UAS Imagery and Computer Vision for Site-Specific Weed Control in Corn

Ranjan Sapkota* and Paulo Flores

1* Agricultural and Biosystem Engineering, North Dakota State University, 221 Albrecht Blvd, Fargo, 58102, North Dakota, USA.
2 Agricultural and Biosystem Engineering, North Dakota State University, 1221 Albrecht Blvd, Fargo, 58102, North Dakota, USA.

Abstract
Currently, weed control in a corn field is performed by a blanket application of herbicides which do not consider spatial distribution information of weeds and also uses an extensive amount of chemical herbicides. Site-specific weed control (SSWC) suggests an appropriate use of chemical herbicides according to the distribution of weeds in a field. Unmanned aerial systems (UASs) can provide high temporal and spatial resolution imagery, which can be used to map weeds across a field to support SSWC. This study assumes that plants growing outside the corn rows are weeds which need to be controlled. The first step to implement such an approach is identifying the corn rows. For that, we are proposing the use of "Pixel Intensity Projection" (PIP) algorithm for a pixel-classification and line detection over the corn rows on an UAS imagery with an accuracy of 99.36%. After being identified, corn rows were then removed from the imagery and remaining vegetation fraction was assumed as weeds. Based on those remaining vegetation fraction, a weed prescription map was created and implemented through a commercial size sprayer. The effectiveness of this SSWC approach was then evaluated by comparing the spatial distribution information of weeds over the SSWC plots and no-SSWC (blanket application) plots using a post-harvest imagery.

Keywords: Precision Agriculture, Remote Sensing, Site specific weed management, Weed mapping, Computer Vision, Prescription map, Crop row detection
1 Introduction

Corn is one of the largest and most important feed grains, accounting for more than 95% of total feed grain production [1]. In 2020, 3.73 million acres of land in North Dakota (ND) was planted to corn [2]. Weed competition is a major cause of corn yield loss in ND and chemical herbicide is the most used option for weed control [3]. In order to optimize weed control efficacy, the use of pre- and post-emergence chemical herbicide treatments have been proven to be the most effective weed control strategy [4, 5]. At present, most of the farmers are using a blanket application of spraying chemical herbicides for the post-emergence weed control in corn. The blanket application sprays chemical herbicide uniformly across the field without considering the spatial distribution information of the weeds, which often results in an overuse of chemical herbicides. Around one billion pounds of conventional chemicals are used annually in the US (including chemicals for weed control) for agriculture purpose [6]. The overuse of chemical herbicides can lead to economic losses, detriment to human health, and adverse effects on environment [7, 8]. In addition, due to increasing number of herbicide resistant weeds, the need for the new weed control approach is profound [9].

Site-specific weed control (SSWC) using remote sensing is an approach that suggests an accurate technique to spray herbicides according to the spatial variability of weeds [10]. The main idea of SSWC is to spray herbicide only to those areas where weeds are present [11]. Since satellite imagery presents problems for many aspects of precision agriculture because of its limitations in providing enough spatial and temporal resolution [12], the use of unmanned aerial system (UAS) with high-resolution camera sensors can provide high-quality imagery which can be processed and analyzed to obtain accurate weed distribution information [13]. Using this weed information, one can further create a weed controlling approach. However, to achieve this, it is vital to detect weeds accurately during the early growing season of crops.

In most crop-weed cases, weed treatment is recommended at the early growth stage of the crop. In this stage, mapping of the weeds becomes most challenging task because of four main reasons: 1) weeds have non-uniform distribution, which necessitates working at a single pixel size on the image [14], 2) crop and weeds have the same reflectance properties, 3) interference of soil background [15], and 4) very small size of weeds which do not appear in the image due to insufficient camera resolution [16].

The first step to identify weeds in an UAS imagery is image segmentation which allows for a clear distinction between plant and soil background. After the image segmentation, second step is to distinguish between crops and weeds [17]. The discrimination between weed and crop has been achieved by identifying crop rows after applying Hough transform on a UAS imagery. The identified rows were further analyzed by simple linear iterative clustering (SLIC), which creates a spatial relationship of super pixels and their positions in the detected crop lines to detect intra-line as well as interline weeds [18]. In
addition, the mapping of weeds on a multispectral UAS image has been achieved by using supervised Kohonen network (SKN), Counter-propagation Artificial Neural Network (CP-ANN), and XY-Fusion Network (XY-F) with 98.64%, 98.87%, and 98.64% accuracies respectively. The approach used around 0.7 million features to feed the neural network models [19]. However, these techniques require a lot of effort such as vegetation detection, classification of detected vegetation, and image labeling which is a time-consuming task.

At present, the use of computer vision and remote sensing technology is increasingly advanced in weed management practices [20]. Some studies have successfully reported the use of object-based image analysis (OBIA) in UAS imagery for assessing weed distribution information [21], [22], [23], [24]. However, the implementation of OBIA is a complex task because this technique requires lots of information such as field structure, crop patterns, plant characteristics, hierarchical relationships, and the OBIA analysis algorithm combines object-based features such as spectral, position and orientation of weeds and crop plants.

Currently, machine learning algorithms have been a great tool for detecting weeds. There are different convolution neural networks (CNNs) that have performed weed detection on different crops. Among all available CNNs, ResNet is regarded as the most recent CNN architecture which has the best results in terms of accuracy and speed for training image data, and the architecture was recognized at the ImageNet Large-Scale Visual Recognition Challenge (ILSVRC) in 2015 [25]. AlexNet, another CNN, was able to detect 97% of weeds on a soybean field using UAS imagery, and it classified the weeds into broadleaf and grasses to apply specific herbicide to those classes of weeds [26]. Following the ResNet CNN, a Region-based Fully Convolution Network (RFCN) technique was developed to perform weed detection and, the module detected the weeds with great accuracy [27]. However, these methods require training of deep learning models with lots of images which is time consuming task.

The use of multispectral and RGB sensors on a ground-based platform has shown their great ability to segment and differentiate vegetation from soil background [15]. Also, some real-time SSWC operations have been attempted by using a ground-based sensing technique that includes the use of real-time optometric, spectrometric, and RGB-NIR imaging sensors [28], [29]. These techniques were successful in the ability to discriminate between vegetation and soil background; however, they could not discriminate weeds from crops during their early growth stage when the weeds and plants have similar reflectance [29], [30]. Although various studies have been able to distinguish weeds from crops using visible NIR spectroscopy [31], [32], [33], their implementation feasibility is limited to laboratory settings only [34], [35].

Some latest commercial SSWC solutions such as the autonomous weed robot by “ecoRobotix” (ecoRobotix, Vaud, Switzerland) and “Deepfield Robotics” (Deepfield Robotics, Renningen, Germany) use ground-based machine vision and image processing techniques to spray only weeds [36]. However, these robotic solutions are not effective for operating in a large commercial agricultural production. Some companies have developed and commercialized
machines like Weedseeker, Greenseeker, and WEED-it which uses optoelectronic sensors to measure the reflection intensity of vegetation and discriminate the vegetation from soil background [30]. The downside of these products is that they could not achieve discrimination of weeds from crops during the early growth stage of crops. “See & Spray” from John Deere Technology (John Deere, Illinois, United States) is the first commercially available advanced spraying technology from John Deere which sprays herbicides to only weeds [37]. However, this sprayer is more ideal to sense and spray herbicides weeds only under fallow ground, and the technology still is not able to detect and spray post-emerged weeds accurately between and within crop rows [38]. Recently, John Deere has launched See & Spray ultimate, a sprayer which enables spraying of herbicides on only weeds among corn, soyabean, and cotton plants [39]. However, the efficiency of this product in terms of spraying herbicides in only weeds during post emergence application is yet to be reviewed by farmers.

Since most of the commercial solutions are still not able to fully discriminate weeds from crop for SSWC application, there is a need of alternate and robust approach to implement SSWC. Most of the earlier literature stated above for crop row identification have not shown the real-world application of those detected crop rows. In order to fulfill the research gap that still exists regarding the use of crop rows for real world weed control application, we propose this research with two major objectives: 1) to use UAS imagery to map and quantify post emergent weed infestation in a corn field; and 2) to integrate that map as a prescription map for weed control on a commercial size sprayer.

2 Materials and Methods

This study can be divided into four phases (Figure 1); acquiring and preprocessing of the UAS data, computer vision algorithm for classification, creation of weed prescription map and field implementation with analysis of results.

2.1 Study site

The study was performed in a corn field, 42 acres in size (approximate), located at NDSU Carrington Research Extension Center (47.51°N, 99.12°W), North Dakota, USA. The soil composition of the field was Heimdall and similar soil: 42%, Emrick and similar soil: 37%, and minor components 21% [40]. The field was planted with silage corn on May 12, 2021, with a 30-inch row spacing. Prior to the planting, on May 7, the field received a pre-emergence herbicide treatment (verdict) which was put down at 14 oz with 10 gallons of water.

2.2 Data collection

The UAS flights for image collection of early growing season to perform SSWC was carried on June 14, 2021, and the image collection of post-harvest field to
evaluate efficacy of the SSWC approach was carried on September 17, 2021. A DJI Matrice 600 Pro (M600) (DJI, Shenzhen, China), outfitted with a Sony Alpha 7R II 42 Megapixel RGB camera (Sony City, Tokyo, Japan) was used to capture the aerial images of the field (Figure 2). The camera was provided with a sensor resolution of 7952 × 5304 pixels (42.4 megapixels), and a focal length of 35mm. Integration of the camera on the drone was made by FieldofView LLC (Fargo, North Dakota, USA), which makes a device (GeoSnap) that allows one to trigger the camera and geotag the images with PPK (postprocess kinematic) accuracy (2 cm). Since the distance between the research field and nearest CORS (Continuously Operating Reference Stations; Cooperstown, ND) was high which would cause a degradation of the geotag accuracy, an iG4 NSS base station (iGage Mapping Corporation, Salt Lake City, USA) was used to implement the PPK correction to the geotags.

The UAS was flown autonomously using the flight missions created on Pix4D Capture app (IOS version) (PIX4D, Prilly, Switzerland). Flights were carried out at 350 feet above ground level (AGL), with the camera at nadir position, with 75% overlap both front and side, and the UAS speed was adjusted (by the app) to allow 1-2 seconds interval between pictures. Altogether three flights were carried on flying the experimental field, collecting a total of 2251 raw images.
Fig. 2: (a) DJI Matrice 600 Pro with a Sony Alpha 7R II, 42.4-megapixel RGB camera mounted on it; a Geosnap PPK system is integrated to the UAS by mounting it on the top part (b) Field of View Geosnap PPK before mounting to the drone (c) Field of View Geosnap PPK mounted on top of drone for triggering aerial geotags at each image capture.

2.3 Image preprocessing and stitching

In order to generate geotag information for each raw image with an accuracy of 2-cm for latitude and longitude, and twice that for elevation, the data collected by the base station was processed into EzSurv software (Effigis, Montreal, Canada). That information was then used to generate an accurate orthomosaic (Figure 3 (a)) using an image stitching software, Pix4D (PIX4D, Prilly, Switzerland). After processing the images into Pix4D for 6 hours and 25 minutes, an orthomosaic with ground sampling distance of 0.63 cm was generated which served as the basis for all the subsequent analyses to implement the SSWC approach described in this document. Figure 3 shows the orthomosaic with the experimental areas where both the SSWC and conventional (No-SSWC) treatments were applied and analysed.
Fig. 3: (a) Orthomosaic generated over a corn field after the images captured by a Sony Alpha 7R II, flown at 350 ft AGL were stitched in Pix4D. (b) The placement of the SSWC (green) and no-SSWC (pink salmon) treatment plots.

2.4 Vegetation Identification

In order to segment the vegetation fraction on the imagery from the background, initially, an excess green index (ExGI) was calculated using equation 1. The ExGI highlights the green portion of the spectrum allowing one to segment the vegetation from the remaining imagery background by using a threshold value [41].

\[ \text{ExGI} = 2g - r - b \]  
\[ (1) \]

where \(r\), \(g\), and \(b\) are the normalized values of the bands red, green, and blue respectively, and these values are calculated using:

\[ r = \frac{R}{R + G + B} \]  
\[ (2) \]

\[ g = \frac{G}{R + G + B} \]  
\[ (3) \]

\[ b = \frac{B}{R + G + B} \]  
\[ (4) \]

where \(R\), \(G\), and \(B\) represent the digital number values of the red, green, and blue color band from the orthomosaic.

Once the ExGI was calculated, a threshold of 0.08 was applied to distinguish all green vegetation from the background, generating a binary imagery with
pixel intensity value 1 for the vegetation and 0 for the remaining background, which was further processed to identify the corn rows.

### 2.5 Algorithm development for crop row detection

We are purposing the use of Pixel Intensity projection (PIP) algorithm for identifying corn rows in the binary imagery described in 2.4. In order to expedite the processing time, only the portions of binary imagery that were assigned for SSWC approach in 3 (b) was processed through the PIP algorithm. Figure 4 shows the flow diagram for the PIP algorithm that was purposed for corn row identification.

Fig. 4: Flow diagram of Pixel Intensity Projection (PIP) algorithm that identifies corn rows in a binary imagery created from the orthomosaic of UAS flown at 350ft AGL

Pixel intensity along X-axis (columns) were summed and projected towards Y-axis (rows) in order to compute the local maximums (peaks) in Y-axis as shown in figure 5. Once the local maximums were computed for each rows, straight lines perpendicular to Y-axis were drawn. The same process was repeated for all sections that were inside the boundary of SSWC treatment plots.
Fig. 5: A section of the binary ExG imagery (3000 x 2000 pixels) with the horizontal orientation of rows, b) local maximums (or peaks) for each corn row on the section of imagery. The imagery was collected by a Sony Alpha 7R II, flown at 350 ft above ground level, and c) lines drawn over each computed local maximum.

Once the lines were drawn over the computed local maximums in each row, those lines were compared with the original corn rows in ArcGIS. The precision and accuracy of the lines were calculated using the standard formula given as:

\[
Precision = \frac{TP}{TP + FP} \quad (5)
\]

\[
Accuracy = \frac{TP + TN}{TP + FN + TN + FP} \quad (6)
\]

where, TP, TN, FP and FN represents true positives, true negatives, false positive and false negative respectively.

2.6 Weed mapping across SSWC treatment plots

Some of the recent studies have applied several methodologies for identifying crop rows [42], [43], [44], [45]. However, the authors could not present the
application of those crop rows in terms of implementing SSWC in the field. Our approach is making the use of those identified corn rows to map the weeds in the field.

Once the corn rows were identified, the next step was to identify the vegetation fraction that would be classified as weeds. Our approach was to identify and delete all corn plants from the treatment plots so that the remaining vegetation would be considered as weeds. In order to implement that approach, we created buffers of 3.5 inches on both sides of the lines that were identified as corn rows. This 3.5-inch size buffers as shown in figure 6 (a) on both side of the lines was wide enough to cover most of the corn plants, leaving the weeds present between the corn rows as shown in figure 6 (b).

![Buffered corn rows](image)

**Fig. 6:** Buffered (3.5-inch on both sides) corn rows (a) that were removed from the imagery to create the weed map across the field (b). Imagery collected by a Sony Alpha 7R II, flown at 350 ft above ground level

In order to create a weed control prescription map, since the weed pressure in the field was unusually high in the 2021 growing season, and due to the individual nozzle control feature on the sprayer, the research team opted to overlay a grid of cells of 1.67 x 10 ft on the imagery. That resulted in an average value of 35% of the cells free of weeds across the SSWC treatment. Any cells that contained at least one fraction of weed complete inside the cell grid was considered to spray the chemical herbicide over the entire cell grid at a rate of 15 gal/acre and the 35% area that were free of weeds were assigned to spray at a rate of 0 gal/acre, which is no-spray. Figure 7 shows the prescription shapefile, which was converted to a prescription map in a later step.
Fig. 7: Variable rate prescription map (green cells = 15-gal ac-1 and red cells= 0-gal ac-1) generated in ArcGIS Pro based on UAS imagery collected over a corn field by a Sony Alpha 7R II, flown at 350 ft above ground level

2.7 Integration of Weed Map into a commercial sprayer

A Case IH (Racine, Wisconsin, USA), Patriot 4440 self-propelled sprayer model year 2021 (Fig.8) used in this study. The sprayer was provided with an AIM command FLEX system, which is the latest technology from case IH that enables consistent, flexible, and accurate application, regardless of speed and terrain. In addition, the system enhances control of liquid product flow and pressure more accurately than conventional rate controller and enables instant on/off of individual nozzles, with a nozzle valve diagnostic system [46].

The sprayer was set up with a Raven RX1 real time kinematic (RTK) receiver (Raven Technology, Sioux Falls USA), which operates at a frequency of 10Hz. Following Case IH engineer’s advice, the application speed for this study was kept below 7 mph (6.5 mph actual speed application) to allow for the sprayer to maintain position accuracy resolution of at least one foot per 1/10th of a second or 10 ft per second. That cab computer requires a certain folder structure, so it can read prescription maps (Rx) from an external storage device, such as a thumb drive. AgSMS Advanced (Ag Leader, Iowa, USA) software was used to create that folder structure. Once the Rx map was brought into the Viper 4+ display, anything outside the area of the Rx map was set to be sprayed with a 15-gal ac-1 rate, which is the same rate that one would use for a blanket chemical application.
**Fig. 8:** Case IH Patriot 4440 series sprayer used to implement site-specific weed control in a corn field. The sprayer was equipped with an AIM command FLEX system, RTK GPS receiver, Viper 4+ cab computer, and 136.6 ft wide boom.

### 2.8 Assessing the spraying performance

Once the spraying was completed, “as-applied map” was downloaded from the cab computer. The sprayer’s performance was assessed based on the spatial area that was sprayed and not sprayed between the Rx maps and the as-applied map. The total area which was not-sprayed in the as-applied map was considered as Measured Value, and the total area which was set to be not-sprayed in the prescription map was considered as Expected Value.

The accuracy of application in terms of spraying was calculated using equation 7:

\[
Accuracy = \frac{measured - value}{expected - value}
\]  

(7)

In order to evaluate the overall effectiveness of this study, post-harvest imagery was collected on September 21, 2021. The process of image collection, image stitching, georeferencing, ExGI calculation, segmentation, and thresholding was done by following the similar steps as in 2.1, 2.2, and 2.3. The area of weeds in six SSWC and six NO-SSWC test plots was calculated and the datasets were analyzed using SAS PROC MIXED (SAS Institute, Cary, USA) with a mixed procedure using REML (restricted maximum likelihood) estimation. The area covered by weeds in six SSWC test plots was compared with the area of weeds present in six no-SSWC test plots using a pair-wise T-test with a significance level of 0.05 (p-value= 0.05).
3 Results and Discussion

3.1 Corn Row Detection Accuracy

The lines generated over corn rows by the PIP algorithm were compared with the actual corn rows in all six SSWC test plots by visually assessing the orthomosaic in the ArcGIS Pro as shown in Fig 9:

![Comparison of actual corn rows with the identified lines created by the Pixel Intensity Projection algorithm on a corn field imagery captured by Sony Alpha 7R II, flown at 350 ft AGL](image)

The number of True Positives (TP), False Positives (FP), True Negatives (TN) and False Negatives (FN) was manually counted for all six SSWC test plots as shown in table 1.
Table 1: The count of TP (True Positive), TN (True Negative), FP (False Positive), and FN (False Negative) generated by the Pixel Intensity Projection (PIP) algorithm in each SSWC plot created on a corn field imagery captured by Sony Alpha 7R II, flown at 350 ft AG.

| Test-plot | TP  | TN  | FP  | FN  |
|-----------|-----|-----|-----|-----|
| SSWC-1    | 392 | 0   | 3   | 1   |
| SSWC-2    | 382 | 0   | 1   | 3   |
| SSWC-3    | 386 | 0   | 4   | 0   |
| SSWC-4    | 385 | 0   | 2   | 1   |
| SSWC-5    | 384 | 0   | 4   | 2   |
| SSWC-6    | 384 | 0   | 1   | 1   |
| Total     | 2313| 0   | 15  | 8   |

1TP indicates the number of lines identified by the PIP algorithm that was exactly above the actual corn rows.
2FP indicates the number of lines identified by the PIP algorithm that was generated where there were no corn rows.
3FN indicates the count where corn rows lines were not generated above the actual corn rows.
4TN indicates the value of background detected by the algorithm (which is zero for all plots).

The comparison of the lines identified by the PIP algorithm with the actual corn rows showed that 2313 lines were exactly on top of the corn rows, 15 lines were generated where there were no corn rows, and 8 lines were not identified by the algorithm where there were corn rows. The overall accuracy and precision of the purposed algorithm was calculated at 99.01% and 99.35% respectively.

Since the pixel intensity values for some corn plants in a row was too small, the algorithm failed to detect lines for those kinds of corn rows which is shown in figure 10 (a). Moreover, the algorithm identified double lines in some places as shown in figure 10 (b) where two local maximums were identified for a single corn row.
Fig. 10: Sample image where the proposed PIP algorithm failed to detect an existent corn row as a line on the ExGI imagery of a corn field (b) Sample image where the proposed PIP algorithm detected two lines over a single corn row on the ExGI imagery of a corn field.

Most of the published studies have made use of Hough Line Transform (HLT) for identifying crop rows [47–50]. The HLT requires edge detection step prior to generate the lines [51]. The edge detection was found to be very weak and ineffective for the imagery covering such large area in this research. Some recent studies have used deep learning methods to identify crop rows in UAS imagery [52] [53] [54], however the deep learning method requires initial training of models with large image dataset which is time-consuming. The processing time for the purposed algorithm is less than 4 seconds for identifying the corn rows as lines over the six SSWC plots, which is approximately 7.6 acres in area. We were unable to find supporting literature that has processed this much amount of land imagery for crop row detection.

3.2 Weed mapping accuracy

As described on section 2.7, when AgSMS software was used to convert the prescription layer created in ArcGIS Pro to a format that the sprayer could understand and act upon it, the setup which was used made some changes between a prescription layer created in ArcGIS Pro and the output from AgSMS software. These random changes as shown in figure 11 (b) generated by the AgSMS led to the loss of accurate spatial distribution of the cells free of weeds across the SSWC plots.
**Fig. 11:** a) Prescription map created in the ArcGIS Pro for SSWC-1 where all red grids were set as no-spray and all green grids were set as spray regions on the imagery of a corn field; b) Overlap of ArcGIS map with the AgSMS no-spray regions (regions enclosed within dark black lines); the red regions outside of the AgSMS no-spray regions was not sprayed.

The area of no-spray regions set on the ArcGIS map as shown in figure 11 (a), and that no-spray area included inside the no-spray region of AgSMS map as shown in figure 11 (b) is listed in table 2 for all six SSWC test plots.

**Table 2:** Impact, in terms of area loss, of the unintended AgSMS software changes to the prescription map in area that was not supposed to be sprayed based on the original (ArcGIS Pro) prescription map.

| Test-plot | ArcGIS Pro map, m² | AgSMS map, m² | Area loss due to AgSMS changes, m² | Area loss due to AgSMS changes, % |
|-----------|--------------------|---------------|----------------------------------|----------------------------------|
| SSWC-1    | 2598.6             | 1600.1        | 998.6                            | 38.4                             |
| SSWC-2    | 3316.9             | 2209.1        | 1107.8                           | 38.4                             |
| SSWC-3    | 2302.3             | 1146.1        | 1156.3                           | 50.2                             |
| SSWC-4    | 1739.2             | 841.8         | 897.4                            | 51.6                             |
| SSWC-5    | 2241.8             | 1280.7        | 961.2                            | 42.9                             |
| SSWC-6    | 1757.8             | 841.8         | 915.9                            | 52.1                             |
From the data on Table 2, one can notice that 43.3% of the original no-spray region (from ArcGIS map) for the six SSWC treatment did not receive the intended application. The total area that was set as no-spray in the prescription map created on ArcGIS Pro was 13,956.7 m², but the AgSMS software reduced the total no-spray regions to 10,098.2 m². In addition, out of that only 7,917.5 m² were free of weeds, which is 78.0% of the total no-spray region in the AgSMS map. Thus, the remaining 22.0% of area was infested with weeds, but the changes made by AgSMS caused those areas to be treated as a no-spray area. That becomes a big issue when trying to evaluate the efficacy of SSWC approach proposed here.

Moreover, when the prescription map was created, the selection of cells that contain weeds in it was done by using ”completely within or within” relationship, which has skipped few small weeds that did not lie perfectly inside the cells. The premise for the proposed approach to be successful is that the weed pressure on the SSWC plots after harvest is equal or less than no-SSWC plots that were sprayed in the spring. Since the AgSMS changes caused the sprayer not spraying cells with weeds in the spring, it is challenging to make a clear assessment of the differences between the treatments.

### 3.3 As-applied map accuracy

The accuracy of as-applied map was calculated based on no-spray regions that were set in AgSMS map. All the regions in figure 12 enclosed by black lines were the no-spray regions set in the Rx map. Purple shaded regions inside the no-spray cells of the Rx map are the no-spray regions recorded in the as-applied map, while all the regions except the purple regions were sprayed. The as applied map where sprayer’s nozzles were turned off for no-spray area was compared to that of AgSMS map in table below. The sprayer was able to turn off its nozzles over 7,919.5 m², from a total of 10,098.1 m², across all six SSWC replicates. Those results show that the sprayer was able to perform no-spray only on 78.4 % of the no-spray. The relative error was calculated at = -0.216, which means the measured value (from the as-applied map) was 21.6% less than the expected value (from AgSMS map).
Fig. 12: Overlap of Rx map, generated by AgSMS, where the regions enclosed by dark black lines where the no-spray regions (0 gal/ac), and the as-applied map. Purple color regions are the area where the sprayer turned its nozzles off while operating at 6.5 mph speed (approximate), while all the remaining area was sprayed (15 gal/ac).

Table 3: Comparison of no-spray regions that was set by using AgSMS software (column 2) with the no-spray regions that was recorded in the as-applied map (column 3) downloaded from the cab computer of Case IH Patriot 4440 sprayer.

| Test-plot | AgSMS map no-spray area, m² | As-applied map no-spray area, m² | Sprayed area in no-spray regions, m² | Sprayed area % in no-spray regions (as-applied map) | Sprayed area % in no-spray regions (as-applied map) |
|-----------|-----------------------------|---------------------------------|------------------------------------|---------------------------------------------|---------------------------------------------|
| SSWC-1    | 1822.3                      | 1600.1                          | 222.2                              | 12.2                                        |                                             |
| SSWC-2    | 2648.99                     | 2209.1                          | 439.8                              | 16.6                                        |                                             |
| SSWC-3    | 1591.2                      | 1146.1                          | 445.1                              | 27.9                                        |                                             |
| SSWC-4    | 1182.3                      | 841.8                           | 340.5                              | 28.8                                        |                                             |
| SSWC-5    | 1688.9                      | 1280.7                          | 408.3                              | 24.2                                        |                                             |
| SSWC-6    | 1164.5                      | 841.8                           | 322.7                              | 27.7                                        |                                             |
| Total     | 10098.1                     | 7919.5                          | 2178.6                             | 21.5                                        |                                             |

The reduction of the no-spray area observed in the as-applied map does not seem to follow a specific pattern across the field, which creates difficulty in understanding the factor(s) driving those results. However, the majority of the reduction in the no-spray area was noticed at the edges of no-spray regions set in Rx map. From the visual comparison of as-applied map with the Rx map, majority of as applied map showed that the sprayer's nozzle stopped spraying
only after reaching the no-spray zone. Most of the edges that were sprayed inside the no-spray regions showed that the nozzles did not start spraying instantly as the no-spray regions started. One of the possible explanations for such behavior might be a combination of the sprayer's travelling direction and speed, where the sprayer is moving too fast to stop spraying right on the edge of cells. Moreover, it was noticed that the sprayer missed spraying some small no-spray regions that were surrounded by spray regions in the Rx prescription map.

3.4 Effectiveness of the SSWC approach

The SSWC and NO-SSWC treatment regions in a post-harvest imagery, were significantly different in terms of weed area ($F_{1,5} = 11.41, \ p < 0.0197$). The number of weeds present in SSWC treatment plots was 3.4 times higher than the amount of weeds that were present in SSWC plots. The estimated sum of the mean value for the area of weeds in six SSWC treatment plots was 87.02 m², which was higher (3.4 times) than the estimated sum of the mean value for the area of weeds in no-SSWC treatment plots (25.59 m²).

**Fig. 13:** Weed area estimated in SSWC and NO-SSWC treatment plots from the post-harvest imagery, calculated from SAS PROC MIXED using REML mixed procedure

One of the possible answers for why the SSWC test plots have higher weeds is that the Rx map integrated with sprayer had almost 22% of the area that was infested with weeds inside the no-spray region of AgSMS (as explained in section 4.2, and figure 14 b), and the application was not able to spray herbicides over that 22% weed infested regions. Because of this, the presence of weeds in the SSWC test plots was 3.4 times higher than the no-SSWC test plots in the post-
harvest imagery. The findings from this study could be a foundation to pursue various research questions that our study could not address, because of time and other limiting factors. There might be other several possible reasons for the number of weeds in the SSWC treatment plots to be higher than the NO-SSWC treatment plots.

Although the imagery obtained from the field had high resolution (GSD= 0.63 cm per pixel), we might have missed smaller weeds during the data collection of the early growing season. Those weed detection skips might be one of the reasons why we observed weeds in the SSWC plots after the corn harvest. One could argue that image resolution should be increased to avoid those skips, but there are other challenges to achieve that, such as cost of better hardware (UASs and sensors), time to collect data (by flying lower with the same equipment used on this study), and time to process the data (lower altitude flight leads to many more pictures captured, which increases processing time). Since the cell size was made to fit for each nozzle of the sprayer, there is a chance that the sprayer missed spraying some weeds that were within corn rows. The width of each grid was 0.5 m [1.67 feet] which was exactly equal to the spacing between each nozzle in the sprayer’s boom, but that is less than the corn row spacing (0.7 m [2.5 ft]). This year was considered a bad year for implementing this research in terms of calculating the effectiveness of research because of the high weed pressure at the time of the post-emergence application. According to information collected from the field crew at the Carrington Research Extension Center, there was a high probability that pre-emergence treatment did not work effectively because of weather conditions. Another possible reason for having more weeds in SSWC plots might be because we applied the post-emergence treatment too late, and the treatment was as not effective as anticipated because of the size of some weeds. That is supported by the imagery collected after the corn harvest, where there was noticeably high weed pressure, even in those areas that received a blanket application of herbicide. Some of the weeds might have been too advanced in their growth stage to be controlled with the chemical rates applied.

4 Conclusion

UAS imagery can be a very useful tool to perform SSWC decisions. We proved that the integration of UAS imagery with a commercial size sprayer can be an efficient alternative to implement SSWC in a corn field. However, the impact on weed control efficacy will depend on the accuracy of weed prescription map, weed morphology, distribution and timing of weed control application. On the other side, the PIP algorithm proposed by the author is easy and fast method of identifying the corn rows. While many other machine learning models and computer-vision algorithms rely on Hough Line Transform and/or training of a lot of images for row detection, our “PIP algorithm” directly estimated lines over
each corn row when the segmented binary imagery was provided as an input. In addition, our approach of identifying the corn rows and removing all corn rows from the UAS imagery is an effective way of discriminating weeds from crops. Our approach of mapping weeds based on grid cells is an effective way to perform section control of the sprayer’s nozzle. Using the prescription map, the workflow proved a promising capability in terms of individual nozzle control.

5 Suggestions for future research

Since the number of weeds that were present in SSWC plots was higher than NO-SSWC plots in post-harvest imagery, we have several future recommendations that could potentially increase the efficacy of the approach. The grids that were generated for the weed prescription map in this study were very small in terms of width (i.e., 1.6×10 ft). Each cell laid under one of the sprayer’s nozzles, which could have reduced the effectiveness of the entire research approach. Alternative map grids with approximately 10×10 ft cell size would have been useful for better efficacy. Therefore, a comparison of bigger cell size prescription maps must be conducted in further research. Furthermore, we suggest that the sprayer would have done a poor job if the sprayer speed was operated at 12 mph or more. Since this study was implemented using a sprayer set at approx. 6.5 mph, a study of this approach at a higher sprayer speed would be very useful in the future. Moreover, the research was conducted on approximately 42 acres of land. In order to make this approach applicable for farming, larger land coverage would be very useful. The scalability of this study needs to increase in terms of land coverage area. In addition, the image collection time during this research was around 52 minutes (early growing season), which may be unfavorable in terms of time value. Identification of new hardware and software for reducing data collection time is required for future improvement of this approach. Since most of the work in this study was done by human intervention, it would be very beneficial if the entire process of row detection to weed mapping could be automated. Real-time weed mapping and field control using this approach would be very useful in the future of weed management.

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References

[1] USDA ERS - Feedgrains Sector at a Glance (2021). https://www.ers.usda.gov/topics/crops/corn-and-other-feedgrains/feedgrains-sector-at-a-glance/

[2] 2020 STATE AGRICULTURE OVERVIEW (2020). https://www.nass.usda.gov/QuickStats/AgOverview/stateOverview.php?state=NORTH%20DAKOTA

[3] Basics of Corn Production in North Dakota (2019). https://www.ag.ndsu.edu/publications/crops/basics-of-corn-production-in-north-dakota#section-36

[4] Kudsk, P., et al.: Optimising herbicide performance. Weed management handbook 9, 323–344 (2002)

[5] Pannacci, E., Graziani, F., Covarelli, G.: Use of herbicide mixtures for pre and post-emergence weed control in sunflower (helianthus annuus). Crop Protection 26(8), 1150–1157 (2007)

[6] Pesticides explained: the toxic chemicals in up to 70(2019). https://www.theguardian.com/us-news/2019/may/29/pesticides-everyday-products-toxics-guide

[7] Peltzer, S., Hashem, A., Osten, V., Gupta, M., Diggle, A., Riethmuller, G., Douglas, A., Moore, J., Koetz, E.: Weed management in wide-row cropping systems: a review of current practices and risks for australian farming systems. Crop and Pasture Science 60(5), 395–406 (2009)

[8] Martín, M., Barreto, L., Fernández-Quintanilla, C.: Discrimination of sterile oat (avena sterilis) in winter barley (hordeum vulgare) using quickbird satellite images. Crop Protection 30(10), 1363–1369 (2011)

[9] Davis, A.S., Frisvold, G.B.: Are herbicides a once in a century method of weed control? Pest management science 73(11), 2209–2220 (2017)
[10] LOPEZ-GRANADOS, F.: Weed detection for site-specific weed management: mapping and real-time approaches. Weed Research 51(1), 1–11 (2011)

[11] Jin, X., Che, J., Chen, Y.: Weed identification using deep learning and image processing in vegetable plantation. IEEE Access 9, 10940–10950 (2021)

[12] Herwitz, S., Johnson, L., Dunagan, S., Higgins, R., Sullivan, D., Zheng, J., Lobitz, B., Leung, J., Gallmeyer, B., Aoyagi, M., et al.: Imaging from an unmanned aerial vehicle: agricultural surveillance and decision support.

Computers and electronics in agriculture 44(1), 49–61 (2004)

[13] Huang, H., Deng, J., Lan, Y., Yang, A., Deng, X., Zhang, L.: A fully convolutional network for weed mapping of unmanned aerial vehicle (uav) imagery. PloS one 13(4), 0196302 (2018)

[14] Mani, P.K., Mandal, A., Biswas, S., Sarkar, B., Mitran, T., Meena, R.S.: Remote sensing and geographic information system: a tool for precision farming. In: Geospatial Technologies for Crops and Soils, pp. 49–111. Springer, ??? (2021)

[15] Thorp, K., Tian, L.: A review on remote sensing of weeds in agriculture. Precision Agriculture 5(5), 477–508 (2004)

[16] L´opez-Granados, F., Torres-S´anchez, J., Serrano-P´erez, A., de Castro, A.I., Mesas-Carrascosa, F., Pena, J.-M., et al.: Early season weed mapping in sunflower using uav technology: variability of herbicide treatment maps against weed thresholds. Precision Agriculture 17(2), 183–199 (2016)

[17] Christensen, S., Søgaard, H.T., Kudsk, P., Nørremark, M., Lund, I., Nadimi, E.S., Jørgensen, R.: Site-specific weed control technologies. Weed Research 49(3), 233–241 (2009)

[18] Bah, M.D., Hafiane, A., Canals, R.: Weeds detection in uav imagery using slic and the hough transform. In: 2017 Seventh International Conference on Image Processing Theory, Tools and Applications (IPTA), pp. 1–6 (2017). IEEE

[19] Pantazi, X.E., Tamouridou, A.A., Alexandridis, T., Lagopodi, A.L., Kashefi, J., Moshou, D.: Evaluation of hierarchical self-organising maps for weed mapping using uas multispectral imagery. Computers and Electronics in Agriculture 139, 224–230 (2017)
[20] Oliveira, M.C., Osipitan, O.A., Begcy, K., Werle, R.: Cover crops, hormones and herbicides: Priming an integrated weed management strategy. Plant Science 301, 110550 (2020)

[21] Penía Barragán, J.M., Kelly, M., Castro, A.I.d., López Granados, F.: Object-based approach for crop row characterization in uav images for site-specific weed management (2012)

[22] Supčík, A., Oršulová, V.: Using obia for detection of canopy and row-gap by using drone images in vineyards. In: Precision Agriculture’21, pp. 531–537. Wageningen Academic Publishers, ??? (2021)

[23] Torres-Sanchez, J., Mesas-Carrascosa, F.J., Jiménez-Brenes, F.M., de Castro, A.I., López-Granados, F.: Early detection of broad-leaved and grass weeds in wide row crops using artificial neural networks and uav imagery. Agronomy 11(4), 749 (2021)

[24] Che’Ya, N.N., Dunwoody, E., Gupta, M.: Assessment of weed classification using hyperspectral reflectance and optimal multispectral uav imagery. Agronomy 11(7), 1435 (2021)

[25] Russakovsky, O., Deng, J., Su, H., Krause, J., Satheesh, S., Ma, S., Huang, Z., Karpathy, A., Khosla, A., Bernstein, M., et al.: Imagenet large scale visual recognition challenge. International journal of computer vision 115(3), 211–252 (2015)

[26] dos Santos Ferreira, A., Freitas, D.M., da Silva, G.G., Pistori, H., Folhes, M.T.: Weed detection in soybean crops using convnets. Computers and Electronics in Agriculture 143, 314–324 (2017)

[27] Sarker, M.I., Kim, H.: Farm land weed detection with region-based deep convolutional neural networks. arXiv preprint arXiv:1906.01885 (2019)

[28] Lin, C.: A support vector machine embedded weed identification system (2010)

[29] LOPEZ-GRANADOS, F.: Weed detection for site-specific weed management: mapping and real-time approaches. Weed Research 51(1), 1–11 (2011)

[30] Peteinatos, G.G., Weis, M., Andu’jar, D., Rueda Ayala, V., Gerhards, R.: Potential use of ground-based sensor technologies for weed detection. Pest management science 70(2), 190–199 (2014)
[31] Slaughter, D., Lanini, W., Giles, D.: Discriminating weeds from processing tomato plants using visible and near-infrared spectroscopy. Transactions of the ASAE 47(6), 1907 (2004)

[32] Zhu, D.-S., Pan, J.-Z., He, Y.: Identification methods of crop and weeds based on vis/nir spectroscopy and rbf-nn model. Guang pu xue yu Guang pu fen xi= Guang pu 28(5), 1102–1106 (2008)

[33] Borregaard, T., Nielsen, H., Nørgaard, L., Have, H.: Crop–weed discrimination by line imaging spectroscopy. Journal of agricultural engineering research 75(4), 389–400 (2000)

[34] Che’Ya, N.N.: Site-specific weed management using remote sensing (2016)

[35] Dammer, K.-H., Intress, J., Beuche, H., Selbeck, J., Dworak, V.: Discrimination of a mbrosia artemisiifolia and a rtemisia vulgaris by hyperspectral image analysis during the growing season. Weed Research 53(2), 146–156

[36] Steward, B.L., Gai, J., Tang, L.: The use of agricultural robots in weed management and control. Robotics and automation for improving agriculture 44, 1–25 (2019)

[37] By Paul SchrimpfGroup Editor Meister Media Worldwide: Deere Launches See Spray Select Technology (2021). https://www.precisionag.com/market-watch/deere-see-spray-select-release/

[38] Wang, A., Zhang, W., Wei, X.: A review on weed detection using groundbased machine vision and image processing techniques. Computers and electronics in agriculture 158, 226–240 (2019)

[39] MS Windows NT Kernel Description. https://www.deere.com/en/news/all-news/see-spray-ultimate/. Accessed: 2022-03-03

[40] Soil Surveys NRCS North Dakota (2021). https://www.nrcs.usda.gov/wps/portal/nrcs/main/nd/soils/surveys/

[41] Pen˜a, J.M., Torres-´Sanchez, J., de Castro, A.I., Kelly, M., L´opezGranados, F.: Weed mapping in early-season maize fields using objectbased analysis of unmanned aerial vehicle (uav) images. PloS one 8(10), 77151 (2013)
[42] Basso, M., Pignaton de Freitas, E.: A uav guidance system using crop row detection and line follower algorithms. Journal of Intelligent & Robotic Systems 97(3), 605–621 (2020)

[43] Rabab, S., Badenhorst, P., Chen, Y.-P.P., Daetwyler, H.D.: A templatefree machine vision-based crop row detection algorithm. Precision Agriculture 22(1), 124–153 (2021)

[44] de Silva, R., Cielniak, G., Gao, J.: Towards agricultural autonomy: crop row detection under varying field conditions using deep learning. arXiv preprint arXiv:2109.08247 (2021)

[45] Ota, K., Kasahara, J.Y.L., Yamashita, A., Asama, H.: Weed and crop detection by combining crop row detection and k-means clustering in weed infested agricultural fields. In: 2022 IEEE/SICE International Symposium on System Integration (SII), pp. 985–990 (2022). IEEE

[46] Case IH (2016). https://www.caseih.com/northamerica/en-us/News/Pages/Case IH News Release Case IH Introduces AIM Command _FLEX Advanced Spray Technology for More Accurate Applications.aspx

[47] Leemans, V., Destain, M.-F.: Line cluster detection using a variant of the hough transform for culture row localisation. Image and Vision Computing 24(5), 541–550 (2006)

[48] Bakker, T., Wouters, H., Van Asselt, K., Bontsema, J., Tang, L., Mülller, J., van Straten, G.: A vision based row detection system for sugar beet. Computers and electronics in agriculture 60(1), 87–95 (2008)

[49] Soares, G.A., Abdala, D.D., Escarpinati, M.C.: Plantation rows identification by means of image tiling and hough transform. In: VISIGRAPP (4: VISAPP), pp. 453–459 (2018)

[50] Soares, G.A., Abdala, D.D., Escarpinati, M.C.: Plantation rows identification by means of image tiling and hough transform. In: VISIGRAPP (4: VISAPP), pp. 453–459 (2018)

[51] Mukhopadhyay, P., Chaudhuri, B.B.: A survey of hough transform. Pattern Recognition 48(3), 993–1010 (2015)

[52] Bah, M.D., Hafiane, A., Canals, R.: Deep learning with unsupervised data labeling for weed detection in line crops in uav images. Remote sensing 10(11), 1690 (2018)
[53] Czymmek, V., Harders, L.O., Knoll, F.J., Hussmann, S.: Vision-based deep learning approach for real-time detection of weeds in organic farming. In: 2019 IEEE International Instrumentation and Measurement Technology Conference (I2MTC), pp. 1–5 (2019). IEEE

[54] de Silva, R., Cielniak, G., Gao, J.: Towards agricultural autonomy: crop row detection under varying field conditions using deep learning. arXiv preprint arXiv:2109.08247 (2021)