Exploring the Aurrent Status of the Application of Drone Remote Sensing Technology in Agroforestry Pest Control

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Abstract. As an essential pillar industry of the national economy, agriculture and forestry industries are often seriously threatened by diseases and pests such as stem-boring pests and stem borers, which lead to crop yield reduction and even crop failure. For this reason, the establishment of a scientific and practical monitoring and early warning mechanism and the implementation of precise prevention and control measures are important measures to ensure the safety of agricultural production and ecological security. The purpose of this paper is to explore the advantages of UAV remote sensing in the application of pest control in agriculture and forestry. Meanwhile, this paper focuses on analyzing the current status of the application of a comprehensive vegetation index combined with deep learning methods. This paper proposes two possible directions for future research: one is to explore the synergistic application mode of satellite remote sensing and UAV remote sensing; the other is to study the changing law of spectral features of different crops in each growth stage to optimize the selection of monitoring parameters. The analyses in this paper can provide a valuable scientific basis for advancing the practical application of UAV remote sensing technology in the monitoring of pests and diseases in agriculture and forestry, and thus promote the sustainable development of pest control in agriculture and forestry.

Keywords: Unmanned aerial remote sensing, multispectral remote sensing monitoring, deep learning.

1. Introduction

Agroforestry is a basic industry of the national economy and is related to national food security, ecological security and sustainable economic development. However, in recent years, global climate change, changes in farming systems and increased resistance to pests and diseases have led to a sustained increase in the frequency and extent of pests and diseases in agriculture and forestry, seriously threatening the production safety of the agriculture and forestry industries. According to the Food and Agriculture Organization of the United Nations (FAO), crop yield losses due to plant diseases and invasive insects are as high as 40% globally each year, with economic losses exceeding US$220 billion and US$70 billion, respectively [1]. Therefore, to prevent pests and diseases in agroforestry and reduce economic losses, monitoring of agroforestry is necessary.

Traditional pest and disease monitoring methods mainly rely on manual field surveys, which are labor-intensive and inefficient and are often more difficult to survey in forested areas and other areas with complex terrain, making it difficult to detect early symptoms of pests and diseases promptly, which can easily result in delays in prevention and control and increase prevention and control costs [2]. With the rapid development of remote sensing technology, especially the wide application of advanced sensors such as multispectral and hyperspectral sensors carried by UAV platforms, new technical means are provided for the rapid, large-area, non-destructive monitoring of agricultural and forestry pests and diseases. With the advantages of high spatial resolution, flexible data acquisition, relatively low cost, and easy operation, UAV remote sensing is particularly suitable for monitoring in forested areas with complex terrain and large-scale farmland and has shown great potential for application in the field of monitoring pests and diseases in agriculture and forestry.

In recent years, scholars at home and abroad have carried out a large number of studies around the application of UAV remote sensing in the monitoring of agricultural and forestry pests and diseases. The relevant research mainly focuses on the following aspects: firstly, the research on the identification of pests and diseases based on spectral features. Wang Yiding showed that vegetation suffering from pests and diseases would show obvious spectral feature changes in the visible to near-infrared bands [3]. Second, the image recognition research of pest and disease symptoms. Song Yining et al. used a drone carrying a high-resolution camera to obtain images of pest and disease areas and identified symptomatic features such as disease spots and wilting through image segmentation and feature extraction [4]. Third, research on the construction of pest and disease early warning models. Shen Yanyan et al. attempted to combine remote sensing monitoring data with meteorology, topography, and other environmental factors to establish a prediction model for pest and disease occurrence and development [5]. In addition, some researchers have also explored the collaborative application of multi-source remote sensing data, such as Gao Xiaowen's classification model (SSCNN-PELM) based on joint spatial-spectral convolutional neural network and parallel heterogeneous extreme learning machine [6].

This paper aims to discuss in depth the current status and development trend of the application of UAV remote sensing technology in the field of monitoring pests and diseases in agriculture and forestry by systematically analyzing the relevant literature and taking multispectral remote sensing monitoring technology as an example. We will focus on the applicability of different monitoring methods and their limitations in various application scenarios, and propose corresponding solutions to the key technical problems encountered in practice. Finally, it is hoped that this paper will provide a valuable scientific basis for promoting the practical application of UAV remote sensing technology, to promote the advanced means and sustainable development of pest control in agroforestry.

2. Theoretical basis for multispectral remote sensing monitoring

The spectral reflectance of plant leaves can change as a result of pests and diseases, and this change is particularly evident in specific wavelength bands. For example, healthy plant leaves typically have high reflectance in visible (e.g., green) and near-infrared wavelengths and low reflectance in red wavelengths. However, when plants are attacked by pests and diseases, their photosynthesis and physiological functions are inhibited, leading to a decrease in chlorophyll content and damage to leaf structure, which results in a decrease in spectral reflectance in the near-infrared wavelengths and a relative increase in the red-light wavelengths [7][8]. This change in spectral characteristics can be captured by multispectral cameras and used for pest and disease identification and monitoring. The spectral information of different bands reflects the reflectance characteristics of plants in different physiological states. For example, the red-edge bands are very sensitive to physiological changes in plant leaves and can effectively reflect the health status of plants. By exploiting the differences in spectral reflectance of these bands, spectral indices (e.g. Normalised Vegetation Index NDVI, Normalised Difference Red Edge Index NDRE, etc.) can be constructed to distinguish healthy plants from those affected by pests and diseases.

However, in the process of constructing the spectral index, if the monitoring target is too small it may lead to poor image quality, which in turn affects the monitoring results. At this time, deep learning algorithms can be an effective solution. The deep learning algorithm is based on artificial neural networks, simulating the information processing mechanism of the human brain, which belongs to an important branch of machine learning. It has a strong learning ability and can complete large-scale, high-precision data processing through the training of a large amount of data. For example, a convolutional neural network (CNN) can automatically extract features in an image, such as the shape, texture, and color of leaves, through convolutional, pooling, and fully connected layers. In addition, certain models, such as the YOLO series, can detect targets of different sizes at the same time with the help of multi-scale feature extraction techniques, which significantly improves the detection ability of small and dense targets, thus effectively solving the problem of poor image quality due to the small size of the target [9].

The Normalised Vegetation Index (NDVI) quantifies vegetation conditions by measuring the difference between the near-infrared band (strongly reflected by vegetation) and the red light band (absorbed by vegetation). The index is most accurate in the middle of the season when crops are most active, and has a range of values between -1 and 1. Positive areas usually indicate the presence of vegetation on the surface, and the index value is positively correlated with vegetation growth: the closer the value is to 1, the denser and better the vegetation cover in the area. On the contrary, negative values usually represent non-vegetated areas, such as water or cloud-covered areas.

The Normalised Difference Red Edge Index (NDRE) can also be used to assess the health of vegetation in multispectral images. Similar to NDVI, NDRE is calculated based on the ratio of the near-infrared to the red-edge bands but is more suitable for monitoring crops at the maturity stage.NDRE also takes values from -1 to 1, with a positive value usually reflecting healthy vegetation growth, while a negative value suggests that the vegetation is stunted or in a state of stress.

The overall architecture of the deep learning method represented by YOLOv5 is divided into four parts: input, Backbone, Neck, and Head. The backbone adopts the Focus structure and the CSP structure for feature extraction, while the Neck is fused by the FPN+PAN structure with the extracted features, and the Head is used to complete the output of the target detection results. For different detection algorithms, the number of branches at the output varies, usually containing a classification branch and a regression branch [10].

3. Multispectral remote sensing studies and results

In modern agriculture, pest and disease monitoring and management is a key link to ensure crop health and improve yield. With the development of science and technology, UAV remote sensing technology has gradually become an important tool in this field, and with its high efficiency and accuracy, it can quickly obtain a large amount of information in the vast farmland and provide strong support for agricultural production.

Wang Chung-ha and Yan Yuncai's research conducted pest and disease monitoring for cotton and kiwifruit orchards, respectively. Wang Chung-hsia constructed a model for chlorophyll inversion and yield estimation in cotton by using an unmanned aerial vehicle (UAV) multispectral remote sensing platform in combination with ground-based measured data and found that spectral parameters such as the normalized vegetation index (NDVI) were significantly correlated with chlorophyll content, which was effective in inverting the chlorophyll content of cotton and predicting the yield [11]. Yan Yuncai, on the other hand, achieved high-precision detection of kiwifruit pest and disease leaves by combining deep learning models (e.g., YOLOv5) with air-ground multi-source information, with a model precision of 99.54% and a recall of 99.24% [12]. These studies show that UAV remote sensing technology combined with multispectral data and deep learning models can effectively identify crop pests and disease patches and assess the health status, which provides strong support for the fine management of agriculture.

3.1. Data sets and pre-processing

The multispectral data used in the experiments come from either the UAV-built high-resolution camera or the Sentinel-2 satellite remote sensing data source, which consists of multiple bands (e.g., red, green, blue, near-infrared, and red-edge bands) Sentinel-2 carries a Multispectral Imager (MSI), which is orbiting at an altitude of 786 kilometers, and has sensors on board that can achieve spectral observations in 13 bands, with coverage extending to 290 kilometers. The coverage extends to 290 kilometers. Its spatial resolution is distributed in three levels: 10 meters for the fine level, 20 meters for the medium level, and 60 meters for the coarse level. In the case of a single star, a revisit can be completed every 10 days, and the revisit period is shortened to 5 days when the two stars are operated together. At high latitudes, such as in Europe, the frequency of observations can be increased to once every three days thanks to the overlapping orbits. The observation capability of the sensor spans the visible, near-infrared, and short-wave infrared wavelength bands, with multi-level spatial resolution. As a unique presence in the optical remote sensing system, Sentinel-2 is currently the only satellite configured with three observation bands in the red-edge region, a feature that gives it a significant advantage in monitoring vegetation growth [13].

3.2. Feature Extraction and Index Calculation

In a study by I Ainunnisa and H Haerani, using rice growing areas in Indonesia, the calculation of Normalised Vegetation Index (NDVI) and Normalised Red Edge Vegetation Index (NDRE) was able to effectively differentiate between the health status of rice and the degree of being affected by pests and diseases [14]. The results of the study showed that rice unaffected by pests and diseases had high NDVI values ranging from 0.7620 to 0.8064, whereas rice infested with pests and diseases had significantly lower NDVI values ranging from 0.3814 to 0.4788. In contrast, the NDRE index, which is more sensitive to phytoplankton chlorophyll, had values that were lower in rice affected by pests and diseases, ranging from 0.2951 to 0.3897, while NDRE values in healthy rice ranged from 0.5726 to 0.6598.

The study further analyzed the correlation between NDVI and NDRE indices and rice yield using simple linear regression. The results showed that the linear regression equation between NDVI and rice yield was $y=11.583x-3.6186$ with a coefficient of determination, R^2, of 0.7943, indicating that 79.43 percent of the variation in rice yield could be explained by NDVI values. Whereas, the linear regression equation between NDRE and rice yield was $y=14.145x-3.509$ with a coefficient of determination R^2 of 0.8077 indicating that 80.77 percent of the variation in rice yield could be explained by NDRE values. This indicates that the NDRE index has higher relevance in assessing rice yield and more accurately reflects the health and yield potential of rice compared to the NDVI index, while the deviation of NDVI is smaller when comparing the estimated yield with the actual yield, which provides an important reference for optimizing the selection of parameters for monitoring the growth period and estimated yield.

3.3. Target Detection and Classification

In their study, Peihua Cai et al. proposed a deep learning-based target detection framework for identifying pine trees infected with pine wilt disease (PWD) [10]. The study combined high-resolution unmanned aerial vehicle (UAV) RGB imagery and freely available Sentinel-2 satellite multispectral imagery for disease detection at the single pine tree level via an improved YOLOv5-PWD model and introduced effective data enhancement methods to improve model performance.

In terms of detection methods, the research team first used the UAV to acquire high-resolution RGB images and combined them with multispectral information from Sentinel-2 satellite images to enhance the identification of diseased pine trees by calculating the Normalised Vegetation Index (NDVI) and the Normalised Red Edge Vegetation Index (NDRE). The YOLOv5-PWD model, based on the original YOLOv5, introduces the efficient intersection and concatenation ratio (EIoU) loss function to enhance the accuracy and convergence speed of target detection. In addition, in order to overcome the problem of a limited number of samples, the study proposes a sample synthesis method based on Sentinel-2 images, which filters the suitable synthesis location by vegetation index and adopts a weighted synthesis strategy to make the synthesized images of diseased pine trees more realistic, so as to improve the training effect of the model and the detection accuracy.

The experimental results show that the model is able to accurately identify pine trees infected with pine wood nematode disease with more than 90% localization accuracy, showing high identification accuracy and reliability. Meanwhile, the spatial distribution of healthy pine trees and infested areas showed obvious stratification characteristics, and the infested patches were mainly concentrated in specific areas, and this difference in spatial distribution provided important spatial information support for early monitoring and precise prevention and control of infestation.

3.4. Pest and disease monitoring and forecasting

In the study, Yanhong Chen used an integrated approach to monitor pests and diseases and predict their outbreak periods. Specifically, the first step was to identify pest and disease areas by integrating Normalised Vegetation Index (NDVI) data and using its sensitivity to vegetation health status [15]. On this basis, the output of the deep learning model was combined to further enhance the model's ability to identify pests and diseases and its prediction accuracy. By learning a large amount of historical data and sample features, the deep learning model can automatically extract the spatial and temporal distribution patterns of pests and diseases, thus providing powerful support for accurate monitoring of pests and diseases and prediction of outbreak periods.

The experimental results showed that the rate of change of NDVI in healthy crops was generally lower than 10, which indicated that the photosynthesis and growth status of vegetation were relatively stable under normal growth conditions, and the changes in NDVI values were small. However, in the area of pests and diseases, the rate of change of NDVI showed a trend of high values, which is mainly because pests and diseases can negatively affect the photosynthesis and growth of vegetation, resulting in changes in the spectral reflectance characteristics of vegetation, which in turn led to a significant increase in the NDVI values. This difference provides an important basis for pest and disease monitoring using NDVI.

Further model validation showed that the developed model has high credibility and applicability. The F-test showed that the F-value of the model reached 25.641, which was much larger than the critical value $F(1,70,0.01)$. This result indicates that the model is statistically significant, can effectively distinguish between healthy crops and infested areas, and has high accuracy in predicting the outbreak period of pests and diseases. This means that the model is not only able to accurately identify current pest and disease areas but also able to warn pest and disease outbreaks in advance, providing important decision support for agricultural production and ecological protection.

4. Challenges and prospects

Although UAS remote sensing technology has made significant progress in the field of agricultural monitoring, it is still facing some technical bottlenecks and challenges. Specifically, UAS are susceptible to environmental constraints, making it difficult to maintain stable flight operations under adverse weather conditions such as strong winds and rainfall. In addition, limited by the performance of the power system, the endurance of the UAV makes it difficult to meet the practical needs of monitoring large areas of farmland. At the same time, as different crops and their growth stages present unique spectral characteristics, this requires targeted construction and optimization of monitoring models, which undoubtedly increases the practical application costs. How to select the optimal monitoring parameters for the changes in spectral characteristics of crops in different growth stages is also a key issue waiting to be solved.

In response to the limitations of UAV remote sensing in farm monitoring, some studies have attempted to complement it with satellite remote sensing data. The study by I Ainunnisa & H Haerani integrated Sentinel-2 satellite remote sensing data with rice at the end of the growth stage. Their study showed that the linear regression analysis revealed that the NDRE index was more highly correlated with crop productivity than NDVI at the rice maturity stage, whereas the deviation of NDVI was smaller when comparing the estimated yield with the actual yield, which provides an important reference for optimizing the selection of parameters for monitoring the growth period and estimated yield. This study reveals two potential research routes: on the one hand, the synergistic application mode of satellite remote sensing and unmanned aircraft remote sensing can be explored to give full play to the advantages of the wide coverage of satellite remote sensing; on the other hand, in-depth research on the changing law of spectral features of different crops at each growth stage can be combined with the field situation, in order to optimize the selection of monitoring parameters and enhance the performance of the model.

In addition, the current problems in the research of UAV remote sensing include: the applicability of different monitoring methods in different application scenarios in agroforestry varies greatly, and there is a lack of systematic comparative analyses and assessment standards; early identification and accurate diagnosis of pests and diseases in complex terrain, mixed forests, or large-scale farmland still face challenges; the level of multi-source data fusion and intelligent analyses needs to be improved; and the cost-effectiveness of the actual application and extension mode need to be further explored [16].

The future research of UAV remote sensing in the field of agricultural monitoring will be further deepened, and the primary direction is to promote the development of multi-source data fusion technology, fully integrate the advantages of satellite remote sensing and UAV remote sensing, and realize an all-weather, wide-range and high-efficiency agricultural monitoring system. Secondly, we will continue to optimize the performance of deep learning models, improve the accuracy and efficiency of pest and disease identification, and improve the practicality of early warning models. In addition, an in-depth study of the differences in the characteristics of different crops at various growth stages, and the establishment of a more accurate monitoring parameter system, to improve the effectiveness of the model early warning. With the deepening of theoretical innovation and technological breakthroughs, UAV remote sensing technology will certainly play a more important role in the development of agriculture and forestry.

5. Conclusion

This paper systematically studies the current status of the application of UAV remote sensing technology in the monitoring of pests and diseases in agriculture and forestry and analyses its effectiveness in pest and disease monitoring by integrating multispectral remote sensing data (e.g. NDVI and NDRE) and deep learning methods (e.g. YOLOv5). The research methodology includes the use of UAV-mounted multispectral cameras to acquire high-resolution image data, identifying pest and disease areas by calculating the vegetation index, detecting and classifying pest and disease patches by combining the deep learning model, and constructing pest and disease monitoring and outbreak prediction models to verify their applicability.

It was found that the NDVI and NDRE values of healthy crops were generally higher, while the vegetation indices of pest and disease areas were significantly lower, indicating that these indices can effectively distinguish between healthy and pest-affected crops. The improved YOLOv5 model achieves high-precision detection of pest and disease areas, with a positioning accuracy of more than 90%, and the model is able to effectively identify the spatial distribution characteristics of pests and diseases, which provides support for early monitoring and precise prevention and control.

In the future, we can focus on the synergistic application of satellite remote sensing and UAV remote sensing, and build an all-weather, wide-range, and high-efficiency pest and disease monitoring system by integrating the advantages of the two. Explore the changing law of spectral features of different crops at various growth stages, optimize the monitoring parameters, improve the adaptability and accuracy of the model, and meet the needs of diversified pest and disease monitoring. On this basis, the deep learning model should be continuously improved to enhance the accuracy and efficiency of pest and disease identification and improve the practicability of the early warning model, so that it is more suitable for complex environments and large-scale application requirements. In addition, it is also necessary to explore the practical application path of UAV remote sensing technology in the monitoring of pests and diseases in agriculture and forestry and strive to reduce the cost and improve the promotion efficiency, so as to provide a solid guarantee for the sustainable development of agriculture and forestry.

Authors Contribution

All the authors contributed equally and their names were listed in alphabetical order.

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