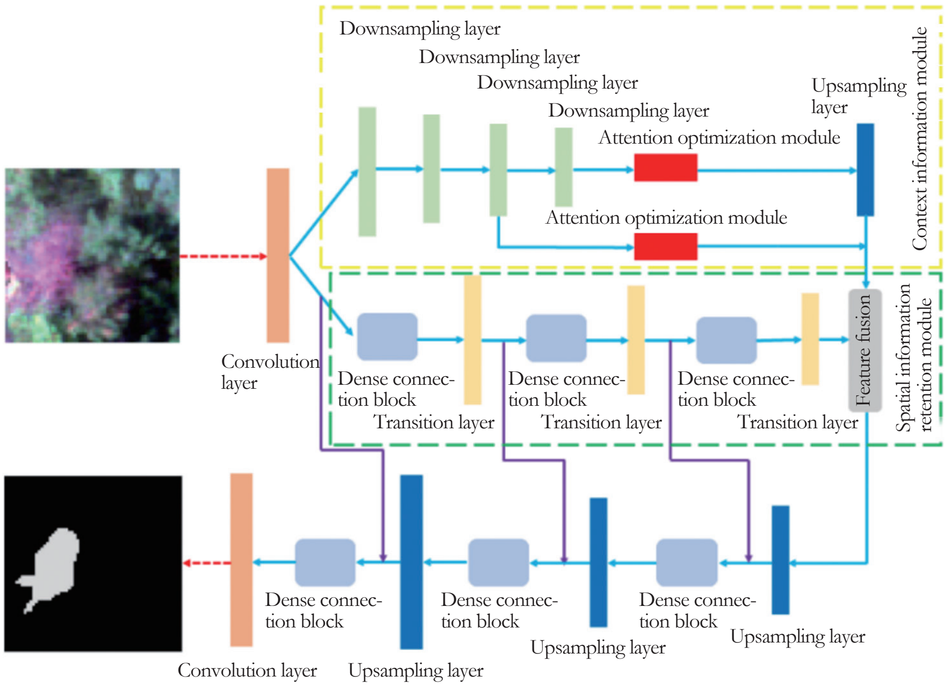

Fig.2 Technical workflow of the SCANet model

and recall, with more complete extraction results (Fig.6, Table 2).

3 Conclusions

The proposed method combining UAV multispectral remote sensing with SCANet deep learning for diseased tree identification has achieved automated and high-precision monitoring of discolored diseased tree in forest areas. The main conclusions are as follows:

(1) The proposed method achieved a precision of 0.909 3 and a recall of 0.808 2 for diseased tree identification, significantly outperforming traditional methods and mainstream deep learning models. It effectively reduced salt-and-pepper noise, misclassification, and missed classification, and yielded extraction results with good completeness.

(2) The diseased tree monitoring approach combining UAV multispectral remote sensing with deep learning offers the advantages of high efficiency, convenience, and high precision. It can

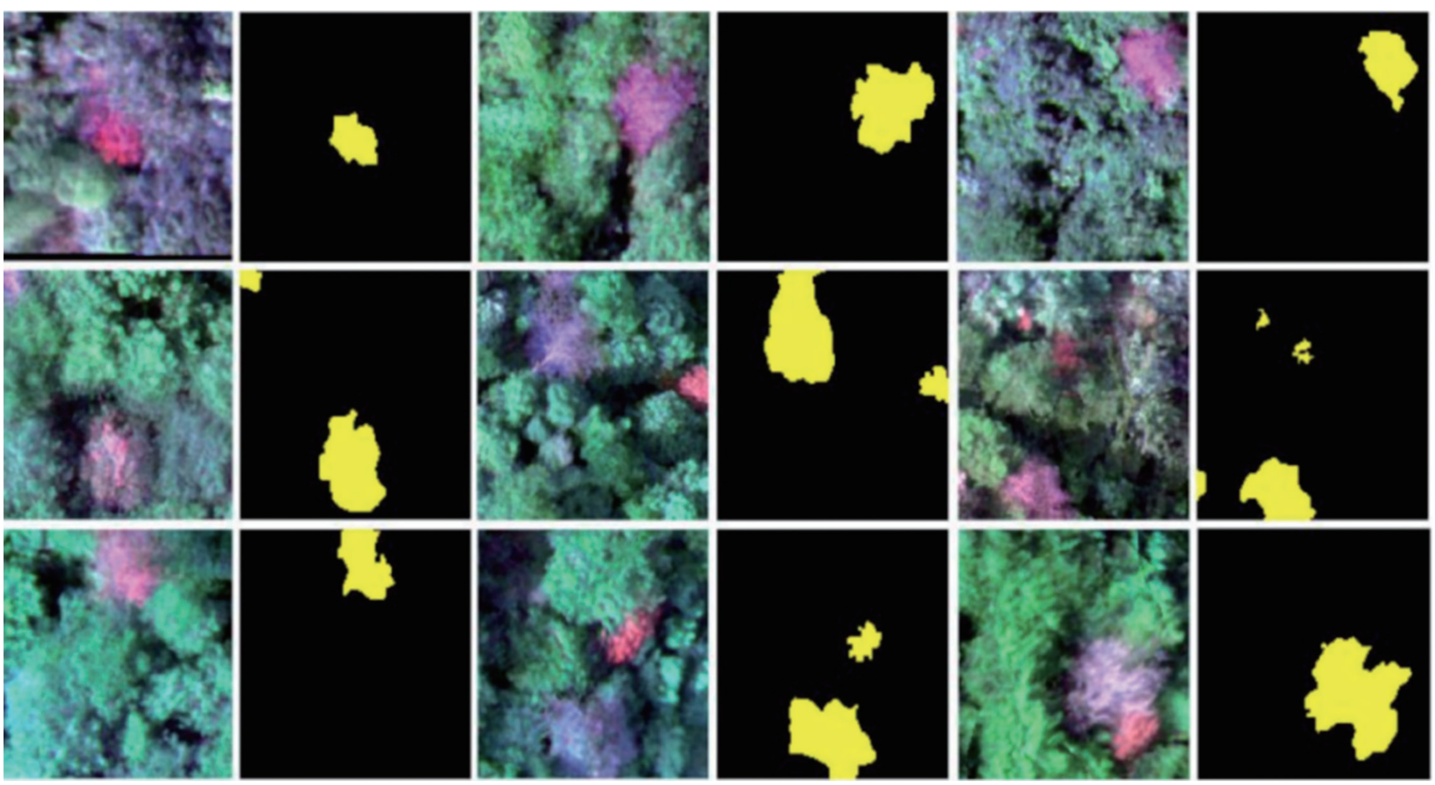

Fig.3 Sample library of diseased trees based on UAV remote sensing images

Table 1 Monitoring precision of SCANet in the pine wilt disease mornitoring area

Model	Number of visual interpretation targets	Number of detections	Number of correct detections	Precision	Recall	Miss rate
SCANet	558	496	451	0.909 3	0.808 2	0.191 8
Support vector machine	558	289	203	0.702 4	0.363 8	0.636 2
BP neural network	558	722	322	0.446 0	0.576 9	0.423 1
Maximum likelihood method	558	474	472	0.098 9	0.845 9	0.154 1

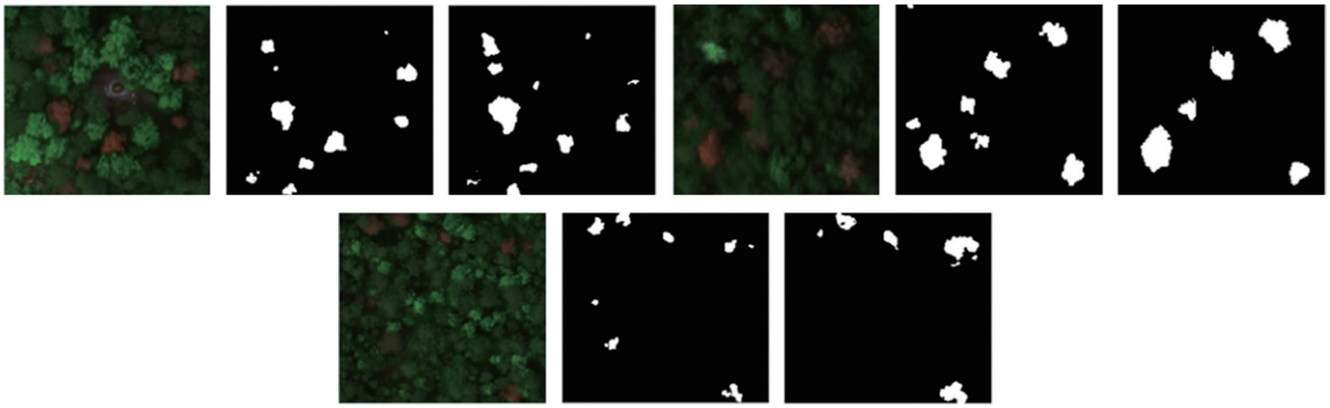

Fig.4 Detection results of discolored diseased trees

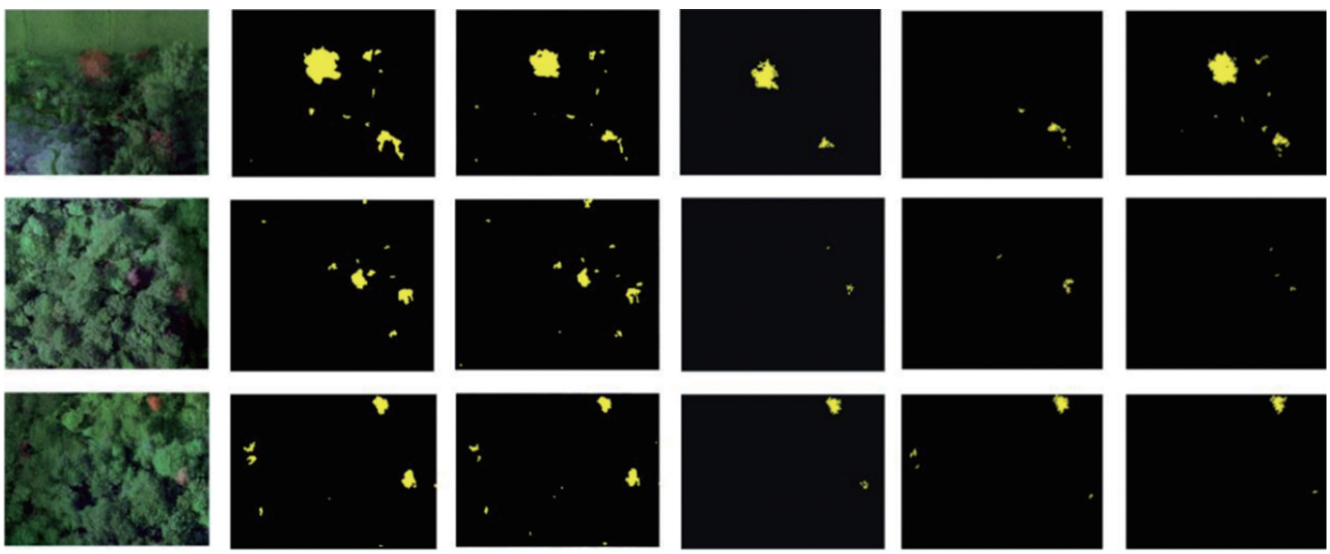

Fig.5 Comparison between the proposed method and traditional methods

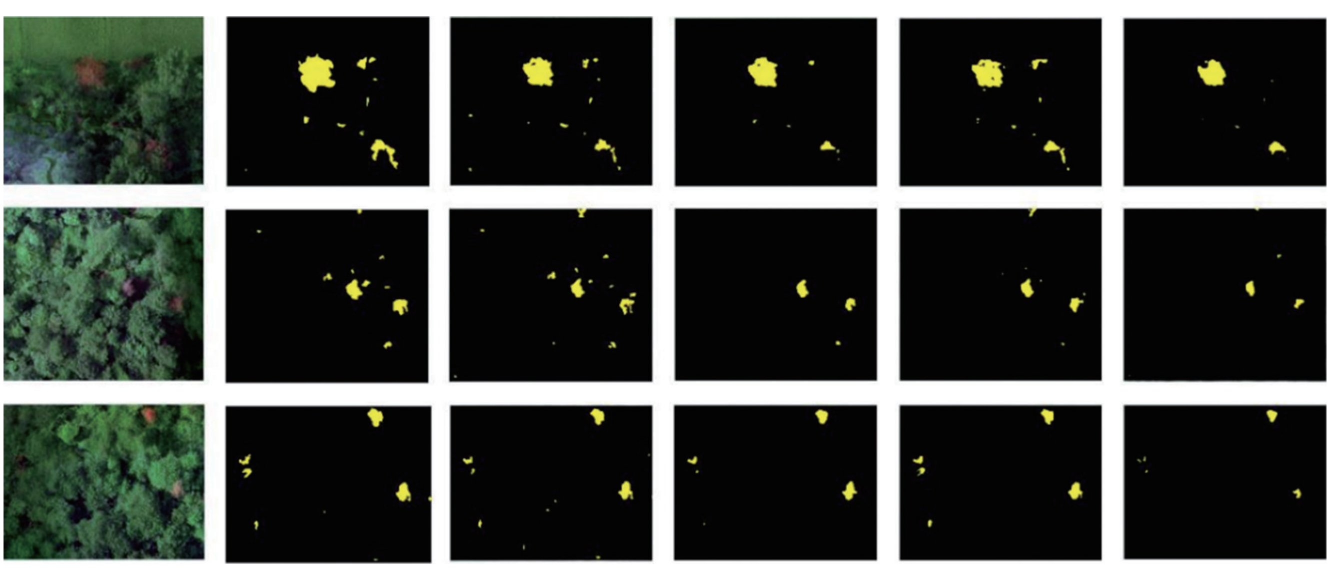

Fig.6 Comparison between the proposed method and other deep learning methods

(To be continued in P15)

scattered settlements located in disaster-prone and ecologically fragile areas. The construction of new rural houses should be strictly prohibited in areas susceptible to steep slopes and landslides. Such measures will effectively eliminate safety risks associated with human settlements at their source and establish a robust natural foundation for the spatial development of rural settlements.

Second, it is essential to promote differentiated regulation through multi-center agglomeration by leveraging the radiation of towns. GWR analysis demonstrates that urban location and economic development exert a significant positive impact on settlement agglomeration. The radiation range of towns should be delineated with the central urban area of Tiancheng Town, key towns, and major transportation arteries as focal points, thereby establishing a multi-nodal agglomeration development system. For low-efficiency settlement patches characterized by dispersion, hollowing, and inadequate supporting facilities in deep mountainous regions, a gradient spatial integration strategy should be adopted to guide the orderly concentration of settlement resources toward suburban areas of towns, central villages, and flatland industrial zones. The concentrated allocation of population, land, and public resources can improve the efficiency of facility utilization, optimize the human-land interaction patterns in mountainous regions, and promote the efficient and sustainable development of regional territorial spaces.

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(Continued from P8)

Table 2 Precision comparison of deep learning methods for diseased tree monitoring based on UAV remote sensing images

Model	Number of visual interpretation targets	Number of detections	Number of correct detections	Precision	Recall	Miss rate
Proposed method	558	496	451	0.909 3	0.808 2	0.191 8
HRNet	558	465	365	0.785	0.654	0.346
DenseNet	558	482	397	0.824	0.711	0.288
ResNet	558	435	375	0.862	0.672	0.327

replace traditional manual surveys and provide technical support for the prevention and control of pine wilt disease and other forest pathogens in large-scale forest areas.

(3) Future research will further enrich the sample library covering multiple scenarios and disease stages, optimize the model's ability to distinguish spectrally confused ground objects, and improve the identification accuracy of early-stage diseases.

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