Agri Articles
(e-Magazine for Agricultural Articles)
Volume: 04, Issue: 05 (SEP-OCT, 2024)
Available online at http://www.agriarticles.com
©Agri Articles, ISSN: 2582-9882

Precision Weed Management and Scaling Technology

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Chemical weed management has been the focus in agriculture ever since the discovery of 2,4-D over 75 years ago. However repeated application of one type of herbicides will sort out resistant strains within the weed population. This became real beginning 1957 in U.K., Hawaii, USA and Canada in the case of 2,4-D. With continuous use of same group of herbicides since that time, herbicide resistance has become a significant global problem. Currently, 262 weed species (152 dicots and 110 monocots), infesting 93 crops and non-crop areas in 70 countries, have been identified to develop resistance to different herbicides. In this situation, weed scientists need to look for alternative weed management approaches that enhance agricultural productivity. One such alternative is precision weed management (PWM) which is inclusive of those methods that will ensure greater farm productivity.

Precision weed management

Generally, weed management inputs are applied uniformly to the whole field, like most other crop, soil, and pest management practices. However, the occurrence and intensity of weeds are not uniform across the field. They are more often patchy (aggregated or clumped) and uneven due to several agroecological factors. Therefore, uniform herbicide application across a field, where target weeds are not uniformly distributed, can waste resources. This may lead to adverse economic, environmental and social concerns about herbicide use.

Gerhards *et al*. (2002) achieved herbicide savings of 60% and 92% for dicot and monocot weeds, respectively, in spring barley cultivation, and 11% and 81% for the same weed groups in maize.

Weed sensing systems

There are two categories of weed-sensing systems: ground-based and aerial-based, (Wang *et al*. 2019) using digital cameras or non-imaging sensors.

Ground-based sensing system: In this, multi-spectral imaging sensors such as colour digital optical cameras are used in a mobile platform that has a sprayer. It works better in the case of spatial treatments at field resolution levels 1, 2 and 3 (Christensen *et al*. 2009). Greater proximity reduces the pixel sizes to millimeters or smaller. This helps in analyzing images of species-specific features, such as shape, texture and plant organization. With spatial resolution lower than 1 mm, images collected from ground-based camera systems and subsequent image processing routines will help delineating individual weed plants from the crop plants (Thorp and Tian 2004). As much greater computational load is on the sprayer control system, it detects and identifies weeds and then determines and administers the appropriate action in real time (Brown and Noble 2005). Data must therefore be processed at a very high rate for the sprayer to progress at a reasonable speed. Unlike the aerial mapping approach, there are no additional tasks and infrastructure required.

Aerial-based remote sensing (ARS) system: This airborne remote sensing, done from either an aircraft or a satellite platform, requires two things. First: suitable differences in spectral reflectance or texture must exist between weeds and their background soil and plant canopy. The second requirement is remote V.S. Rao 212 sensing instrument must have sufficient spatial and spectral resolution to detect weed plants. ARS methods can be successfully applied to detect distinct weed patches which are dense and uniform, and have unique spectral characteristics (*i.e.* weed patches larger than 1×1 m). Therefore, this method is only applicable for whole-field treatments or to treat weed patches or sub-fields with clusters of weed plants. A major disadvantage of ARS is that it can be difficult to acquire the data when needed, particularly if weather conditions are not ideal when the satellite or the aircraft passes over. In this situation, data acquisition can be delayed for days or weeks (Christensen *et al*. 2009).

Components of scaling technology

Spectral Differences: Multispectral and hyperspectral imaging capture reflectance data across different wavelengths of light (visible, near-infrared, and short-wave infrared). Weeds and crops reflect light differently due to variations in pigment composition, leaf structure, and water content. These subtle differences can be used to classify and differentiate between weed species and the crop. For example, chlorophyll content and canopy structure can vary between weeds and crops, leading to distinguishable spectral signatures in the imagery.

Vegetation Indices: Vegetation indices such as the Normalized Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI) can help identify weeds. Crops and weeds often exhibit different values of these indices due to their varying biomass, leaf area, or chlorophyll levels. By analyzing these indices, remote sensing can pinpoint areas in the field where the NDVI signature deviates from the crop's signature, indicating the presence of weeds.

Spatial Resolution: High-resolution satellite imagery, UAVs (drones), and ground-based sensors provide detailed spatial information. This helps detect the exact location of weeds within a crop field, even at a plant-level resolution. Drones equipped with high-resolution cameras or sensors can create detailed maps that differentiate between individual weed plants and crop plants based on their spatial patterns.

Thermal Imaging: Weeds and crops often have different transpiration rates and water content. Thermal cameras detect heat emissions from the plants, and these differences can be used to identify weed species since they might respond to environmental conditions differently from crops.

Machine Learning & AI: Advanced machine learning algorithms can analyze large datasets from remote sensors and classify plants based on their features. Training these algorithms on labeled data (crops *vs*. weeds) allows for automated identification and classification, improving the precision of weed detection.

AI systems can be trained to identify specific weed species by recognizing the shape, size, and other characteristics from aerial or satellite imagery.

LIDAR (Light Detection and Ranging): LIDAR can be used to map the three-dimensional structure of the vegetation canopy. Since different plants (weeds and crops) have different growth patterns and heights, LIDAR can differentiate between them based on their structural characteristics.

Time Series Analysis: Time series data collected throughout the growing season can be used to track plant growth. Weeds and crops often follow different growth patterns and rates. By monitoring these differences over time, remote sensing can help distinguish weeds from crops.

Proximal sensors for weed image acquisition using deep learning

In the past years, the application of multispectral and hyperspectral sensor has been explored mostly in remote sensing and proximal sensing. With all the advancements made in sensor technology, hyperspectral sensors (HS) are also looked upon as a possible solution for weed classification because of their high spectral data channels. Although these types of sensors offer image information in narrow bands, the application of deep learning (DL) techniques demands intense labeling procedure and optimization on a large number of parameters to improve mode performance on the test dataset. Additionally, training high-dimensional large-sized data will demand heavy computational adequacy. But, according to the present research scenario, advances made in specifically designed graphical processing units (GPU) hardware are enabling the application of DL for hyperspectral images. Numerous studies have deployed machine learning techniques on HS images to classify weeds from crop plants. However, training HS data using DL techniques with the possibility of extracting spatial and spectral features together holds great benefit (Bioucas-Dias *et al*., 2013). In short, the application of DL techniques to classify weeds from crop plants is emerging in the HS domain as well (Fig. 1 a & b)

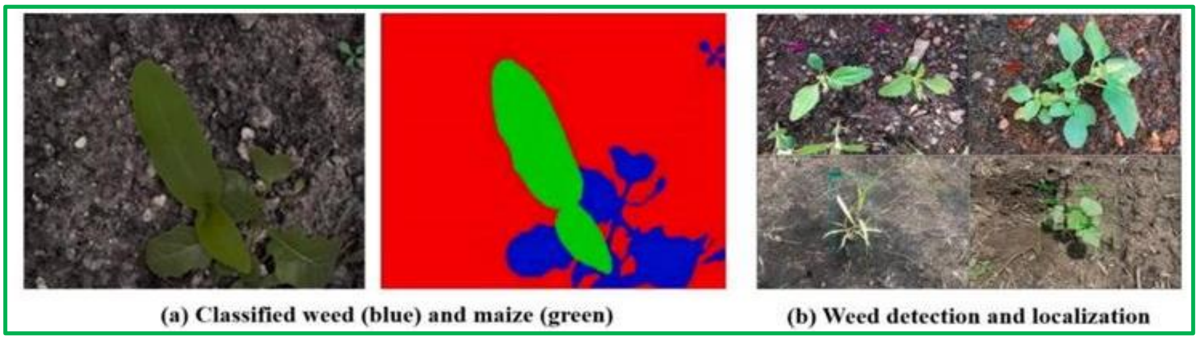
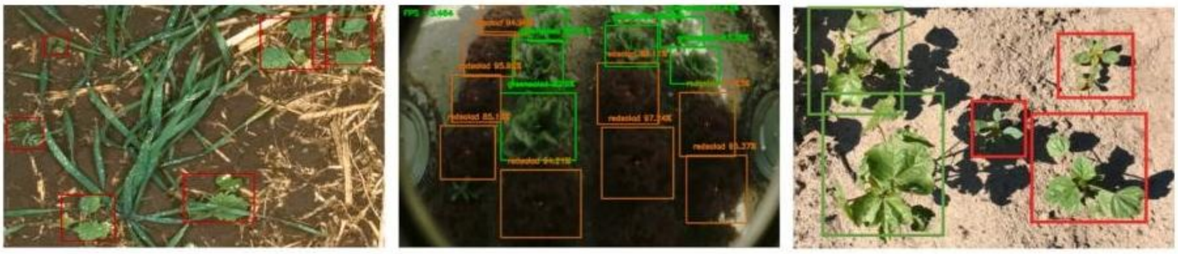


Fig.1. Classified weeds as seen in color space

Unmanned weeding robots (UWRs) for real-time weed detection

High-throughput edge computers integrated with a vision-based system for autonomous navigation and real-time weed detection are emerging. DL on resource-constrained edge computers is widely adopted due to less space requirements, low power consumption, and less latency during data transfer and processing. But one of the major challenges of implementing DL on edge computers sprawls in its requirement of training weed and crop plants each time. Since weed management in agriculture is accomplished on open farms with dynamic environment, onboard computers need to be trained with images of new weed species. This manual training or customization might slow down the adoption rate of these technologies by farmers thereby affecting its scalability on multiple field conditions. Also, weeds need to be destroyed at a specific growth stage; therefore, a very robust perception system is required to build a DL model that is able to destroy weeds at an appropriate stage. Along the same line of thoughts, to build a very robust DL model, large amount of data is required at the training stage to identify weeds in an extreme dynamic condition (Fig.2.). The data fed to the network needs to be carefully annotated under the expertise of a weed scientist to ensure correct weed labelling procedure is accomplished. Although an expert might be able to differentiate between look-alike crop plants and weeds at an early growth stage, a key limitation of DL algorithms might be observed in this area during realtime analysis (Serre, 2019).



a) Weed detection (Agrointelli) b) Weed detection in vegetable crops c) See and Spray

Fig. 2 Weed detection accomplished by in-field weeding robots

Next generation weed scientists

Weed scientists of next generation will face challenging issues in developing and implementing best weed management practices. Herbicides will continue to be used, though perhaps in a more limited fashion. Therefore, intensive training in herbicide chemistry, physiology and technology must continue. Weed biology will continue to grow in importance because of growing weed resistance to herbicides. Development of herbicide resistant biotech crops will continue, despite problems in their adoption over long time. Precision weed management, now in initial stages of development, will grow. All of these require weed scientists develop skills in the following:

- Fundamental mechanisms underlying plant-plant interactions.
- Plant population modelling.
- Weed genomics (genome sequencing), metabolomics (metabolome analysis) and methods of high-throughput screening of herbicides.
- Evolution of resistance of weeds to herbicides, particularly non-target resistance; their infestation and spread.

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