Current status and future directions of weed recognition by UAV remote sensing

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Abstract: Weed mapping is essential for Site Specific Weed Management (SSWM), which may reduce the negative effects of chemical control while enhancing the effects. The UAV remote sensing platform can rapidly collect the imagery of large scale fields, which may provide efficient decision making information of SSWM applications. This paper explores extensive literature on weed recognition by UAV remote sensing, and classified them into weed classification, weed detection and weed mapping categories according to the research objectives and the corresponding techniques. For each category, we introduce several state of the art researches and summarize its limitations according to the general experimental results. Further, we draw the future directions of the weed recognition, which may effectively address the technique limitation of the current research. In general, the deep learning methods may benefit the weed recognition by UAV remote sensing with its strong data interpretation capability.

Keywords: weed mapping; UAV imagery; OBIA; semantic segmentation; semi-supervised learning
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1 Introduction

Weed mapping is essential for Site Specific Weed Management (SSWM), which may reduce the negative effects of chemical control while enhancing the effects[1]. In recent years, UAV (Unmanned Aerial Vehicle) equipped with remote sensing technologies have emerged as powerful tools for collecting high-resolution imagery of agricultural fields[2,3]. These platforms offer a bird's-eye view that enables the capture of detailed information about the spatial distribution, growth patterns, and health status of crops and weeds. This wealth of data, when coupled with advanced machine learning techniques, has the potential to revolutionize weed recognition and management by providing timely, accurate, and site-specific information. However, the transition from raw imagery to actionable insights requires robust and adaptable algorithms capable of differentiating between crops and weeds amidst varying illumination, occlusion, and environmental factors.

With the remote sensing data captured by the UAV platform, the machine learning plays an important role in the data interpretation. In recent years, the synergy between UAV remote

With the remote sensing data captured by the UAV platform, the machine learning plays an important role in the data interpretation. In recent years, the synergy between UAV remote sensing and machine learning has led to significant advancements in weed recognition. Researchers have developed models capable of not only accurately detecting weeds but also identifying specific weed species and their growth stages. These advancements have the potential to transform weed management strategies from blanket herbicide applications to targeted interventions, reducing environmental impact and operational costs. Additionally, the ability to provide real-time insights through UAV imagery enables farmers to make informed decisions, optimizing resource allocation and enhancing overall crop health.

In general, weed recognition by UAV remote sensing represents a transformative advancement in modern agriculture. The combination of high-resolution imagery and sophisticated machine learning algorithms has the potential to revolutionize weed management practices, minimizing the impact of weeds on crop yield while promoting sustainable farming. As technology continues to advance, the fusion of UAV remote sensing, machine learning, and domain expertise offers the prospect of transforming the way we perceive and address the traditional challenge of weed infestations in agricultural landscapes. By exploring the capabilities of UAV remote sensing and machine learning in weed recognition, this article aims to provide farmers with an efficient and sustainable solution to managing weeds in their crops.

2 Current status

Generally, the research of weed recognition by UAV remote sensing can be classified into weed classification, weed detection, and weed mapping. The research of weed classification only

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considered the category of one patch of UAV imagery, while the weed detection search for the location of the weeds, and the weed mapping conduct pixel wise classification over the whole UAV imagery.

2.1 Weed classification by UAV remote sensing

Adnan Farooq et al.[4] proposes a novel method for weed classification using remote sensing images. Their approach integrates Convolutional Neural Networks (CNN) and Superpixel-based Local Binary Pattern (LBP) analysis across multiple resolutions. The study quantitatively evaluates the performance, achieving improved accuracy in weed species classification compared to individual methods. Austin Eide et al.[5] presents a groundbreaking study on UAV-assisted weed detection for glyphosate resistance. It employs thermal infrared and multispectral imaging to analyze weed canopies. The research quantitatively assesses the effectiveness of this approach, achieving notable success in identifying glyphosate-resistant weeds. Olee Hoi Ying Lam et al.[6] presents an innovative study on weed mapping in native grasslands using unmanned aerial vehicles (UAVs). Focusing on Rumex obtusifolius as a case study, the research introduces an open-source workflow for accurate weed mapping. The study quantitatively evaluates the effectiveness of this approach, achieving significant success in identifying and mapping the target weed species. Shahbaz Khan et al.[7] introduces an innovative semi-supervised framework for crop/weed classification using UAV imagery. The study presents a novel approach to efficiently classify crops and weeds. Quantitative experiments demonstrate the effectiveness of this method, achieving notable accuracy in distinguishing between crops and weeds. Reenul Reedha et al.[8] presents a pioneering study on weed and crop classification using high-resolution UAV images. The research introduces a Transformer Neural Network (TNN) for accurate and efficient classification. Through quantitative experiments, the study demonstrates the effectiveness of the TNN approach, achieving remarkable results in distinguishing between weeds and crops. Mohd Anul Haq[9] presents an innovative study on automated weed detection using UAV imagery. The research employs Convolutional Neural Networks (CNN) for accurate weed identification. Quantitative experiments demonstrate the efficacy of the CNN-based system, achieving significant success in detecting weeds.

From the related researches, it can be seen the weed classification researches develop rapid over the last decade, and the applied algorithms evolved from the vegetation indices, normal machine learning to deep learning. Accordingly, the classification accuracy has increased by a large margin, which has proven its feasibility in real applications. However, most of the current researches only consider the weed classification problem as one category problem, while the related imagery may contain two or more types of weeds. Therefore, the multi task technique may be suitable to address this problem.

2.2 Weed detection by UAV remote sensing

Arun Narenthiran Veeranampalayam Sivakumar et al.[10] presents a comparative study of deep learning models for mid- to late-season weed detection in UAV imagery. The research compares Object Detection and Patch-Based Classification models. Quantitative experiments analyze their performance, revealing their effectiveness in weed detection. Shahbaz Khan et al.[11] presents a deep learning-based identification system for distinguishing weeds and crops in strawberry and pea fields, aimed at precision agriculture spraying. The research utilizes advanced deep learning techniques for accurate classification. Quantitative experiments demonstrate the system's efficacy, achieving significant success in differentiating between weeds and crops. Aaron Etienne et al.[12] introduces a novel approach utilizing deep learning for weed identification through UAS (Unmanned Aerial System) imagery. The study develops a sophisticated object detection system specifically designed for accurate weed detection. This innovative framework leverages advanced deep learning techniques to locate and distinguish weeds within the UAS imagery. Muhammad Hammad Saleem et al.[13] presents a significant advancement in weed detection using the Faster R-CNN model. The study introduces an innovative approach that enhances the anchor box methodology. By optimizing the anchor box configuration, the research achieves improved precision and recall rates in weed detection. Jiqing Chen et al.[14] introduces a novel approach for weed detection in sesame fields using a YOLO model. The study presents an enhanced attention mechanism and feature fusion technique to improve the accuracy of weed detection. By incorporating these innovations, the research achieves notable success in accurately identifying weeds amidst sesame crops. Ignazio Gallo et al.[15] focuses on crop weed detection using the YOLOv7 model on a real-case dataset of UAV images. The study evaluates the performance of YOLOv7 in accurately identifying crop weeds. It presents results demonstrating the model's efficacy in detecting weeds within agricultural fields. Oluibukun Gbenga Ajayi et al.[16] investigates the effectiveness of the YOLOv5 model in automatically classifying crops and weeds in UAV images. The study evaluates the model's performance in accurately distinguishing between crops and weeds. The research contributes by presenting results that showcase the YOLOv5 model's capability for precise crop and weed classification. Fernando J. Pérez-Porras et al.[17] addresses early and on-ground image-based poppy (Papaver rhoeas) detection in wheat fields using YOLO architectures. The study pioneers the application of YOLO models for identifying poppy weeds within wheat crops. By focusing on early detection and ground-level imagery, the research introduces a practical solution for weed management. Xinle Zhang et al.[18] presents a novel study on weed identification in soybean seedling stages using an optimized Faster R-CNN algorithm. The research focuses on developing an enhanced method for accurately identifying weeds amidst soybean seedlings. By optimizing the Faster R-CNN algorithm, the study achieves significant success in weed detection. Haoyu Wu et al.[19] introduces a pioneering study on small-target weed detection using an improved YOLO-V4 model. The research focuses on enhancing the backbone and neck structures of the YOLO-V4 architecture to better detect small weeds. The study achieves notable success in accurately identifying weeds within challenging conditions. This research's innovation lies in optimizing the YOLO-V4 model for precise small-target weed detection, offering valuable insights for improving weed management practices in agriculture through advanced image analysis techniques.

From the above literature, it can be seen most of researches applied the newly evolved object detection models in deep learning to search the location of the weeds. Generally, the pretrained weights on the public dataset were transfered and finetuned on the weed dataset to prevent the problem of overfitting caused by the shortage of the weed dataset. The main problem is that the classification phase may be stuck by some weed categories that are insufficient in data samples. In this occasions, the few shot learning may be suitable to extent the limitation of weed detection.

2.3 Weed mapping by UAV remote sensing

Huasheng Huang et al.[20] conducted a comparative study between deep learning and Object-based Image Analysis (OBIA) for weed mapping using UAV imagery. The research aimed to assess the effectiveness of both approaches in accurately mapping weeds. Results indicated that deep learning outperformed OBIA in achieving more precise and detailed weed mapping results. This study highlighted the superior performance of deep learning techniques in weed mapping, contributing valuable insights for advancing weed management practices through advanced image analysis methods. Joseph E. Hunter et al.[21] conducted a study focused on the integration of remote weed mapping and an autonomous spraying unmanned aerial vehicle (UAV) for site-specific weed management. The research aimed to combine remote sensing technology with UAV-based autonomous spraying to improve precision in weed control. The innovative approach allowed for targeted and efficient application of herbicides based on remote weed mapping data. This study built the integration of remote sensing and autonomous UAV technology, offering a novel solution for effective and environmentally friendly weed management practices. Mateo Gašparović et al.[22] presented an innovative method for weed mapping in oat fields utilizing UAV imagery. The research aimed to develop an automated approach for accurate weed identification. The study successfully implemented this method, achieving reliable weed mapping results. The research's contribution lies in the creation of an automatic and efficient process for weed mapping using UAV imagery, offering valuable insights for improving weed management practices in oat fields through advanced image analysis techniques. Yubin Lan et al.[23] conducted the research focused on real-time identification of rice weeds using low-altitude UAV remote sensing and an improved semantic segmentation model. The study aimed to enhance the accuracy of weed identification in rice fields, and successfully developed and applied an improved semantic segmentation model for real-time weed identification. This study built the integration of UAV technology and advanced image analysis techniques, offering a practical solution for efficient and precise weed management in rice fields through real-time identification. Tibor de Camargo et al.[24] conducted the research on optimized deep learning models for rapid UAV mapping of weed species in winter wheat crops. The study aimed to enhance the efficiency of identifying weed species using UAV imagery. The research successfully developed an optimized deep learning model that significantly improved the speed and accuracy of weed mapping in winter wheat fields. The innovation of this paper lies in the creation of a high-performance deep learning model tailored for efficient UAV-based mapping of weed species, offering valuable insights for streamlining weed management practices in winter wheat cultivation through advanced image analysis techniques. Kunlin Zou et al.[25] conducted research on a novel method for field weed density evaluation using UAV imaging and a modified U-Net model. The study aimed to improve the accuracy of assessing weed density in agricultural fields. The research successfully developed and applied a modified U-Net model that demonstrated enhanced performance in estimating weed density from UAV images. This study successfully combined the UAV remote sensing and the modified U-Net model, providing an efficient and reliable approach for evaluating weed density in fields, which contributes to optimizing weed management practices through advanced image analysis techniques. Jorge Torres-Sánchez et al.[26] focused on early detection of broad-leaved and grass weeds in wide row crops using artificial neural networks (ANNs) and UAV imagery. The study aimed to enhance the timeliness of weed detection in agricultural fields, and successfully applied ANNs to UAV imagery, achieving accurate and early identification of weeds in wide row crops. The study utilized the ANNs and UAV technology for early weed detection, which contributes to optimizing agricultural practices through advanced image analysis techniques. Nahina Islam et al.[27] conducted research on early weed detection in an Australian chilli farm using image processing and machine learning techniques. The study aimed to improve the efficiency of weed detection in agricultural settings, and successfully integrated image processing and machine learning methods, achieving accurate and early identification of weeds in chilli fields. The innovation of this study lies in the application of advanced image analysis and machine learning techniques for early weed detection, offering valuable insights for optimizing weed management practices in chilli farming. Nik Norasma Che Ya et al.[28] focused on evaluating weed mapping through the integration of hyperspectral reflectance and optimal multispectral UAV imagery. The study aimed to enhance the accuracy of weed classification in agricultural settings, and successfully combined hyperspectral and multispectral data, achieving improved identification of weed species. The study integrated advanced remote sensing techniques, offering valuable insights for optimizing weed management practices through a more precise and comprehensive approach. Leila Hashemi-Beni et al.[29] investigated the use of Deep Convolutional Neural Networks (DCNNs) for discriminating between weeds and crops using UAS (Unmanned Aerial System) imagery. The research aimed to improve the accuracy of distinguishing between these two categories, and successfully applied DCNNs to UAS imagery, achieving reliable discrimination between weeds and crops. The main innovation of this research lies in utilizing advanced deep learning techniques for precise differentiation between weeds and crops, offering valuable insights for optimizing weed management practices and enhancing agricultural decision-making through advanced image analysis methods. Paolo Fraccaro et al. focused on utilizing deep learning to map the spatial extent of weeds using imagery from Unmanned Aerial Vehicles (UAVs). The research aimed to improve the accuracy of weed spatial mapping, and successfully applied deep learning techniques to UAV imagery, achieving precise mapping of weed distribution. The study utilize the advanced deep learning algorithms for accurate and efficient weed spatial mapping, providing valuable insights for optimizing weed management practices and enhancing agricultural decision-making through advanced image analysis methods.

From the above literature, it can be seen that the main solution for weed mapping mainly contained the object based image processing and semantic segmentation. Thanks to the strong capability of feature extraction brought by deep learning, the semantic segmentation has greatly surpassed the OBIA series. However, the weed mapping model requires large amount of annotated data to train the parameters, and this requirement consumes laborious manual annotation which limit the development of the weed mapping research. Therefore, the unsupervised and semi-supervised methods can be explored to address this problem.

3 Future directions

3.1 Multi-task learning

Current advancements in UAV technology have enabled the collection of high-resolution imagery across large agricultural fields. This wealth of data provides a unique opportunity to develop accurate weed recognition models. However, traditional single-task learning methods may struggle to fully exploit the richness of these datasets and efficiently handle the various aspects of weed management. This is where multi-task learning (MTL) comes into play. By simultaneously training models to perform multiple tasks, MTL aims to improve generalization, reduce overfitting, and enhance the capabilities of weed recognition models.

MTL offers several key advantages that make it particularly suited for weed recognition using UAV imagery. Firstly, it can enhance the efficiency of training by enabling the sharing of lower-level features between tasks. This is especially relevant in scenarios where labeled data for each individual task is limited. Secondly, MTL can lead to improved accuracy by encouraging models to learn shared representations that capture common features among tasks. This joint learning process can help in capturing nuanced patterns that might be missed by single-task models. Moreover, MTL promotes a more holistic understanding of the field by considering multiple aspects simultaneously, such as weed species classification, weed density estimation, and crop health assessment. This comprehensive view can result in more informed decision-making in weed management.

While MTL offers promising benefits, it also poses challenges that researchers must address. One notable challenge is task interference, where the optimization of one task negatively impacts the performance of another. Proper task selection, weighting, and architectural design are crucial to mitigate this interference and harness the full potential of MTL. Additionally, the complexity of MTL architectures and the need for sufficient computational resources can pose practical challenges. Researchers must strike a balance between model complexity and feasibility, particularly in the context of UAV-based weed recognition where real-time processing is often desirable.

3.2 Few shot learning

Few-shot learning leverages the inherent capabilities of neural networks to generalize knowledge from a small number of examples. This learning paradigm is particularly well-suited for the domain of weed detection, where the variability in weed species, growth stages, and environmental conditions poses a significant challenge for traditional supervised learning methods. By learning from a few labeled instances, few-shot learning models can capture essential features and characteristics that distinguish weeds from crops, enabling accurate discrimination even with limited training data.

Few-shot learning offers several advantages that make it a promising approach for weed detection using UAV imagery. Firstly, it reduces the dependency on large labeled datasets, mitigating the time and effort required for data collection and annotation. Secondly, few-shot learning models exhibit remarkable adaptability and generalization capabilities, enabling them to recognize new weed species or variations in field conditions. Additionally, this approach can lead to more robust and transferable models, as the learned representations are driven by essential features that are shared across different scenarios.

The application of few-shot learning in weed detection using UAV imagery opens up intriguing future directions for research and development. One avenue is the exploration of meta-learning approaches that enable models to quickly adapt to new weed species or scenarios with minimal examples. Incorporating domain-specific knowledge, such as agronomic expertise, can further enhance the accuracy and applicability of few-shot learning models. Additionally, the integration of few-shot learning with other learning paradigms, such as transfer learning and domain adaptation, can enhance the robustness and adaptability of weed detection models.

3.3 Unsupervised or semi-supervised learning

Unsupervised learning aims to identify patterns and structures within data without explicit supervision, while semi-supervised learning harnesses the power of both labeled and unlabeled data for training. These approaches offer exciting opportunities for weed mapping, but they also present challenges. Unsupervised learning can struggle to produce accurate labels for distinct weed species, and semi-supervised learning requires effective strategies to leverage the information present in both labeled and unlabeled samples. Balancing model complexity, scalability, and interpretability remains a critical consideration.

Unsupervised and semi-supervised learning offer several compelling advantages for weed mapping using UAV imagery. Firstly, these approaches can exploit the intrinsic structures of the data, enabling them to identify hidden relationships and patterns that may not be evident in labeled datasets alone. Secondly, they provide a more cost-effective way to utilize the vast amount of unlabeled data collected by UAVs, potentially reducing the need for labor-intensive labeling efforts. Furthermore, these methods can enhance model generalization, as they are exposed to a broader spectrum of field conditions, leading to more robust and adaptable weed mapping models.

As the field of unsupervised and semi-supervised learning in weed mapping continues to evolve, several exciting directions emerge. The development of innovative algorithms that can effectively leverage unlabeled data and guide learning processes is crucial. The integration of domain knowledge and expert annotations can help bridge the gap between raw data and actionable insights. Furthermore, exploring the combination of unsupervised and semi-supervised approaches with other learning paradigms, such as transfer learning and reinforcement learning, can amplify the accuracy and applicability of weed mapping models.

4 Summary

This paper explores extensive literature on weed recognition by UAV remote sensing, and classified them into weed classification, weed detection and weed mapping categories according to the research objectives and the corresponding techniques. For each category, we introduce several state of the art researches and summarize its limitations according to the general experimental results. Further, we draw the future directions of the weed recognition, which may effectively address the technique limitation of the current research. Generally, the development of weed recognition by UAV remote sensing is closely connected to the newly evolved deep learning technology, and the interdisciplinary research may consistently promote more innovation of weed recognition by UAV remote sensing.

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