Remote Sensing Technique in Rice Weed Detection

Subjects: Remote Sensing
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Remote sensing technology aims to monitor and capture the earth's information without making direct contact and destroying it. The utilization of the electromagnetic spectrum, ranging from visible to microwave for measuring the earth's properties, is the main idea behind remote sensing technology. Machine learning (ML) and deep learning (DL) remote sensing techniques have successfully produced a high accuracy map for detecting weeds in crops using RS platforms. Therefore, this technology positively impacts weed management in many aspects, especially in terms of the economic perspective. The implementation of this technology into agricultural development could be extended further.

precision agriculture | remote sensing | rice farming | site-specific weed management

1. Introduction

It is undoubtful that weeds, also known as invasive plants, have their roles in the ecosystem. However, their presence in crops such as rice, oil palm, rubber, and other mass plantations influences productivity, causes significant economic consequences, decreases land prices, and reduces company profits [1].

It is necessary to construct systematic and strategic planning to improve the precision agriculture (PA) sector, especially in weed management, to control and increase yield production, leading to a better economy for the country and farmers. Therefore, remote sensing-based techniques were used to construct and optimize weed management. Remote sensing is a comprehensive framework that monitors and captures earth surface images without direct contact with it. In PA sectors, the data gathered can be used in various applications, such as monitoring rice's morphology [2], yield estimation [3], and mapping irrigated areas for food security and water resource management [4]. However, even though remote sensing has been widely used in weed management, it may not be a permanently adopted by developing countries anytime soon since local farmers still prefer the traditional practices.

2. Controlling Weed in Paddy Fields at Different Growth of Stages

In general, rice growth periods can be identified in three stages. They are the vegetative stage, reproductive stage, and maturative or ripening stage [5]. Depending on agricultural and environmental conditions, the whole cycle takes about 120 to 125 days. The International Rice Research Institute (IRRI) splits the growth cycle into five stages [6]. A general idea of the growth cycle is presented in **Figure 1**, with morphology examples.

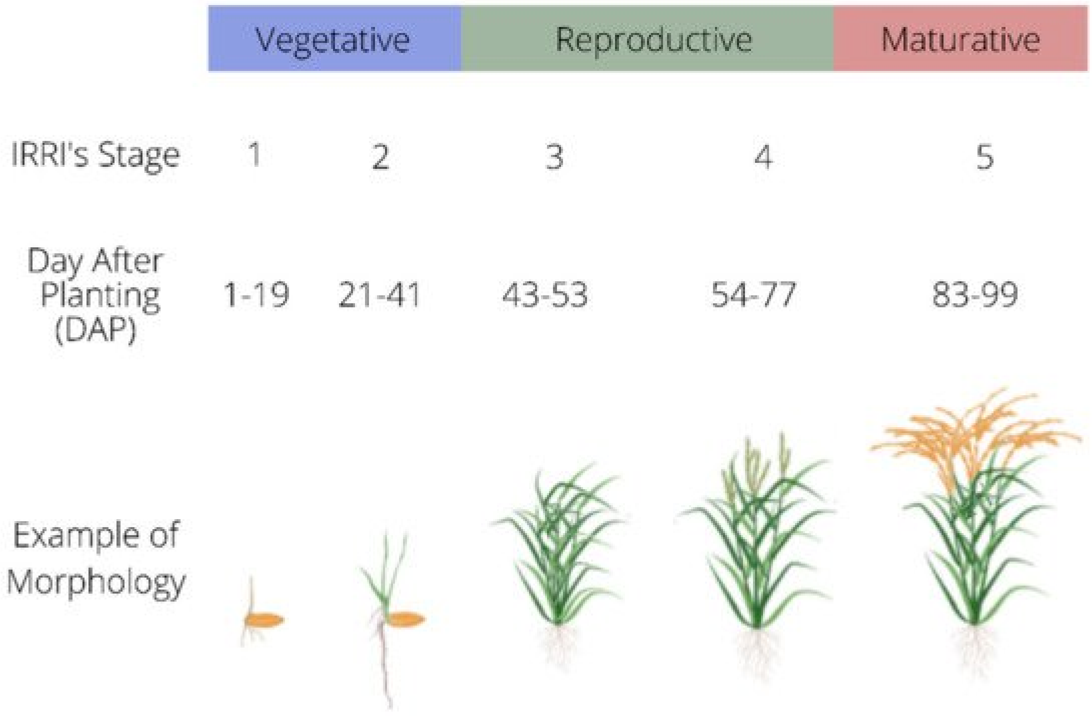

Figure 1. The growth cycle of a rice plant corresponds to the IRRI scale and sample structure.

Rice is generally a weak competitor with weeds. Therefore, the vegetative stage is critical in the paddy growth cycle. Successfully controlling weeds at this stage can deliver a 95% weed-free yield [7].
However, if we fail to prevent weeds from spreading in the vegetative stage, they will dominate the area, leading to a lack of sufficient space, light, and nutrients to grow and develop [8]. As a result, crops will experience uneven flowering and will not mature uniformly for the scheduled harvest [9][10].

Once the tillering reaches its maximum number, the reproductive stage will occur, followed by the maturative or ripening stage. Excess water in the fields is drained, resulting in a drop in the overall biomass due to lower moisture content. The grain is maturing and becoming heavier. At this stage, the presence of weeds will not affect the development of the crop. Nevertheless, we cannot save the yield losses because weeds dominated the paddy plot and the number of paddy crops that survive the competition is nominal. In general, weed in paddy can be classified into three types. They are grasses, sedges and broad leaved weeds [11].

The environmental relationship between weed and rice is very complicated and complex [12]. The weed management system needs improvement to control the spreading of weeds. The traditional practices that include burning, hand sowing, manual spot spraying, herbicide pre-emergence or post-emergence application, and repetitive blade hoeing are not practical anymore. These practices impacted the non-target species and the ecosystem rather than benefiting production [13].

Advanced weed management methods are required to manage weeds effectively. The process may include targeted and site-specific weed control, selection of weed seeds, different herbicide application (depending on weed distribution, spatial arrangement and soil properties), destruction of weed seeds over predation and microbial loss, nano herbicides, and optical spraying techniques. Advanced vision-guided robotics that can be adopted for site-specific weed management (SSWM) are transgenic herbicide-resistant crops, weed control and spraying robots, decision support systems, and pattern recognition modelling [14]. Implementing these technologies will help prevent unwanted species and improve existing weed management systems [15].

3. Weed Detection Using Remote Sensing Technique

The image processing workflow to detect weed in paddies can generally be divided into five stages: image data collection, pre-processing, feature extraction and selection, training, image classification and validation [16].

3.1. Image Data Collection

There are multiple platforms available for data gathering for weed detection in crops, such as digital cameras [17], hand-held spectroradiometers [18], polarization spectroscopy [19], and satellites [20]. However, unmanned aerial vehicles (UAV) are the most popular platforms researchers use to identify weeds in crops, due to their availability, high-quality data delivery, and ease of handling [21]. Nevertheless, the data collection differs in the types of sensors attached to UAVs: RGB, multispectral, or hyperspectral.

3.2. Image Mosaicking and Calibration

Images acquired from UAVs can be mosaicked using a Pix4D mapper (Pix4D, Prilly, Switzerland), Agisoft Photoscan Pro (Agisoft LLC, 52 St. Petersburg, Russia), and any available commercial software to generate qualitative, high-resolution orthomosaic images. After mosaicking, the process will continue with radiometric calibration and rescale the intensity of the electromagnetic radiation or digital number (DN) into the percentage of reflectance values [22]. There are numerous methods that have been implemented by researchers, such as the traditional empirical line correction approach and modern automatic radiometric calibration using available commercial software.

3.3. Feature Extraction and Selection

Following the spectral calibration, feature extraction can be extracted or computed for different image processing purposes using various approaches. This process will be helpful for the classification and identification of weeds in paddy fields. Feature extraction techniques are beneficial, especially in shape and pattern recognition. As features define the behavior of an image, they show its place in terms of storage taken, classification efficiency, and, obviously, in time consumption [23]. Therefore, optimizing the feature subset is required before feeding it into the machine learning (ML) and deep learning (DL) algorithms for improving the classification process and making it cost and time-efficient [24].

3.4. Image Classification and Validation

Many machine learning (ML) and deep learning (ML) algorithms are available for image classification. However, choosing the best one that fits the research's objective is crucial, because different algorithms have different difficulty levels.

Overall, the assessment can be carried out by comparing the classified pixels with ground truth pixels using a confusion matrix [25]. The result for weed classification is presented in terms of producer accuracy and overall accuracy. Producer accuracy (Equation (1)) is the probability that a pixel in the classification correctly shows class X. Given the ground truth class is X, producer accuracy can be calculated using

$$Producer\ accuracy = \frac{c_{aa}}{c_{\cdot a}} \times 100\%$$

where: c_{aa} = element at a position *a*th row and *a*th column; $c._a$ = column sums.

Overall accuracy (Equation (2)) is the total percentage of pixels correctly classified, and it can be calculated by using

$$Overall\ accuracy = \frac{\sum_{a=1}^{U} c_{aa}}{Q} \times 100\%$$

where: Q = total number of pixels; U = total number of classes.

The agreement between variables with ground truth data can be represented by using the kappa coefficient (Equation (3)), and its value can be calculated by using

$$Kappa\ coefficient,\ K = \frac{\sum_{a=1}^{U} \frac{c_{aa}}{Q} - \sum_{a=1}^{U} \frac{c_a \cdot c_a}{Q^2}}{1 - \sum_{a=1}^{U} \frac{c_a \cdot c_a}{Q^2}} \times 100\%$$

where: c_a = row sums.

4. An Overview of Machine Learning in Agriculture

In recent years, machine learning (ML) has provided a new criterion for agriculture with big data technology and high-performance computing. The development of ML has created new opportunities in agriculture operational management to unravel, measure, and analyze complex data [26]. Generally, the ML framework involves learning from 'experience', known as training data, to execute the classification, regression, or clustering tasks. These training data are usually regarded as a feature described by a set of attributes or variables. The machine learning model works by predicting the pattern and trend of future events in crop monitoring and assessment [27]. The ML model's performance in a particular task is evaluated by performance metrics improved by experience over time. As a result, classification techniques have been a prominent research trend in machine learning for many years, informing various studies. This method seeks to create features from the input data. Furthermore, it is highly field-specific and requires significant human effort, leading to deep learning techniques [16].

In deep learning (DL), CNN is the most well-known and widely used algorithm [28][29][30]. The fundamental advantage of CNN over the other DL algorithms is that it automatically detects significant elements without the need for human assistance [36]. Comparable to the multi-layer perceptron (MLP), where it consists of three layers known as the input, output, and hidden layer [31], CNN has many convolution layers before sub-sampling (pooling) layers, with fully connected (FC) layers as the last layers. An illustration of the CNN framework for image classification is shown in **Figure 2**.

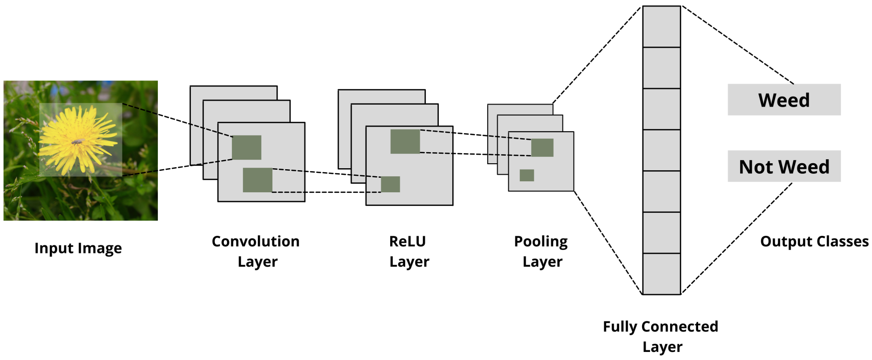

Figure 2. An illustration of the CNN framework for image classification.

4.1. The Application of Remote Sensing and Machine Learning Technique into Weed Detection

Choosing remote sensing (RS) and machine learning algorithms for SSWM can improve precision agriculture (PA). This situation has resulted in integrating remote sensing and machine learning becoming critical, as the need for RGB, multispectral, and hyperspectral processing systems has developed. Numerous researchers who tested the RS technique successfully produced an accurate weed map with promising implications for weed detection and management.

4.1.1. Machine Learning (ML)

Machine learning is a part of artificial intelligence that enables machines to recognize patterns and judge with little or no human input. Back during the early introduction to machine learning, Aitkenhead et al. [32] proposed a simple morphological characteristic measurement of a leaf shape (perimeter^2/area) and a self-organizing neural network to discriminate weeds from carrots using a Nikon Digital Camera E900S. Their proposed method enables the system to learn and differentiate between species with more than 75% accuracy without predefined plant descriptions. Meanwhile, Eddy et al. [33] tested an artificial neural network (ANN) to classify weeds (wild oats, redroot pigweed) from crops (field pea, spring wheat, canola) using hyperspectral images. The original data were 61 bands that were reduced to seven bands using principal component analysis (PCA) and stepwise discriminant analysis. A total of 94% overall accuracy was obtained from the ANN classification.

4.1.2. Deep Learning (DL)

Deep learning has recently become a machine learning component widely utilized in agricultural crop monitoring and management. It has taken a directive in many crop monitoring objectives such as weed detection, nutrient disorder, and disease detection. Huang et al. [34] utilized the fully convolutional network (FCN) method to map weeds in rice using unmanned aerial vehicle red-green-blue (UAV-RGB) imagery. Transfer learning was used to optimize the generalization capacity, and skip architecture was chosen to boost prediction accuracy. The result was then compared with the patch-based convolutional neural networks (CNN) algorithm and the pixel-based CNN method. The findings showed a proposed FCN method that outperformed others, both in efficiency and efficacy in terms of accuracy. The overall accuracy of the FCN method was up to 93.5%, and the accuracy for weed recognition was 88.3%.

5. Advantages of Implementation of Remote Sensing in Weed Detection through PA

The usage of herbicides, also known as agrochemicals, to control weeds in paddy fields has caused several impacts on the environment and human health [35]. Therefore, the authorities can consider reducing these inputs to follow an environmentally friendly rice production practice. A study by Jafari, Othman, and Kuhn [36] showed that a 10% reduction in agrochemical grants would reduce agrochemical use. However, it dramatically reduces national welfare and decreases food safety. Nevertheless, we can overcome these issues by implementing remote sensing SSWM techniques into precision agriculture (PA).

6. Future Direction

Machine learning such as deep learning algorithms should be implemented for extracting higher abstract levels of weeds and their relation to the seasonal changes of the paddy for more accurate weed identification. It is challenging to implement remote sensing techniques into paddy. However, when referring to the previous study, De Castro et al. [37] successfully classified Cynodon dactylon (bermudagrass) in a vineyard by integrating OBIA with a decision tree (DT) algorithm. De Castro et al. [38] also managed to produce a weed map of *Convolvulus arvensis* L. (bindweed) in a soybean field. Meanwhile, Huang et al. [39] successfully generated a grass and sedge weed map in a paddy field using a deep learning technique. This study has similarities in shape, texture, and pattern that machine learning and deep learning techniques can classify. In addition, the integration of various platforms, such as ground-based and machine vision technologies, should be considered. Besides, various yield-determining factors, such as climatic or agronomic, should be considered during the developmental stages of paddy. By maintaining the vigorous development of paddy, the existence of weeds can be minimized due to the biological mechanisms of the crops, which can be used to suppress the growth response of weeds towards the crops during the competition process.

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