UNMANNED AERIAL SYSTEMS AND REMOTE SENSING FOR CRANBERRY PRODUCTION

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ABSTRACT. *Wisconsin is the largest producer of Cranberries in the United States with 5.6 million barrels produced in 2017. To date, Precision Agriculture technologies adapted to cranberry production have been limited. The objective of this research was to assess the feasibility of the use of commercial remote sensing devices and Unmanned Aerial Systems in cranberry production. Two commercially available sensors were assessed for use in cranberry production: 1) MicaSense Red Edge and 2) Zenmuse XT. Initial investigation assessed the cranberry beds during the growing season. Multi-spectral remote sensing and vegetative index images have previously been used to identify regions within the cranberry beds where fertilizer deficiencies exist and the presence of pest damage. Images were collected bi-weekly during the growing season and variations in vegetative indices were successfully detected within the beds. These could be attributed to fertilizer deficiencies or other potential issues within the bed. Further ground truthing of the data is required. Continuation of this research is currently underway to utilize the combination of the above remote sensing technologies to detect regions within the cranberry beds infested by cranberry insect pests. A replicated trial was conducted by introducing sparganothis fruitworm (Sparganothis sulfureana Clemens) and fall armyworm (Spodoptera frugiperda Smith) larvae onto cranberry plants in a greenhouse setting. Multi-spectral and thermal images of the damaged cranberry plants were collected weekly. Results showed Normalized Difference Vegetative Index values decreased as insect damage increased. The vegetative index values were shown to increase again as the plants grew and more biomass was present. Larvae density was not sufficiently high to cause noticeable increases in temperature of the plants. Field scale assessment of these technologies will be conducted during the 2018 growing season.*

Keywords: *Unmanned Aerial Systems, remote sensing, multi-spectral, thermal, insects*

INTRODUCTION

In 2015, over 5 million barrels of cranberries were produced in Wisconsin (USDA-NASS, 2016). In the U.S., over 8 million barrels of cranberries were produced (USDA-NASS, 2016). This high production number in Wisconsin makes cranberries a very important crop in the state.

Spatial variation within cranberry beds exists and can affect yield. Causes of this variation can be related to water, disease, soil, and pests (Hughes et al. 1999). Yield variation was characterized at three scales by Pozdnyakova et al. 2003. Medium scale, 100 variably spaced 0.9 m^2 from 21 cranberry fields proved to characterize the yield variation the best. Remote sensing technologies have been utilized in the past to quantify production variation within cranberry beds. Oudemans et al. 2002 utilized Geographical Information System (GIS) software and remote sensing for detecting yield loss in cranberry. Normalized Difference Vegetative Index (NDVI) and Structurally Independent Pigment Index (SIPI) were used to assess yield loss. Images were collected from a multi-spectral satellite images with 4 m (13 ft) square ground resolution. Areas with variations in yields were successfully identified and analysis showed that these areas occurred in similar locations from year-to-year. Diagnosis of specific problems causing the reduction in yield were difficult to identify. Pozdnyakova et al. 2002 assessed spatial and spectral properties of phytophthora root rot on cranberry yield using color-infrared photography taken from a manned aircraft. Resolution for the images in this case were 0.3 m (1 ft) square per pixel at ground level. NDVI was used to assess the plants and results showed that in late summer, the red band from color-infrared images correlated well with low soil infiltration rates causing the root rot. Yield and vine density can also be estimated using this technology. Cranberry beds in Wisconsin tend to be approximately 1.6 ha (4 ac) in size. Achievement of a higher measurement resolution per pixel could provide producers with more information about their beds when assessing them with remote sensing technologies.

Remote sensing, and specifically NDVI measurement has been used in other crops (corn and wheat) to detect nitrogen deficiencies and adjust fertilizer application rates (Ruan et al. 2001, Freeman et al. 2006). Utilization of this remote sensing technology allows producers to manage their crops spatially and apply chemicals and fertilizers where they are needed. This practice reduces inputs to the crop thus decreasing the cost of production and increasing profit margins. Assessment of cranberry beds in a similar manner could provide the same benefit to producers.

Thermal imagery has recently been identified as a remote sensing technology that will be beneficial to agricultural producers. Canopy temperature (infrared thermography) relates well to the water contained in the plant, having direct impact on irrigation scheduling in corn and soybeans (Chen et al. 2005). Thermal imaging has also been utilized to identify insect infested kernels in wheat (Manickavasagan et al. 2008). Results of this work showed that insect infestation of wheat kernels could be identified by thermal imaging due to temperature increase, but development stage of the insect could not be distinguished. Another study by Aldea et al. 2005 assessed thermal imagery and transpiration of insect damaged leaves in soybean. Transpiration increased and temperature of damaged leaf areas declined due to insect damage. Damaged areas not visible to the naked eye were detected by the thermal imagery.

Unmanned Aerial Vehicles (UAV/drones) are a new and exciting technology that can be implemented as a data collection tool in the agriculture industry. These small helicopters and fixed wing aircraft haul remote sensing payloads and can efficiently fly over production fields to measure crop properties throughout the growing season. These devices provide a much higher measurement resolution (2 cm/1 in per pixel or less) than traditional remote sensing technologies such as satellites and manned aircraft. Utilizing UAV based remote sensing producers could assess crop health at any time during the growing season and these assessments will provide information about the crop that producers have not had access to previously. Utilizing this information, producers will be able to make better management decisions that will reduce inputs, increase yield, and improve profit margins.

This study seeks to focus on detecting plant damage due to insect infestation utilizing available remote sensing technologies. Combining the information from commercial vegetative index (NDVI) sensor and a thermal imaging sensor, an algorithm will be developed to identify plants and fruit that have been infested by sparganothis fruitworm or fall armyworm. The hypothesis for this study is that the fruitworm and armyworm larvae feed on new leaves and berries of the plant (Cockfield and Mahr, 1993) which damages these parts. Plant damage causes the affected tissues to respire less, which decreases the cooling capacity of the plant, resulting in localized hot spots. Such hot spots have been shown in diseased and/or nematode-infested plants in New Jersey test plots (Oudemans et al. 2002, Oudemans pers. comm.). Also, when leaves and fruit are damaged the green-ness of the plant will be reduced, which is detectable via NDVI sensor. Combining the measurements from these sensors could provide spatial data on damaged parts of the bed allowing producers to correct the problems during the growing season and estimate potential yield loss. Specific objectives of this research are as follows:

Project Objectives:

1. Conduct greenhouse experiments with sparganothis fruitworm and fall armyworm on cranberry plants measuring NDVI and temperature of the plants with commercial sensors to develop an algorithm for detecting damage.
2. Implement these sensors on an Unmanned Aerial Vehicle (UAV) platform for deployment over Cranberry Marshes.

MATERIALS AND METHODS

A randomized complete block design was implemented to assess the impact of insect damage on growing cranberry plants with remote sensing sensors under controlled environment settings. Specific parameters of the experiment are outlined below.

Plants.
Cranberry plugs (cv. 'Stevens') were obtained from Evergreen Nursery (Sturgeon Bay, WI) mid-June 2017 and transplanted into 15 cm pots composed of 50% peat moss (Fafard; Agawam, MA) and 50% potting soil mix (Pro-Mix HP Mycorrhizae;Quakertown, PA). Four plugs were planted into each pot. Plants were kept outside for the duration of the summer. In early September, plants were taken inside the greenhouse and clipped back to remove any unhealthy vegetation and to promote new growth. Greenhouses were maintained at 25 ± 2˚C with a 16:8 light to dark (L:D) photoperiod.

Insects.
Sparganothis fruitworm (Sparganothis sulfureana Clemens) used for the experiment were from a lab colony maintained on Stonefly Heliothis Diet (Ward's Science; Rochester, NY) in incubators set to 24°C and 16-h light/8-h dark photoperiod.

Fall armyworm (Spodoptera frugiperda Smith) were purchased as eggs from Frontier Agricultural Sciences (Newark, DE) and once they eclosed they were fed the same Stonefly Heliothis Diet at 18˚C to slow their development and wait for Sparganothis to catch up. All insects were placed on the plants during their second-third instars.

Experimental conditions.
The experiment took place in two greenhouse rooms maintained at 25 ± 2˚C with a 16:8 L:D photoperiod. Each experimental unit consisted of four adjacent pots placed in a 2 x 2 grid, contained within an insect box. Each insect box was a cube of with sides of approximately 1.4 m and were constructed in house with wooden 2 x 4s covered with mosquito netting (Skeeta; Bradenton, FL) (Figure 1). Treatments consisted of a high and low insect pressure and control with no insects. There were four replicates of each treatment, randomly distributed through the two greenhouse rooms. Low insect pressure consisted of eight fall armyworm and eight Sparganothis in each cage, and high insect pressure consisted of 20 fall armyworm and 16 Sparganothis in each cage.

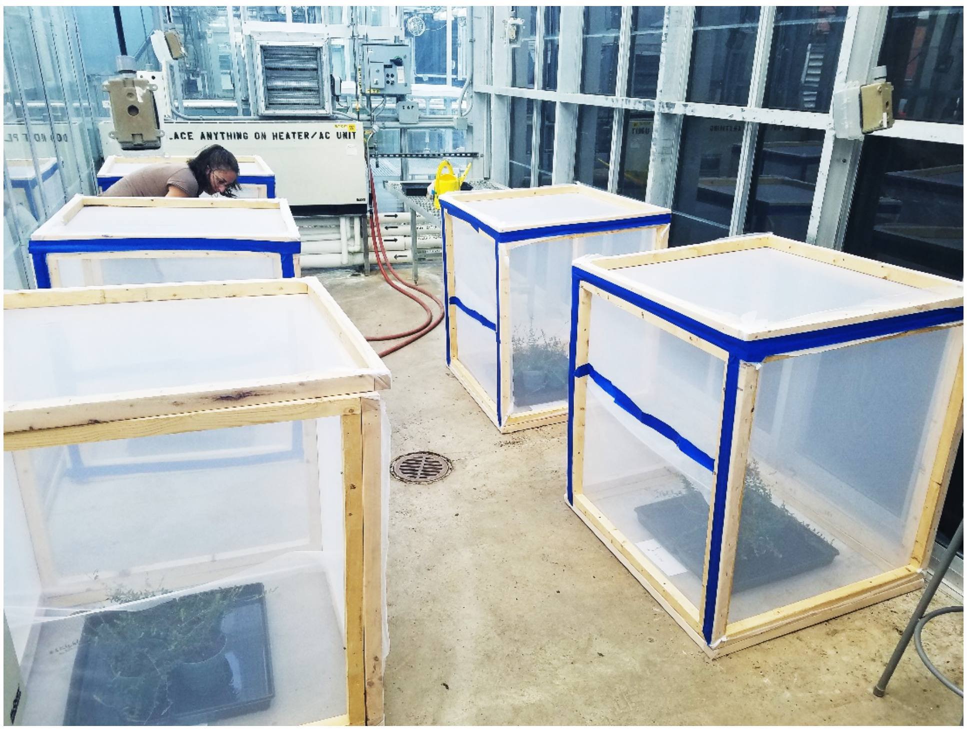


Figure 1. Greenhouse experimental setup with insect boxes, taped seams, and cranberry plants in place.

Image capture.
Multispectral images were taken with RedEdge camera (MicaSense; Seattle, WA) and ADC Snap camera (Tetracam Inc., Chatsworth, CA). In addition, images of calibrated reflectance panels were captured for post processing of images. Thermal images were obtained with the Zenmuse XT (FLIR, Wilsonville, OR) and visible light images were taken (D7100, Nikon, Japan). A frame was placed over each cage during image acquisition to steady the cameras and align images over the center of the cages. Pieces of white plastic were placed at the floor of each cage to facilitate image alignment during image processing. The first images were captured the day before insects were placed in cages to capture a baseline image. Thereafter they were taken every two-three days. Image capture continued for four weeks while the insects were allowed to defoliate the cranberry plants.

Image analysis.
ImageJ software was used to calculate the surface area of plants as captured with the Nikon camera. Each image was opened in the software and the scale was set by denoting the diameter of one of the pots. Area was measured by adjusting the color threshold, using the default method and adjusting the upper and

lower hue, saturation and brightness thresholds until the area contained within the thresholds consisted of as much of the plants and as little non-plant material as could be defined.

A radiometric calibration of the spectral images captured with the RedEdge camera was conducted before analysis to convert raw pixel values to spectral radiance values [W m^{-2} sr^{-1} nm^{-1}] using manufacturer specifications and ambient lighting conditions (Micasense, 2015). Because each of the five lenses are offset from each other, the five channels were registered (Mathworks, 2018) to a single channel to allow for algebraic manipulation of the data (Figure 2). False color images of each cage were then created by mapping the red, green, and NIR to the red, blue, and green channels, respectively. K-means clustering (Arthur & Vassilvitskii, 2007; Lloyd, 1982; Mathworks, 2018) was used to create a mask to separate plant material from the background for each image to determine the NDVI and NDRE of plant material within each cage (Figure 3).

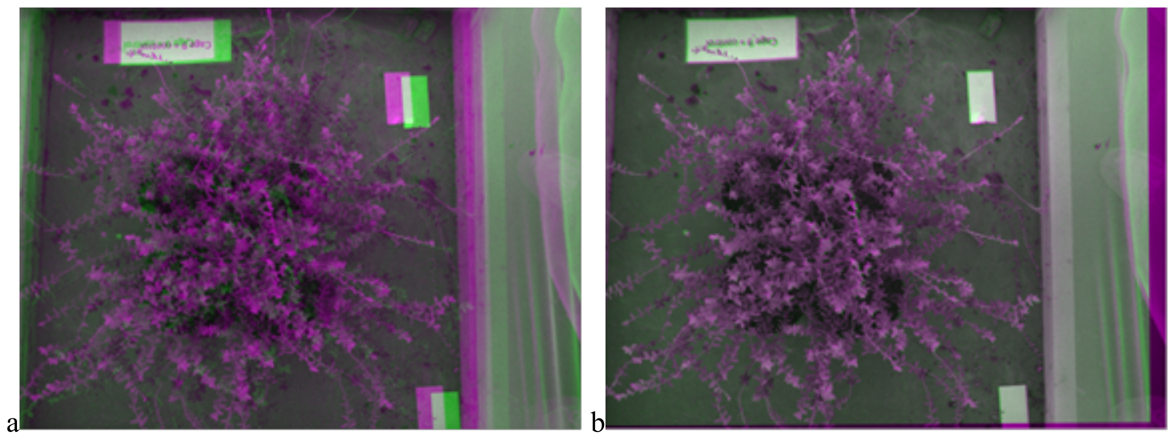


Figure 2. Example of (a) two unregistered images overlaid, (b) two registered images overlaid. One image has a green tint and the other magenta to highlight areas of overlap.

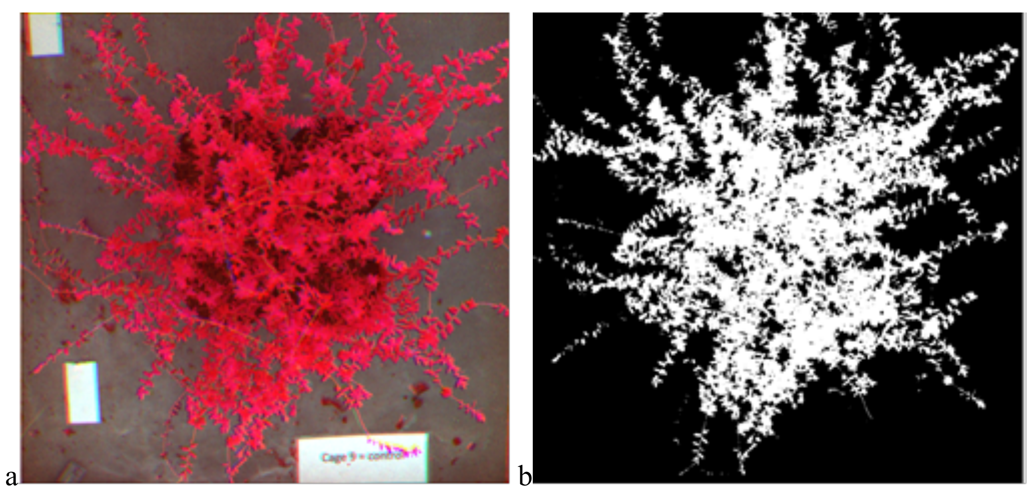


Figure 3. Example of (a) false color image and (b) resulting mask from k-mean analysis.

Raw sensor values from the IR camera were converted to temperature, accounting for attenuation due to atmospheric transmission and scene emissivity using manufacturer specified calibration parameters (FLIR, 2013).

In-field validation.

A cranberry marsh in central Wisconsin was selected for assessment due to heavy pest pressure and other issues within the bed that might be readily detected with the remote sensing technologies. A four-rotor Unmanned Aerial Vehicle (UAV) (Matrice 100, DJI, Los Angeles, CA) (Figure 4) was used to transport the multi-spectral and thermal camera simultaneously. Autonomous parallel flight paths were flown over the beds at an altitude of 45.7 m and at a frequency of twice per week, depending on weather conditions. Ground truthing assessment was completed by dividing the beds into quadrants and visual assessment of plant damage was quantified spatially. Hula-hoops were tossed into each quadrant at three random locations and field notes were taken on the various weeds, plant damage, and other areas of plant stress contained within (Figure 5).

Figure 4. DJI Matrice 100 equipped with multi-spectral camera and visible light camera used for data acquisition over cranberry beds. This platform also had the ability to implement thermal measurements in place of the visible light camera.

Figure 5. Example of ground-truthing method for the UAV based data collection within cranberry beds. The hula-hoop defines the boundary for assessment and any weeds (top of image), damaged plants, or insect presence was documented. These assessments will be cross-referenced to the data collected by the remote sensing instruments to identify and map any problem areas within the beds.

Statistical Analysis.

Statistical analysis of NDVI as a function of day post insect infestation and insect level was conducted using the MIXED Procedure in SAS account for the effect of repeated measures of each cage (Sas, 2013). The effect of room was considered to be a random effect. Means were separated using Tukey's method (Sas, 2013). The NDVI data were assessed for the assumption of normality of residuals and constant variance using graphical methods.

RESULTS

Plant area was successfully calculated utilizing ImageJ over the duration of the experiment. Insect level treatments and date treatments showed statistically significant results ($\alpha = 0.1$, P-value = 0.09). All plant area increased by day across all insect level treatments (Figure 6). Insect level treatments had a significant impact on the rate of plant area increase.

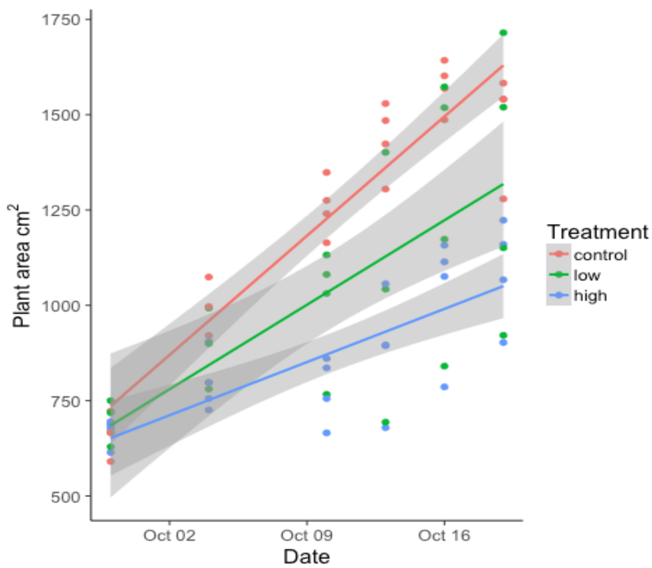
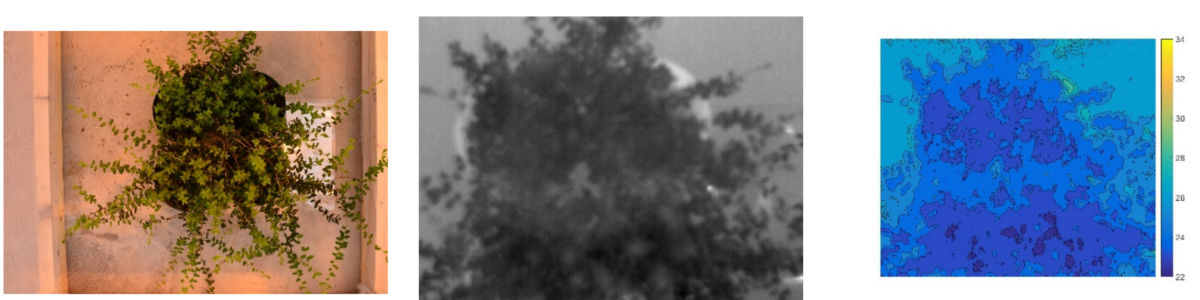


Figure 6. Plant area versus assessment date. Plant area increased by day. Insect treatment levels had an effect on the rate of plant area increase over the duration of the study. Area shaded in gray represents a 95% CI around the mean.

Infrared assessment of the different treatment levels showed a general trend of increased plant temperature with increased plant damage (Figure 7). Data analysis to find statistical differences between treatments are currently ongoing.



a b c

d e f

Figure 7. Thermal imaging results for the control cranberry plants (a: visible light, b: unprocessed thermal image, and c: calibrated false color thermal image) versus the high insect population cranberry plants (d: visible light, e: unprocessed thermal image, and f: calibrated false color thermal image). Thermal measurement generally showed higher temperature in the high insect population plants (d, e, and f) compared to the control plants (a, b, and c).

Normalized Difference Vegetative Index response showed a decrease in NDVI across all treatments approximately 7 days after insect application (Figure 8) in the greenhouse study. While no statistically significant differences were found between insect level and NDVI (P-value = 0.69), NVI was significantly different by day (p=<0.0001) under a significance level of 0.1. While the insect treatment did not show a response, there is potential for detecting other problems within the plants (i.e. water stress, nutrient deficiency, etc.). This study will be repeated with an eye toward identifying causes of decreased NDVI measurements within cranberry plants.

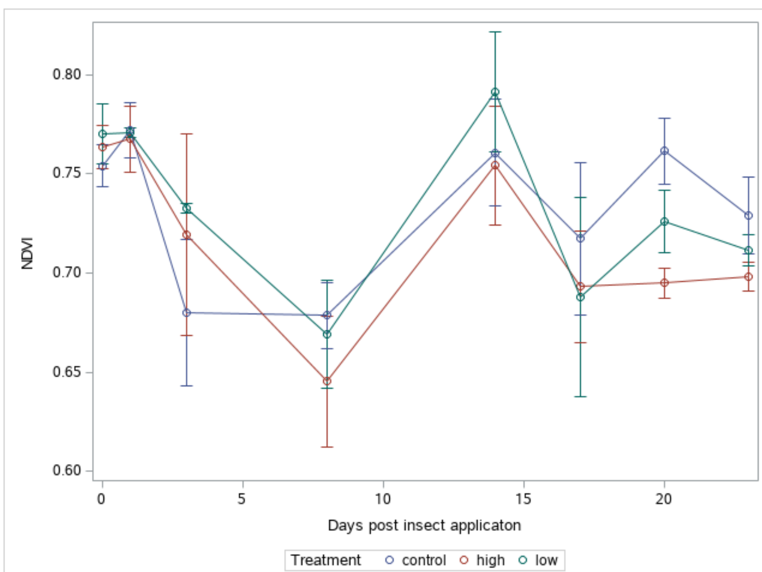
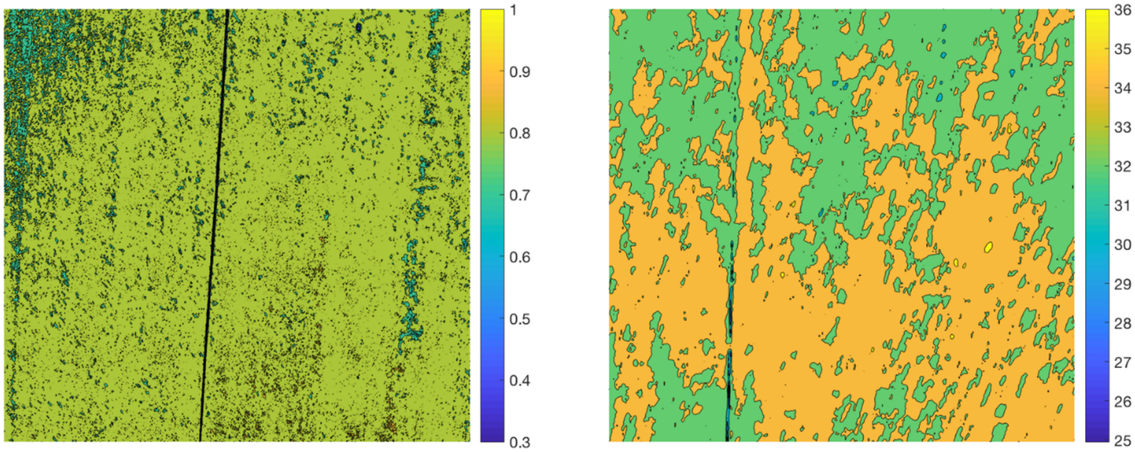


Figure 8. Normalized Difference Vegetative Index response to insect damage (days after insect application). NDVI decreased approximately 7 days after application, but the plants generally recovered from the damage 14 days after insect application. The cause for this reduction can not be attributed directly to insect feeding due to the control plants being reduced as well.

Data collection via the UAV with the multi-spectral camera and the thermal camera has shown variation within the beds (Figure 9). Normalized Difference Vegetative Index shows areas within the image of lower values (Figure 9a). These can be attributed to plant thinning, bare soil, or damaged plants. Visual assessments of these areas will be paired with the images to identify the cause of these low NDVI values. Thermal imagery of the cranberry beds also shows variation (Figure 9b). Temperature variations of 2 °C have been detected and ground-truthing efforts are seeking to identify the cause of these temperature differentials.



a b

Figure 9. Unmanned Aerial Vehicle captured multi-spectral (a) and thermal (b) images over cranberry beds. Lower Normalized Difference Vegetative Index values can be seen within the bed indicating damaged plants or bare soil areas. Thermal imagery shows temperature variation within the bed. Further analysis and algorithm development are currently ongoing.

Future work aims to develop an algorithm using these data streams and the results from ground truthing efforts to identify areas within the beds that need attention due to plant stress. The goal of this algorithm would be to identify areas of plant stress and hopefully indicate causes for the stress based on the training data set collected within this research project.

CONCLUSIONS

A combination of greenhouse experiments and in-field data collection were performed to assess remote sensing in cranberry plants. Multi-spectral imaging produced results in the greenhouse experiments showing a decrease in Normalized Difference Vegetative Index (NDVI) 7 days after insect application and then indicating a recovery of the plants around 15 days. All treatments, including the control, exhibited these results, thus the cause can not be attributed to the insect pressure. Likely causes of the reduction in NDVI could be water stress or nutrient deficiency. Thermal measurements of the plants within the greenhouse showed an increase in temperature due to defoliation and damage to the plant caused by insects. Field experiments are currently ongoing to assess production cranberry beds for weed infestation, insect infestation, and potential stress due to nutrient deficiencies or water stress. Initial results show that plant stress can be detected with these sensing platforms. Algorithm development for combining the different sensing techniques is currently ongoing to provide maps of effected areas and to determine if the cause of plant stress can be identified within this data set.

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