CROP GROWTH & PHYSIOLOGY

RESEARCH & EXTENSION

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9. TITLE: Can We Predict Wild Blueberry Plant Stress Using Drones?

OBJECTIVES

- Combine wireless sensors and drones (unmanned arial vehicles or UAVs) to detect both temporal and spatial variation in wild blueberry water status.
- Develop a low-cost, low-energy, farmer-friendly way of monitoring wild blueberry plants using recent advances in technology.
- Validate the application of the infrared and RGB-based Crop Water Stress Index on wild blueberries.

LOCATION: Deblois, ME
PROJECT TIMEFRAME: April 2019 – December 2020

INTORDUCTION

The agricultural systems in Maine face everyday challenges due to unpredictable weather caused by anthropogenic climate change (IPCC, 2012; Cohn et al. 2017). Farmers and researchers have already noticed an increasing frequency of extreme weather events. These include a five-year “summer drought” from 2013 to 2018, an exceptionally warm fall in 2017, and an extreme freeze event in June to top off the late spring of 2018. Drought effects and temperature anomalies are predicted to increase in the future (Dai 2013). Bruce Hall, an agronomist at Wymans of Maine has indicated that “soil on the barrens can go from fully saturated to drought condition in as little as 30 hours”. For growers who irrigate, these quick and sometimes unforeseen fluctuations in soil moisture make it difficult to maintain stress-free plants.

We know that wild blueberry requires an average of 0.5 and 1.0 inch of water per week (Hunt 2006). We also know that wild blueberry soil varies between production regions and within fields. Given advances in technology, field and plant specific estimates of water needs could be determined. Sensors, cameras, and drones are now common plant health tools used on large farms. The use of these tools and the improvement of efficiency on farms is now referred to as precision agriculture. These tools collect a lot of data that is used to improve on-farm efficiency, thereby improving plant health, yield, and quality.
Together, on-ground wireless sensors and drones can bring useful monitoring data to farms (Honkavaara et al. 2013). While drones provide good spatial resolution, they cannot monitor farms continuously and their performance relies heavily on clear, sunny flying days. Ground-based wireless sensors can monitor crops continuously yet cannot cover the whole farm. Existing wireless sensors are costly and lack energy-efficiency.

There is a need to bring appropriate technologies to wild blueberry production. By designing a platform to investigate the crop-soil-atmosphere interactions of wild blueberry, the project team hopes to shed light on production efficiency and potential climate change adaptation strategies. In this project, a low-cost and low power Cyber

Physical System (CPS) network was developed to monitor temporal variation in the water status of wild blueberries on one field in Deblois, Maine.

METHODS

Two fields were selected for this study in collaboration with Wyman's of Maine. One field was 40 acres with irrigation and the second field was 39 acres without irrigation. One weather station was set up in each field. Twenty wild blueberry plants were selected at random within each field for in-depth sensor and drone data collection. Drone and ground samples were taken at four major crop stages (peak bloom, green fruit, color break, and pre-harvest) in both irrigated and non-irrigated fields (Table 1).

Drone Data Collection

A new integrated drone-based camera that has sensors to collect red, green, blue (RGB), thermal and multispectral data was purchased (Altum, MicaSense, WA, USA). This drone-based system was used to capture high-resolution RGB and thermal images at the plant and field level. The drones collected fine-scale elevation, temperature, and crop water stress data in addition to high definition RBG imagery used to calculate the NDVI (normalized difference vegetation index). The NDVI is an estimation of the density of green color based on the visible and near-infrared reflectance of the vegetation present (Drisya et al. 2018). Aerial imagery and field samples collected during the 2019 field season are still being calibrated and analyzed, all results below are preliminary, and observation based. Thermal images will be analyzed in accordance with Sela et al. (2007) to calculate crop water stress index (CWSI) based on canopy temperature and used to map the CWSI across the entire field.

Table 1. 2019 dates of UAV flight sampling in accordance with wild

Crop Stage	**Date**
Peak Bloom	June 4, 2019
Green Fruit	July 3, 2019
Color Break	July 25, 2019
Pre-Harvest	August 14, 2019

On-ground Wireless Sensor Network and Data Collection On the ground, Dr. Zhang's and Dr. Calderwood's teams conducted pest scouting and collected leaf temperature, soil moisture, leaf chlorophyll and anthocyanin contents, and leaf water status (leaf water potential) at each pinned location in Figure 1. For pest scouting, one 0.37 m^2 quadrat was placed in the center of each plant where the presence of weed species, insect and disease pressure were recorded on. Pest severity was established using equal intervals between 0 and 6, where: 0 = not present, 1 = ≤1%-17%, 2 = 17%-33%, 3 = 33%-50%, 4 = 50%-67%, 5 = 67%-83% and 6 = 83%-100% severity. Weeds were identified into two groups: grass and broadleaf, each of which were also given a severity rating on the same 0-6 scale. Leaf temperature was measured using a Fluke 62 MAX Plus IR Thermometer (Fluke Corp., Everett, WA, USA) and soil moisture was collected using a TDR 150 soil moisture sensor (Spectrum Technologies Inc., Aurora, IL, USA). Leaf chlorophyll content was measured by a SPAD Chlorophyll Meter (SPAD 502; Minolta Corp., Osaka, Japan) and anthocyanin content was measured with an ACM-200 anthocyanin meter (Opti-Sciences Inc., Hudson, NH, USA). The leaf water status was quantified with leaf water potential determined by a leaf pressure chamber (PMS Inc., Albany, OR, USA). Leaf water potential measurements will be used to validate the application of imagery-based crop water stress index (CWSI) on wild blueberries.

In order to set up and test a wireless sensing network, six sensor stations were assembled and will be established in 2020 across the study area (3 on each field) in Deblois, ME. A wireless sensing network including sensors with backscattered wireless communication units and a wireless hub has been developed. Sensors included one soil moisture sensor, one infrared thermal sensor, and one RBG color sensor (Figure 2). The wireless hub included microcontrollers, battery, Zigbee communication units, and other functional units. Wireless power transfer enabled recharging for the batteries was employed (Guo and Sun 2014; Guo et al. 2017) and the system was designed to operate for up to 10 years without changing batteries. The GRB and thermal images were used to calculate crop water stress index (Sela et al. 2007).

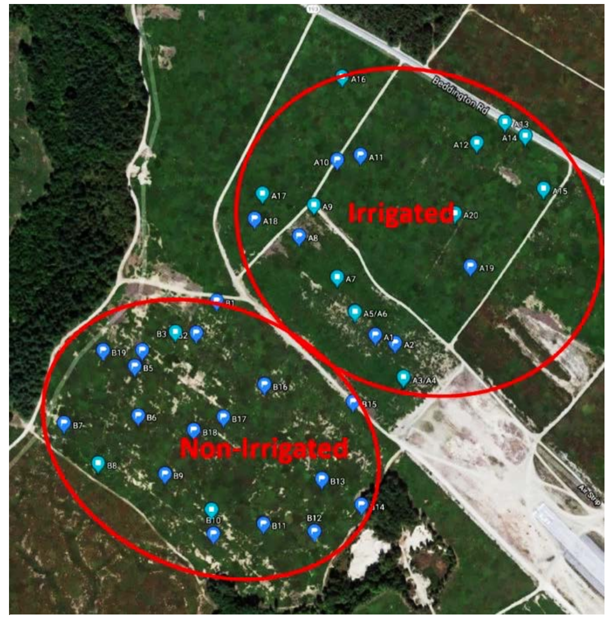

Figure 1. Study site in Deblois, ME. Blue dots indicate on-ground and drone data collection sites.

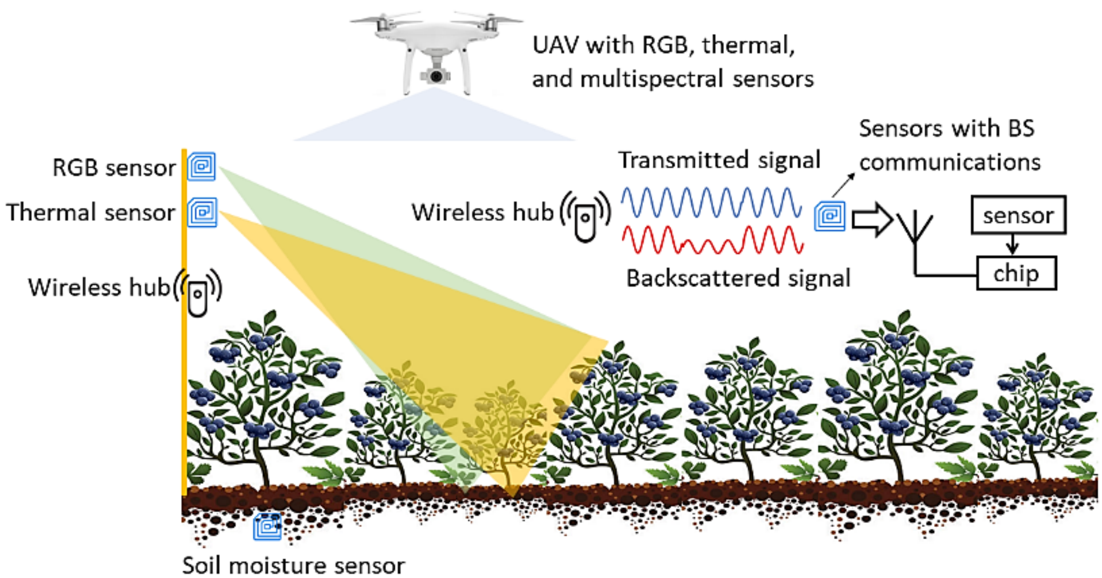

Figure 2. The design of this project and the architecture of the wireless sensor station.

RESULTS - Preliminary

While imagery and index calibration are still underway, preliminary and observed results show the wide-range of potential uses for this technology to quantify the plant-soil-atmosphere dynamics of wild blueberry. There are many ways this technology could be used to improve crop management and physiological understanding. Figures 3-5 show the same fields as figure 1 with graphic overlays of the different parameters collected by the drone. As expected, the irrigated field was slightly cooler (Figure 2) than the non-irrigated field on the initial sample date (June 4th, 2019) due to the greater cooling effects of higher evaporation and transpiration (Taiz and Zeiger 2015). A digital elevation model (DEM) showed that the irrigated field is lower in elevation than the non-irrigated field. This could also further affect the thermal gradient.

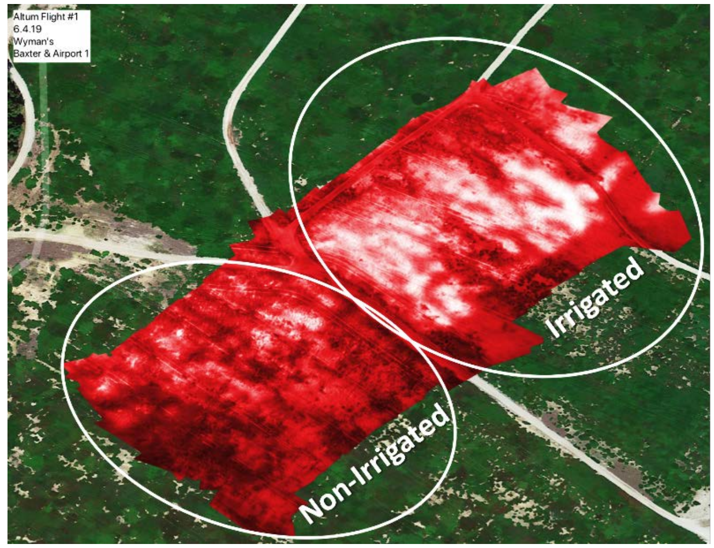

Figure 3. UAV thermal imagery of the non-irrigated and irrigated fields at Wyman's of Maine. Dark = warm, light (white) = cool.

Vegetative health was quantified using the NDVI index (Figure 3). Here, both irrigated and non-irrigated fields showed healthy plants within the yellow (0.7) to blue (1.0) range. A moisture stress index was also captured using the drone. Both fields were dry with little variation at the time of this measurement. Irrigation was difficult to evaluate in 2019, as we had a wet spring and the overall need for irrigation was low. Overall, our preliminary data suggests that 1) drone-based sensors can detect spatial variations in crop water status and health, 2) leaf temperature may be a good predictor of leaf water potential and thermal images will be useful for improving the efficiency of irrigation.

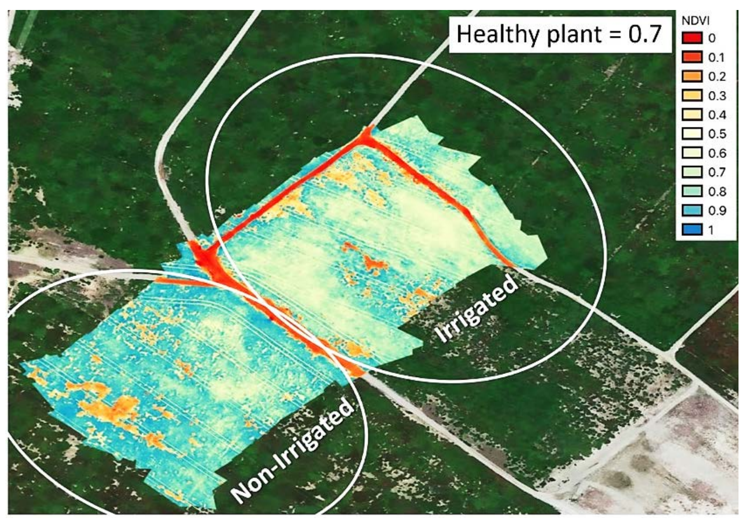

Figure 4. NDVI of the irrigated and non-irrigated fields at Wyman's of Maine. In this relative vegetative health gradient, the healthiest plants are closest to the 1.0 level.

DISCUSSION

While imagery and index calibration are still underway, preliminary and observed results show the wide-ranging potential uses of this technology in quantifying the plant-soil-atmosphere dynamics of wild blueberry. There are many ways this technology could be used to improve crop management and physiological understanding.

CURRENT RECOMMENDATIONS
None at this time.

NEXT STEPS
<u>On-going:</u>

- Validate imagery-based Crop Water Stress Index for wild blueberries.
- Evaluate the effectiveness of current irrigation practices.

<u>Future goals:</u>

- Expand the platform to include fertility and pest management.
- Develop an AI system to analyze and report crop-environment interactions automatically in the long-term.

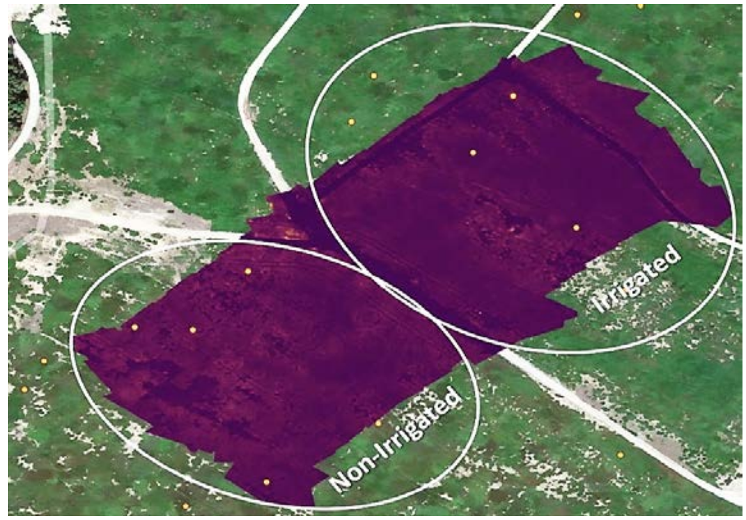

Figure 5. Moisture stress index of the irrigated and non-irrigated fields at Wyman's of Maine. Here, lighter tones have higher moisture, while the darker (purple) tones are dry.

ACKNOWLEDGEMENTS
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