Project/Proposal Title: Modeling orchard effects on meteorological measurements

Primary PI: Joe Boomgard-Zagrodnik
Organization: Washington State University
Telephone: 414-916-1771
Email: joe.zagrodnik@wsu.edu
Address: 4009 32nd Ave SW
City/State/Zip: Seattle, WA 98126

Co-PI 2: David J. Brown
Organization: METER Group
Telephone: 509-335-1859
Email: dave.brown@metergroup.com
Address: 2365 NE Hopkins Ct
City/State/Zip: Pullman, WA, 99163

CO-PI 3: Lee Kalcsits
Organization: Washington State University
Telephone: 509-293-8764
Email: lee.kalcsits@wsu.edu
Address: 1100 N Western Ave
City/State/Zip: Wenatchee, WA 98801

Cooperators: METER Group, Pullman, WA

Report Type: Continuing Project Report

Project Duration: 3 Year

Total Project Request for Year 1 Funding: $
Total Project Request for Year 2 Funding: $
Total Project Request for Year 3 Funding: $65,113

Other related/associated funding sources: None

WTFRC Collaborative Costs: None

Budget 1
Primary PI: Joe Boomgard-Zagrodnik
Organization Name: Washington State University
Contract Administrator: Anastasia Mondy
Telephone: 916-897-1960
Contract administrator email address: arcgrants@wsu.edu

Item	**2020**	**2021**	**2022**
Salaries	$13,245.75	$40,693	$42,321
Benefits	$4,517.25	$14,223	$14,792
Equipment	$36,150	$0	$0
Travel	$6,000	$8,000	$8,000
Total	$60,025	$62,916	$65,113

Footnotes:

[1] Salaries include 2 months of postdoc time at AgWeatherNet in year 1 and 4 months in years 2-3, 1.5 months of research associate time in the Kalcsits lab (years 1-3), 1 month of field meteorologist time at AgWeatherNet (years 1-3), and 1.75 months of systems analyst/programmer time (years 1-3).

[2] Benefit rates are budgeted for 35%.

[3] Equipment includes 8 weather sensors, 8 soil moisture sensors, and 2 instrument towers.

[4] Travel budgeted for travel to field sites, meetings with collaborators and presentation of results at industry winter meetings in Washington State.

OBJECTIVES

1) Measure the effects of irrigated orchard canopies on meteorological measurements relative to standard unobstructed, unirrigated meteorological sites.

2) Construct statistical models that estimate the magnitude of orchard effects on air temperature, relative humidity and wind speed as a function of weather conditions and irrigation.

3) Develop and implement algorithms in AgWeatherNet to dynamically correct for orchard effects and support orchard-specific delivery of weather data, forecasts and decision-support tools.

Progress on objectives was consistent with the timeline reported in the proposal submitted in fall 2019:

Year 1 –
Goal: Identify paired sites, acquire instruments, initiate field measurements for both paired Atmos 41 stations and met towers. Restructure database as needed to secure Tier 3 station data.
Progress: Deployed 8 sets of paired ATMOS-41 stations in early summer 2020 which continue to operate. Completed two weeks of met towers observations at Sunrise research orchard in early August 2020. Completed database restructuring to support Tier 3 station data.

Year 2 –
Goal: Complete full year of field data acquisition, initiate modeling, code framework required to implement transformation models.
Progress: Data collection has continued at existing paired stations from 2020. Additional stations have been added to more carefully target (1) netting; (2) within-orchard variability. Research met towers have been moved to an Allen Bros site and are currently collecting data. Irrigation event detection methodology has been completed.

Year 3 –
Goal: Continue field data acquisition as needed, complete modeling, complete coding to automate model implementation in the AWN system.
Updates: Emphasis has been to move away from transfer modeling, since data shows there is considerable variability between orchards and

SIGNIFICANT FINDINGS

1) Microspray and overhead irrigation effects:
    a. Microspray and overhead irrigation events are best detected by the rain gauge on an in-orchard weather station. Leaf wetness sensors are unreliable due to orchard sprays that coat the sensor and soil moisture detection lags events by at least a few hours.
    b. The dynamic effect of microspray cooling might be greater in weak canopies than strong canopies.

2) Orchard effects have a seasonal cycle:
    a. Orchards are cooler and moister in summer/fall as a result of irrigation, evaporative cooling, and evapotranspiration. Both daytime and nighttime temperatures are cooler in orchard.

b. Orchard effects are generally less but more variable depending on the orchard in wither/spring.
c. In-orchard stations generally have lower wind speed in the summer (relative to out-orchard stations) and higher wind speed in the winter—presumably due to the effect of wind machines.

3) Orchard effects are highly dependent on orchard configuration, station siting, and management activities. But overall:
   a. Overhead netting causes the same effects as irrigation (cooler/moister in summer), but the effects are subdued relative to microspray cooling. The weaker humidity effect may be beneficial for disease prevention.
   b. The stronger Smart Orchard 2 canopy had a >50% greater orchard effect than the weak canopies this past summer.
   c. The orchard effect will appear to be stronger if the in-orchard weather station is located below the canopy (at a lower height than the paired outside-orchard station).

METHODS

Methods from the original proposal submitted in winter of 2020 are summarized below. Changes to the methods are summarized at the end of each objective.

Objective 1 – Observations

Standard meteorological observations

AWN has begun collecting observational data under a variety of orchard conditions in order to build a long-term database of in-orchard stations paired with nearby non-orchard AgWeatherNet (AWN) stations. The construction of this database is an essential foundation for modeling the orchard effect (Objective 2) and implementation (Objective 3). Increasing the number of stations in the classification database, particularly from grower-participants, remains a priority because the ability of the data to predict in-orchard conditions in orchards without a weather station will be strengthened with a longer period of record and more stations in the system.

Objective 2 -- Statistical Modeling

AWN will construct three statistical models for each target variable (temperature, humidity, wind speed). These models will have both continuous and categorical predictors and it may be necessary to construct separate models for different seasons or synoptic meteorological conditions. The general framework of these models is given below. All three models will be examined for consistency between transformation pathways.

- ***Trellis post station -> reference station***
- ***Trellis post station -> canopy conditions***
- ***Reference station -> canopy conditions***

Ultimately, we want to run models and decision-support tools using weather conditions within the canopy. For orchardists who install weather stations on trellis posts, this requires construction of models that estimate within canopy conditions using trellis post measurements.

Changes for 2022:

- Results indicate that it is better for growers to install an in-orchard station than to rely on outside-orchard statistical corrections which are highly variable between orchards.
- The modeling focus in 2022 will be on the dynamic effects of irrigation and statistically adjusting in-orchard data to account for irrigation events.

Objective 3 -- Implementation

Database modifications:
In 2020, AgWeatherNet established an in-orchard station "type" designation in the existing database, ensuring that data from producer-owned stations is secure, and only available to the station owner unless they opt to make their weather data (and associated weather-driven tools) public. AgWeatherNet is also continuing to develop additional site-specific metadata fields in order to collect and store information from in-orchard station owners on crop type, irrigation systems, training systems, and sun shading where relevant.

Model implementation

All three models from Objective 2 will be coded into the AWN system. First, any data acquired from an in-orchard station will be transformed using the trellis-to-reference model for implementation of station comparison QA/QC procedures. This transformed data will also be used to train machine-learning based forecast models as these are built upon physical atmospheric models that assume meteorological standard ground station data. Forecast predictions will subsequently be back transformed for site-specific delivery using the reference-to-trellis-to-canopy model. Current weather data will be directly transformed to estimate within-canopy conditions. Within canopy weather data and forecast estimates will be used to drive AWN (and potentially DAS) models and decision support tools.

When an in-orchard station isn't available, orchard managers can select and weigh up to three AWN stations to estimate site-specific weather conditions, and the reference-to-canopy model will be used to transform reference data for site-specific delivery of weather conditions, forecasts and tools. The new AWN app will include clear indications when transformed data is being used, and allow users to easily compare with raw in-orchard station data or reference station data.

Changes for 2022:

- Rather than implementing transformations as discussed above, weather forecast predictions will be trained directly on in-orchard weather data (after the in-orchard data has been corrected for irrigation events). The process of developing the forecast models is already underway, funded by a WSDA specialty crop block grant that began on 10/1/2021.

RESULTS AND DISCUSSION

Additional paired inside- and outside-orchard ATMOS-41 and ATMOS-14 all-in-out weather stations were installed in 2021. New studies include (1) a row orientation study (north-south vs. east-west) at the Mike Skeels orchard; (2) a height comparison study at the Smart1 orchard; and (3) a weak vs strong canopy comparison at the Smart2 orchard.

						Outside - Inside Difference		
Comparison	**Install Date**	**Experiment type**	**Height-out**	**Height-In**	**Days**	**TEMP (F)**	**RH (%)**	**WIND (mph)**
AMT	2020-Jun-9		5.5 ft	5.5 ft	471	1.4	-3%	1.1
CSC	2021-Apr-27		5.5 ft	5.5 ft	183	0.8	-3%	0.2
Dietz-high	*2020-May-29*		*5.5 ft*	*12 ft*	*516*	*0.5*	*-1%*	*-1.0*
Fir	2020-Jun-5		5.5 ft	5.5 ft	470	2.3	-9%	0.2
O-Road	2020-Aug-9		5.5 ft	5.5 ft	431	2.3	-8%	0.2
Quincy	2020-Jul-17	Overhead netting	5.5 ft	5.5 ft	468	0.8	-2%	1.2
Skeels-NS	2021-Apr-27	N-S orientation	5.5 ft	5.5 ft	183	1.7	-9%	3.0
Skeels-EW	2021-May-18	E-W orientation	5.5 ft	5.5 ft	162	1.0	-5%	1.1
Smart1-high	*2021-Apr-13*	*Multiple heights*	*5.5 ft*	*12 ft*	*197*	*0.0*	*+2%*	*-0.1*
Smart1-mid	2021-Apr-13	Multiple heights	5.5 ft	5.5 ft	197	1.1	-4%	NA
Smart1-low	*2021-Apr-13*	*Multiple heights*	*5.5 ft*	*2.5 ft*	*197*	*2.0*	*-6%*	*1.2*
Smart2-weak	2021-Jun-08	Weak canopy	5.5 ft	5.5 ft	141	3.1	-11%	1.1
Smart2-strong	2021-May-04	Strong canopy	5.5 ft	5.5 ft	106	5.1	-24%	1.5
Vanderbilt	2020-June-11		5.5 ft	5.5 ft	249	1.2	-5%	0.8
Average						**1.7**	**-7%**	0.8

Table 1: Metadata and summary statistics from paired station deployments. Stations in italics have different out-in heights.

Seasonal variability

At the locations with over a full year of data and equivalent in-out station heights (AMT, Fir, O-road, Quincy, and Vanderbilt) it is now possible to quantify the seasonal variability in orchard effects. Figure 1 shows the monthly-averaged outside-inside difference in air temperature (top), RH (middle), and wind speed (bottom). The Quincy-Net site (discussed below) is plotted separately.

Irrigation and evapotranspiration are the primary sources of temperature and RH effects. These effects peak in July (irrigation season) but linger into the fall. In late winter/spring the orchard effect is weak.

The wind speed effect is greatest in the late spring and early summer. In winter, we observed stronger winds inside the orchard at times, this was surprising and is most likely a result of wind machine usage, given the timing in February/March. Wind effects are also strongly dependent on station height – for instance, the 12 ft inside-orchard Dietz station recorded stronger winds year-round than the 5.5 ft outside-orchard station. It must be strongly emphasized when placing in-orchard stations to **locate the station in the exact spot where weather observations are needed**. If the station is above the canopy, the weather conditions will not be reflective of in-canopy conditions.

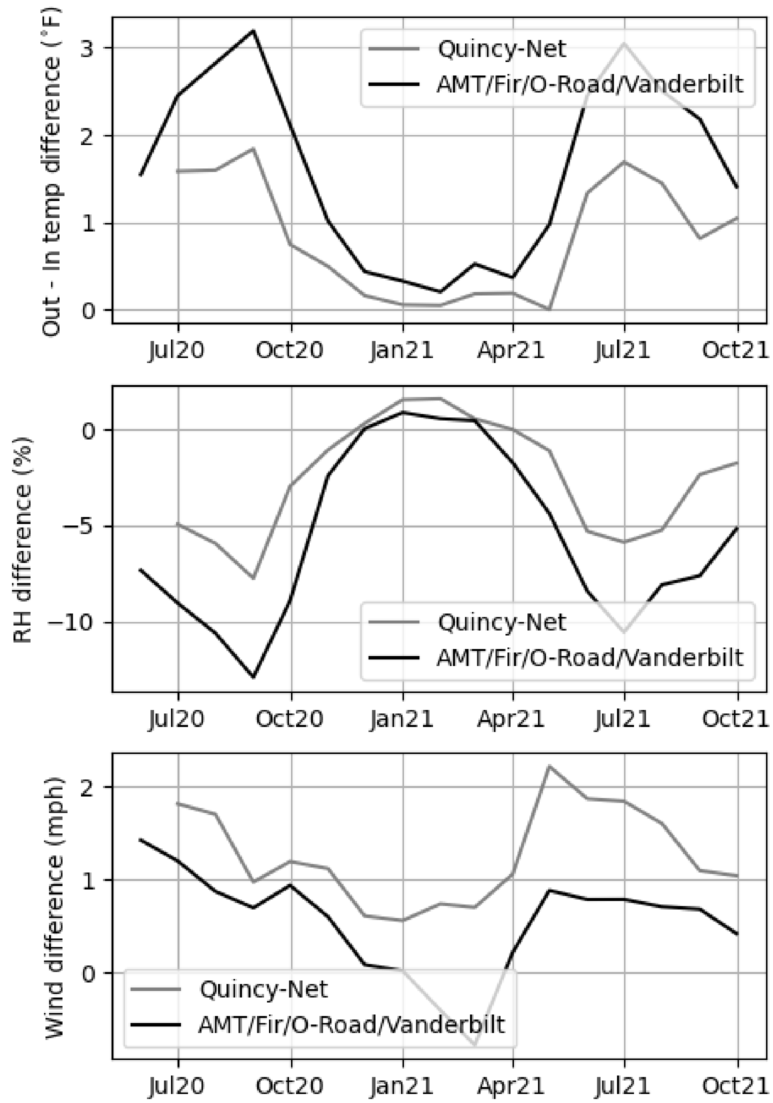


Figure 1: Monthly average out-in difference in air temperature, RH, and wind.

Effect of overhead netting

The Quincy site with overhead netting in summer, plotted in Figure 1, shows that shade netting results in slightly different orchard effect. The netting does not have as strong of a cooling effect as microspray orchards. The relative humidity comparison shows a potential advantage of using overhead netting instead of microspray, as a weaker humidity effect is beneficial for disease prevention.

Difference between a weak and strong canopy

Outside   Inside-Weak Canopy   Inside-Strong Canopy

Figure 2: Photos of the Smart2 orchard installations

The dynamic effect of irrigation is best illustrated using an example from the Smart2 orchard (Figure 2), which had two in-orchard stations, one in a weak canopy (small/young trees), and a second in a strong canopy (large/established trees).

Figure 3 shows a comparison from June 2021 between morning-only irrigation (left column) and additional irrigation as a result of the extreme heat wave in late June 2021 (right column). Prior to the heat wave, the temperature was cooler in the orchard at night but similar to outside during the day. Moisture effects were stronger in the early period.

During the heat wave, temperature effects were dramatic, with over 10 °F cooling achieved in afternoon hours on average. The cooling effect lingered into the overnight hours. The effects were greater in the strong canopy compared with the weak canopy.

This example offers one of the most extreme examples of how targeted microspray irrigation can cool an orchard. The average dew point in the strong canopy reached over 70 °F in the afternoon hours during the heat wave, effectively turning the orchard into a “swamp-like” environment. While the desired cooling effect was achieved, the extreme moisture increase is favorable for the spread of disease.

Dynamic effect of overhead cooling

The Smart2 orchard also revealed how an in-orchard weather station can detect the response to irrigation events. The black line at the bottom of Figure 4 shows the times when the in-orchard rain gauge detected microspray irrigation events. Based on 5-minute observations, we were able to detect that the irrigation pattern was on a 15-min on / 15-min off cycle for most of the period, except from the evening/overnight of June 28-29 when the irrigation was left on continuously.

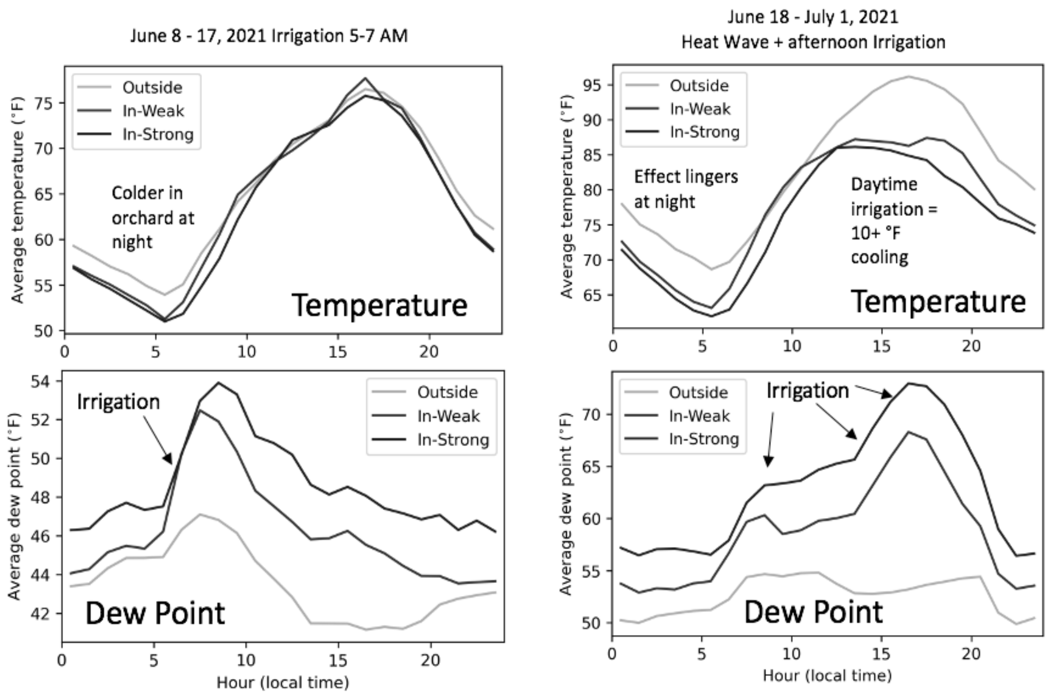


Figure 3: Diurnal comparison of Smart2 temperature (top row) and dew point (bottom row) between early June 2021 (left column) and late June 2021 (right column).

The "squiggly" nature of the inside-weak temperature (Fig 4, lower panel) indicates a rapid recovery period between 15-min irrigation cycles as the temperature rebounded by as much as 5 °F between evaporative cooling cycles. In contrast, the inside-strong temperature (Fig. 4, top panel) had much less variability between irrigation cycles, likely a result of the increased surface area of the canopy.

Perhaps less evaporative cooling is needed in strong canopies, but it is important to measure the in-orchard temperature and dew point to see the response to the cycle and adjust accordingly.

In terms of the objectives of this proposal, we can easily remove overhead cooling events from in-orchard weather data using the rain gauge. Unfortunately, we found that leaf wetness sensors were not as accurate at detecting the dynamic effect of irrigation and cooling. It is believed that dirt and pesticide residues render in-orchard leaf wetness sensors unreliable.

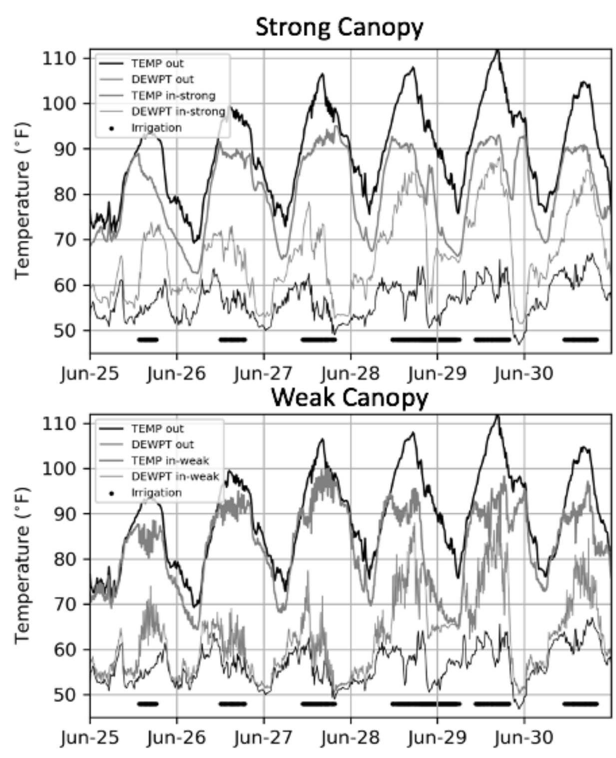


Figure 4: Timeseries of Smart2 temperature, dew point, and irrigation during the June 2021 heat wave.

Discussion

The results of this ongoing study indicate that the decision to install weather sensors in-orchard has a number of benefits for growers and their decision making. However, growers must be aware that **management activities will modify in-orchard weather measurements** and must be corrected for. Besides irrigation and overhead netting, it is clear that the use of wind machines increases the temperature and detected wind speeds inside the orchard in the spring. This is clear even in monthly-averaged data. These efforts counter the seemingly universal tendency of **orchards to be cooler than surrounding open sites at night, year round**.

The diurnal and seasonal cycles of orchard effects are fascinating from a scientific perspective. This study represents the best effort in the literature to quantify these effects and is a significant step forward in developing models to account for these effects. Efforts moving forward will increasingly emphasize model development and weather forecasting based on these in-orchard observations, and growers are strongly encouraged to measure weather conditions directly within the canopy in order to benefit from these research efforts.

One useful configuration is an ATMOS-41 station outside the orchard and an ATMOS-14 station inside the orchard, both at 5-6 ft height. If the paired stations are not at the same height, it induces additional uncertainty that is hard to correct for.

Project/Proposal Title: Validation of plant-based sensors for making irrigation decisions

Primary PI: **Lee Kalcsits**
Organization: Washington State University
Telephone: 509-293-8764
Email: lee.kalcsits@wsu.edu
Address: 1100 N Western Ave.
City/State/Zip: Wenatchee, WA 98801

Co-PI 2: **Jenny Bolivar-Medina**
Organization: Washington State University
Telephone: 509-786-9201
Email: jbolivarmedina@wsu.edu
Address: WSU IAREC
City/State/Zip: Prosser, WA 99350

Co-PI 3: **Victor Blanco**
Organization: Washington State University
Telephone: 509-293-8764
Email: victor.blanco@wsu.edu
Address: 1100 N. Western Ave.
City/State/Zip: Wenatchee, WA 98801

Cooperators: Lav Khot (WSU), Steve Mantle (Innov8ag), Bernardita Sallato (WSU), Karl Wirth (Dynamax)

Report Type: Continuing Project Report

Project Duration: 2-Year

Total Project Request for Year 1 Funding: $ 60,355
Total Project Request for Year 2 Funding: $ 45,050

Other related/associated funding sources: Awarded
Funding Duration: 2021 - 2027
Amount: 20,000,000
Agency Name: NSF/USDA AI Institute
Notes: This sensor project allowed us to leverage this as a key contributor to the water ag thrust and getting a running start on data analysis and collaborations for this project.

Budget 1
Primary PI: Lee Kalcsits
Organization Name: Washington State University
Contract Administrator: Darla Ewald/Stacy Mondy
Telephone: 509-293-8800
Contract administrator email address: darla.ewald@wsu.edu/arcgrants@wsu.edu
Station Manager/Supervisor: Chad Kruger
Station manager/supervisor email address: cekruger@wsu.edu

Item	2021	2022
Salaries	18,000[1]	18,720[1]
Benefits	8,437[2]	8,774[2]
Wages	7,800[3]	8,112[3]
Benefits	1,749[4]	1,819[4]
Equipment		
Supplies	20,344[5]	3,600[5]
Travel	4,025	4,025
Miscellaneous		
Plot Fees		
Total	60,355	45,050

Footnotes:
[1] Support of a research assistant at 50% for the duration of the project to collect and curate data, maintain experiments and prepare results for reporting and publication
[2] Benefits are at a rate of 46.87%
[3] Wages are to support a summer staff person to aid in collecting data, writing extension material, and for maintaining experiments
[4] Benefits for the summer staff position is 22.4%
[5] Supplies include the purchase of stem and fruit dendrometers, field consumables, and cellular data loggers. Both the sap flow system and microtensiometers were already purchased.

Objectives

1. Deploy and evaluate the accuracy and precision of dendrometers, sap flow sensors, and stem microtensiometers in measuring plant water status
2. Identify critical factors affecting the adoption of these technologies in Washington state tree fruit production
3. Develop Extension materials and train growers in using these technologies.

In 2021, all proposed sensors were installed in the smart orchard site. Some of the sensors were delayed from a lag in funding and purchasing administration within the University. These challenges have been resolved. Dynamax is now a cooperator with the project and has independently installed and is collaborating with the Smart Orchard project to provide data from their instrumentation. This led to more intensive instrumentation at the two smart orchard sites than anticipated. We have made progress on all three objectives including a concerted Extension/outreach effort led by Jenny Bolivar-Medina. We have started compiling and integrating the different layers of continuous data from the season

Significant Findings

- Florapulse microtensiometers were highly accurate and precise in measuring stem water potential in real-time. These can be a viable replacement to making pressure chamber measurements manually.
- Florapulse sensors had a ~90% installation success. Minimum trunk diameter for installation is ~40 mm. Smaller trunks make installation difficult.
- Fruit growth sensors are difficult to maintain. They are knocked off the fruit easily and need to be checked daily. Furthermore, orientation of the sensor on the fruit affects measurements and the spring tension affects fruit growth. These factors suggest that irrigation decisions cannot be made with fruit sensors alone. Fruit growth rates are heavily influenced by many factors that are difficult to account. These sensors will help us better understand the relationship between fruit growth and plant water status in the soil-plant-atmosphere continuum. Other higher throughput methods of diameter sensing (stationary or mounted RGB cameras) are likely more fruitful for estimating temporal fruit growth and sizing profiles in an orchard.
- Stem dendrometers and sap flow sensors have been more commonly used as a research tool. There is evidence that crop load, environmental conditions, etc., can affect trunk shrinkage and more research is needed to tease apart these contributing factors.
- In order of ease of interpretation of data: Florapulse = Pressure Chamber > Stem Dendrometer > Sap flow > Fruit diameter
- In order of ease of installation: Fruit diameter> Stem dendrometer > Florapulse > Sap flow

Methods

Smart orchard deployment

We deployed commercially available dendrometers (fruit, trunk, and stem), sap flow sensors, and stem microtensiometers into the WTFRC-funded sensor orchards (in collaboration with Bernardita Sallato, Lav Khot, Dave Brown, and Steve Mantle) (Figure 1). Two trees were selected from a high and low vigor site within the spatially variable block. These same sites were aligned with the deployment for other sensors and monitoring equipment from other collaborators.

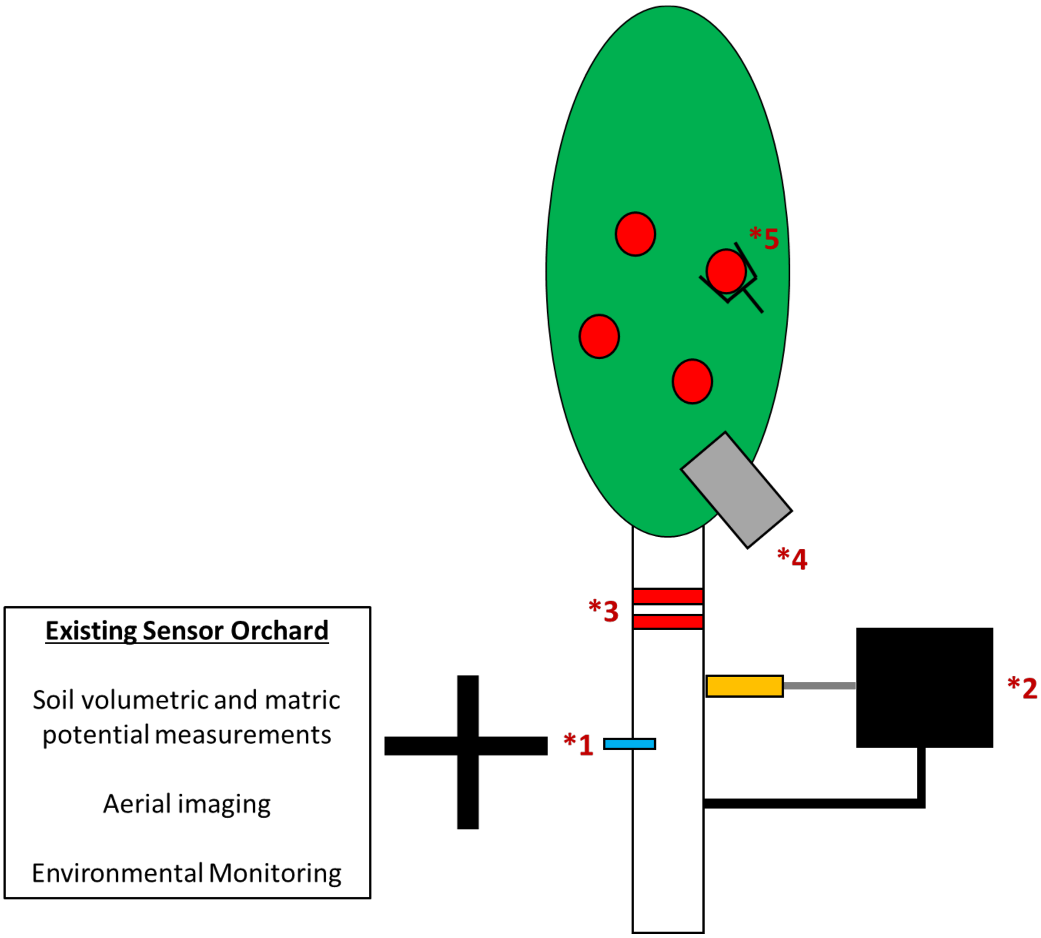


Figure 1. Plant-based monitoring approaches that are proposed to be added to the sensor orchard in Grandview, WA that will include: 1. Microtensiometers, 2. Stem dendrometers, 3. Sap flow sensors, 4. Traditional stem water potential checks, and 5. Fruit dendrometer sensors.

Table 1. Sensor deployment in Smart Orchard in 2021

Plant Sensors	Environmental Sensors	Soil Sensors
Stem dendrometer (June 28 to September 30) Fruit dendrometer (June 28 to September 30) Microtensiometer (April 24 to present) stem water potential Scholander chamber (Four times during the season) stem water potential Sap flow (July 16 to present)	Air temperature Relative Humidity Wind speed Radiation	Soil volumetric water content Soil matric potential

Pear study site and irrigation treatments

The experiment was conducted during the 2021 growing season at the experimental orchard of the Washington State University located in Rock Island (Washington State, USA, 47° 19′ N, 120° 04′ W) on a 2 acre pear block (*Pyrus communis* L.), planted in 2007 on a shallow sandy loam soil. 'D'Anjou'' pear trees were grafted on OHxF.87 rootstock and trained on a central leader system at a tree density of 344 trees per acre. Horticultural practices (e.g. fertilization, pruning and weed control) were the same for all trees in the block and followed commercial regular practices. Full bloom was in April, and harvest was in late August. Trees were drip irrigated by a system consisted of a single drip line per tree row and five emitters per tree of 0.5 gallon h-1 discharge rate.

Two irrigation treatments were imposed, a control treatment (CTL) irrigated at 100% of crop evapotranspiration (ET_c) to ensure non limiting soil water conditions and a reg-ulated deficit irrigation treatment (DI), irrigated at 100% of ET_c from April 1st to June 27th, and 50 % of ET_c from June 28th to October 15th. Crop water requirements (ET_c) were calculated using the methodology proposed by Allen et al. (1998): $ETc = ET_o \times K_c \times K_r$, where ET_o is the reference evapotranspiration, K_c is the crop-specific coefficient reported for adult pear trees (Marsal, 2012), and K_r is a factor of localization (Fereres et al., 1982). Treatments were distributed according to a completely randomized block design with three replicates per treatment. Within each replicate, two trees were selected to assess their tree water status during the season. All measurements were conducted in the same 12 trees selected for their uniformity (average ground cover of 41 % and mean trunk diameter of 10.5 ± 0.23 cm).

<u>Measurements</u>

Four representative days with different atmospheric water demand, air temperature and solar radiation served to assess tree water status under a wide range of environmental conditions: (i) a sunny, warm day with low evaporative demand (June 12th, 2021); (ii) a hot, sunny day with high evaporative demand (July 2nd, 2021; five days after the irrigation change for DI trees); (iii) a hot, cloudy day with high evaporative demand (July 31st, 2021; 35 days after the irrigation change for DI trees); (iv) a hot, sunny day with high evaporative demand (August 11th, 2021; 46 days after the irrigation change for DI trees).

<u>Environmental data and soil water content</u>

Air temperature, relative humidity, wind speed, precipitation, solar radiation and reference evapotranspiration were continuous recorded by an AgweatherNet weather station located at the experimental orchard (http://www.weather.wsu.edu; "Sunrise sta-tion"). Moreover, two temperature and relative humidity sensors (ATMOS-14, METER Group Inc., Pullman, WA, USA) were installed in the pear block. Every 15 minutes, mean air vapour pressure deficit (VPD) was calculated using air temperature and relative humidity data (Allen 1998). Soil volumetric water content (SWC) was obtained with two capacitance/frequency domain sensors (TEROS 11, Meter Group, Pullman, WA, USA) per replicate at 10 and 20 inch depths located under the canopy projection at 10 inches from the drip emitter per replicate.

<u>Stem water potential</u>

Leaf Ψ_{stem} was measured by two different methods with the Scholander pressure chamber (PC) and with the microtensiometers (MT) in the same 6 trees at 6:00, 8:00, 10:00, 12:00, 14:00, 16:00, 18:00 and 20:00 h. Ψ_{stem} measured with the PC (Model 615D, PMS Instrument Company, Albany, OR, USA) was done according to the methodology proposed by McCutchan and Shackel (1992). Mature and healthy leaves close to the trunk were wrapped with black polyethylene bags and aluminum foil two hours prior to the measurement. Measures were per-formed on one leaf per tree, two trees per replicate. In the same six trees, six MT (FloraPulse, Davis, CA, USA) were embedded into the tree trunk away from the sunlight at 1.0 m height. Ψ_{stem} measurement with MT were taken every 20 minutes. Ψ_{stem} values were classified in a scale from 0 to 5 according to the tree water status, from the absence of water stress (0) to severe water stress (5): 0 for those values higher than -0.4 MPa, 1 between -0.4 and -0.7 MPa, 2 between -0.7 and -1.0 MPa, 3 between -1.0 and -1.3 MPa, 4 between -1.3 and -1.6 MPa and 5 for lower Ψstem values than -1.6 MPa. The sensitivity (S) was calculated according to Goldhamer (2000) for Ψstem measured with PC and MT. S is calculated as the result of the division of the Signal Intensity (SI), calculated as the relation between Ψ_{stem} of CTL and DI, by the coefficient of variation (CV).

Additional sensor deployment

Florapulse sensors were deployed in a 5th leaf Honeycrisp block with either B.9 or G.890 in three trees each. Installation of the sensors in small trunks like B.9 were problematic and one of the sensors failed on installation and another stopped logging correctly during the season. Sensors installed in G.890 continue to record data into the fall. They will remain in the trees during the winter continuing to log stem water potential and to test multi-season viability of sensors to continuously log data.

Results and Discussion

Smart orchard data examples and data analysis plan (Apple)

All datasets have been collected for the summer of 2021. Connectivity limited real-time data monitoring but we will aim to improve this in 2022 by placing data loggers on poles extending above the canopy. We have collected microtensiometer, dendrometer, sap flow, fruit growth, soil moisture, and environmental conditions from the orchard location. We did not have dendrometers in both high and low vigor locations but we have all other data sets for high and low vigor locations within the orchard. Data will be organized and provided to the AgAID project for model development to predict plant water status from these various parallel datasets. This will help provide feedback for users with soil-based or weather-based sensors for making irrigation decisions as well as to fine tune baseline values for making stem-water potential-based irrigation decisions.

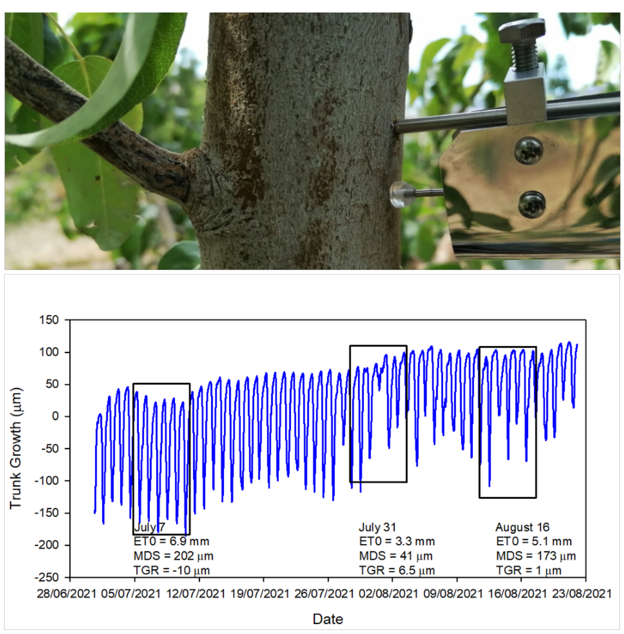


Figure 2. Daily fluctuations in trunk growth for 'Honeycrisp' apple. The three black boxes represent three different times (July 7, July 31, and August 16) during the summer of 2021 at the Smart Orchard

location in Grandview. ET$_o$ = Evapotranspiration estimatation; MDS = maximum daily shrinkage; TGR = trunk growth rate. ET$_o$ for the three dates were 0.27", 0.13", and 0.20" for July 7, July 31, and August 16, respectively. Maximum daily shrinkage was directly related to potential evapotranspiration.

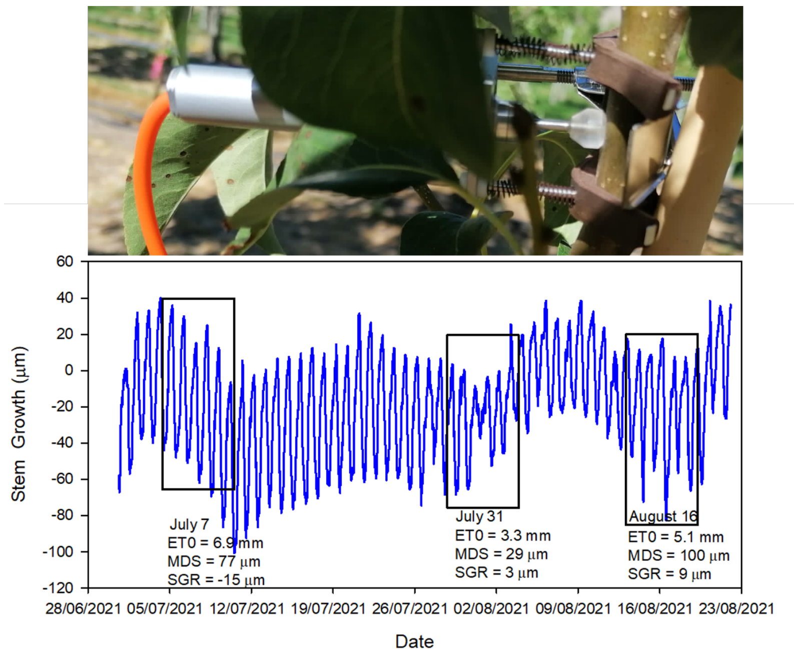


Figure 3. Stem growth measured on a lateral apple branch at mid-canopy height in the high vigor area.

Since stem growth is negligible for mature trees, these measurements did not correspond well to environmental conditions. Like trunk diameter, the maximum daily shrinkage corresponded well to environmental conditions where shrinkage was highest when temperature and water demands were the greatest.

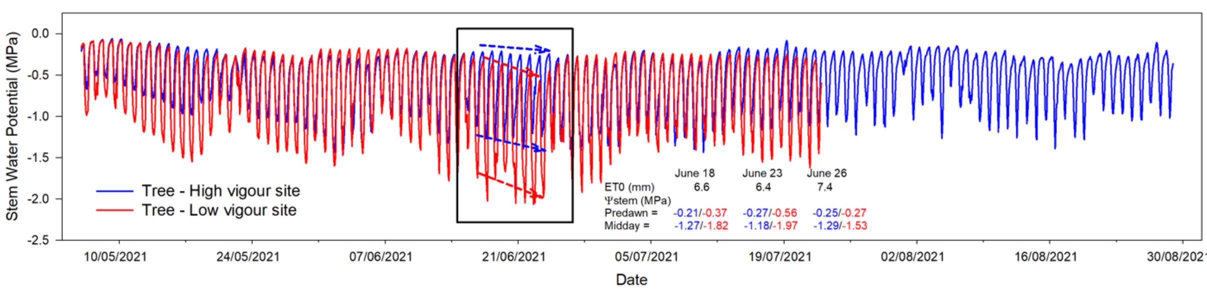


Figure 4. Microtensiometer stem water potential measurements made for 'Honeycrisp' apple in high (blue) and low (red) vigor sites at the Grandview smart orchard location. Measurements were expressed in MPa (1 MPa = 10 bars). Numerical values in the lower middle part of the graph represent pressure chamber measurements made during three days in June, 2021.

Trees at the low vigor site consistently had lower stem water potential than the high vigor site which has implications for not just overall tree vigor but also fruit growth and size potential. When measured with a pressure chamber on June 18, June 23, and June 26, both predawn and midday stem water potential was lower (more stressed) in the lower vigor area. These values corresponded well to those measured with the microtensiometers.

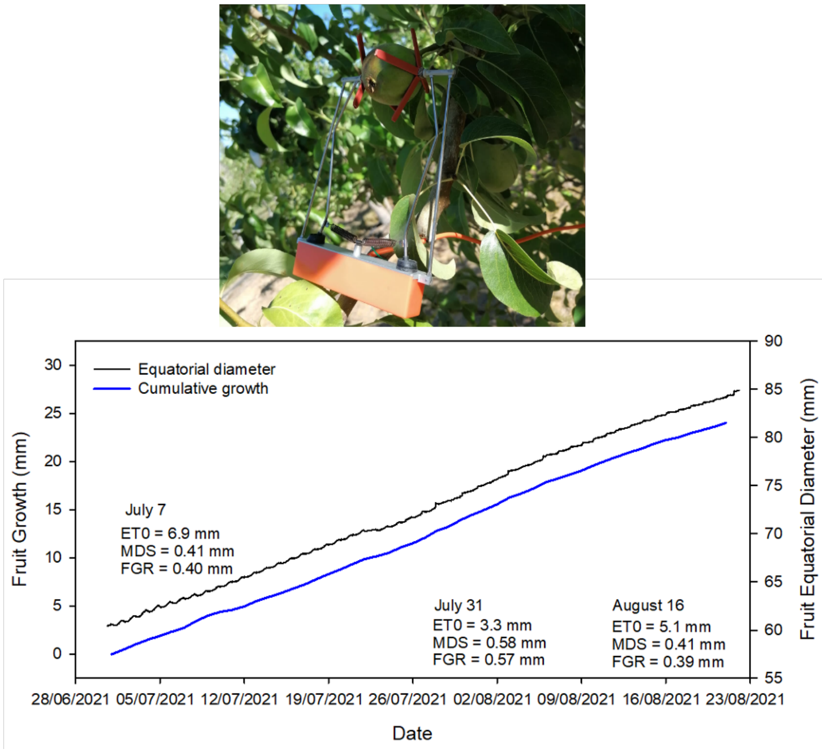


Figure 5. Fruit diameter measurements for 'Honeycrisp' apple from June 29 to August 25, 2021. ET_o = evapotranspiration, MDS = maximum daily shrinkage (fruit), and FGR = fruit growth rate.

Fruit growth rates were the highest when evapotranspiration demand was the lowest on July 31. We are still working on processing all the sensor data we acquired during the season and will be able to pull apart contributing factors to fruit growth during the summer at different times.

Inducing differences in plant water status to detect sensitivity of real-time stem water potential sensing (Pear)

Soil water content (SWC) was strongly influenced by the irrigation strategy applied. On June 12th, both treatments (CTL and DI) were equally irrigated to satisfy tree water requirements (100 % ET_c), so consequently, both treatments showed a similar mean value of 23.06 % (Figure 1A). However, from June 28th onwards, trees from the DI treatment were irrigated to satisfy 50 % of the ET_c so differences in soil water content between treatments appeared and increased as season progressed (Figure 1 B, C, D). SWC was similar all the selected days in the CTL treatment with daily mean values that ranged between 23 and 28 %. However, daily mean SWC values for DI trees were 23 % on July 2nd, 16 % on July 31st and 14 % on August 11th, which showed the progressive decreased of the soil water availability to trees from the DI treatment.

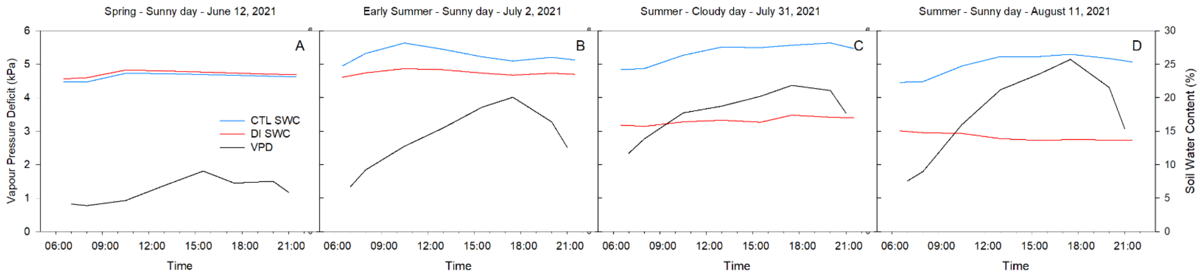


Figure 6. Diurnal course of volumetric soil water content (SWC) (Control (CTL) = blue line and deficit irrigated (DI) = red line) and vapour pressure deficit (VPD; black line) on four representative days during 2021.

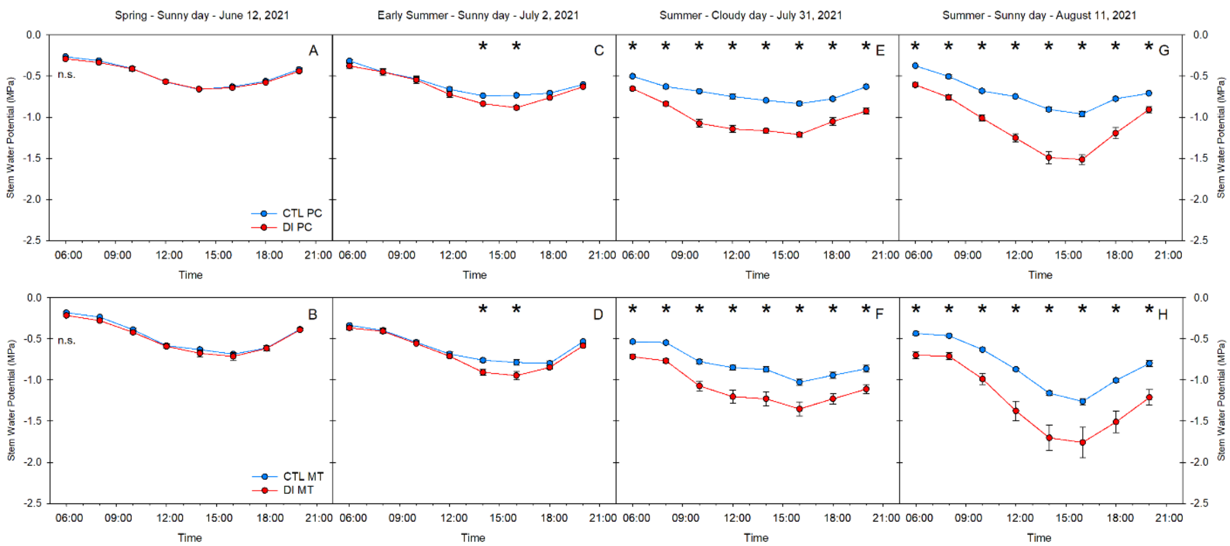


Figure 7. Diurnal course of stem water potential measured with the pressure chamber (PC) (A, C, E, G) and with the microtensiometer (MT) (B, D, F, H) for control (CTL – blue lines) and deficit irrigated (DI – red lines) trees on four representative days during the growing season. Each point is the average of four six trees. Asterisks indicate statistically significant differences between irrigation treatments according to ANOVA ($p \leq 0.05$).

Table 1. Sensitivity analysis of the stem water potential measured with the pressure chamber (PC) and the microtensiometers (MT) for different periods throughout the day.

Ψstem	Morning		Midday		Afternoon		Evening	
	PC	**MT**	**PC**	**MT**	**PC**	**MT**	**PC**	**MT**
CTL	-0.42	-0.39	-0.63	-0.66	-0.79	-0.90	-0.65	-0.74
DI	-0.54	-0.52	-0.84	-0.86	-1.05	-1.16	-0.81	-0.94
SI[1]	1.26	1.30	1.30	1.26	1.31	1.26	1.23	1.23
CV	0.06	0.09	0.07	0.07	0.04	0.07	0.04	0.05
S	19.48	14.44	17.65	18.16	34.02	18.16	29.93	23.89

[1] SI: Signal intensity (DI CTL^{-1}); CV: Coefficient of variation; S: Sensitivity (SI CV^{-1})

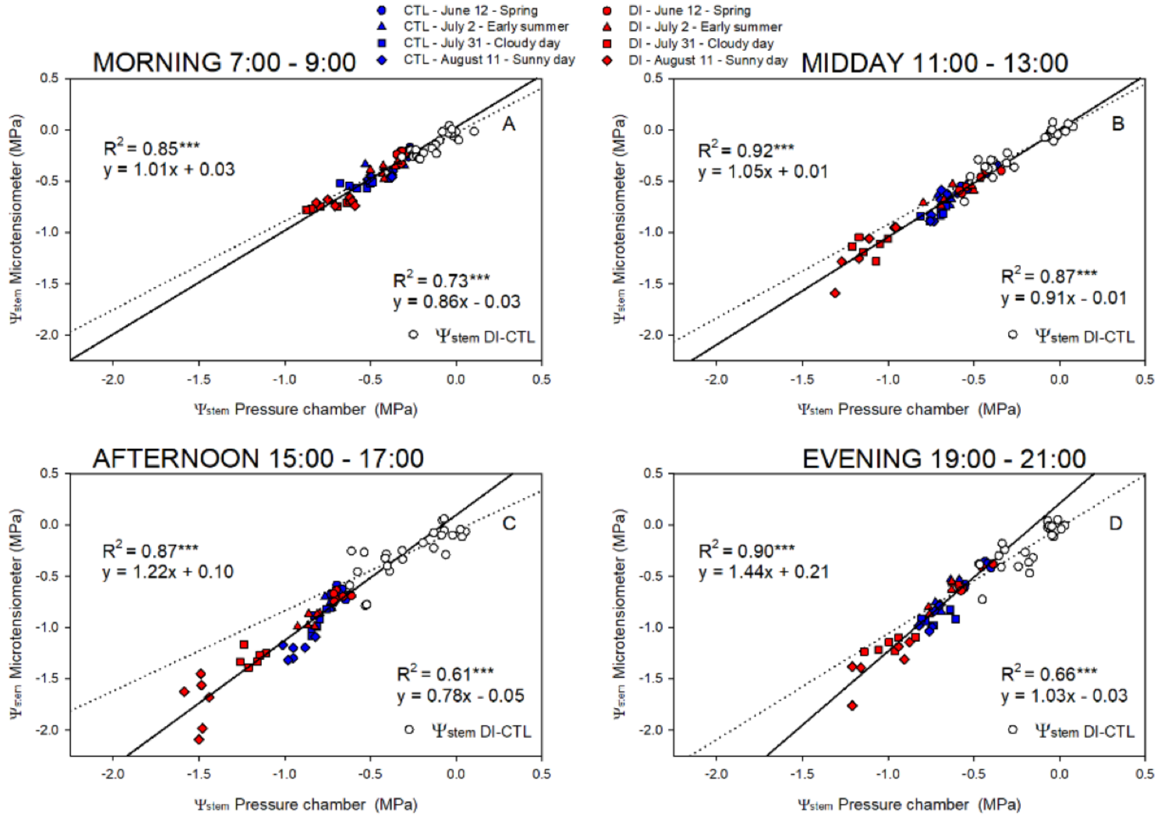


Figure 8. Relationship between stem water potential measured with the pressure chamber and the microtensiometers and relationship between CTL and DI stem water potential (DI - CTL).

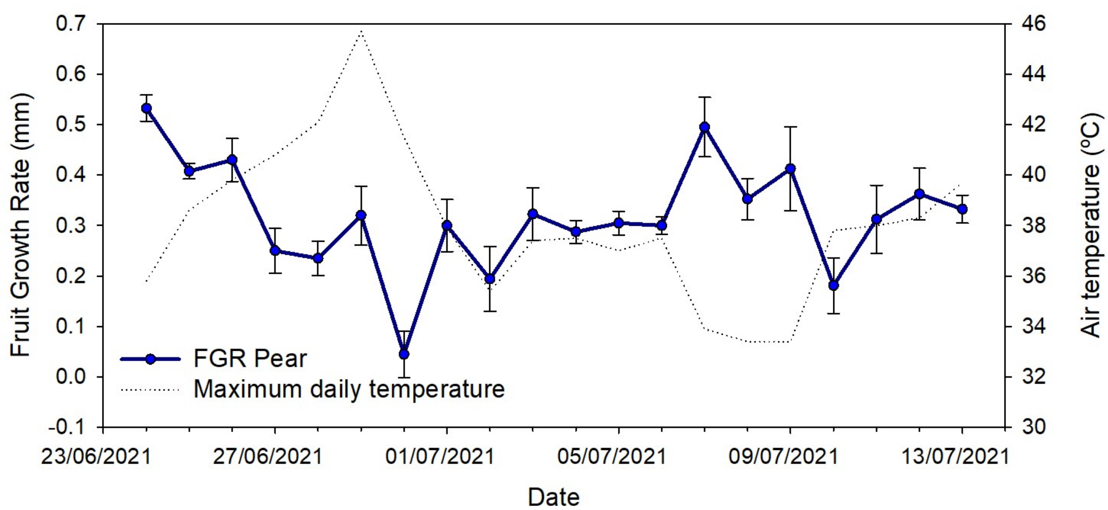


Figure 9. Mean daily fruit growth rate for pear (blue line) compared to maximum daily temperature (dotted line) during the heat even from June 23, 2021 to July 13, 2021. When daily temperatures exceeded 38 °C (100 °F) fruit growth slowed to almost half of what it was when temperatures were below this threshold.

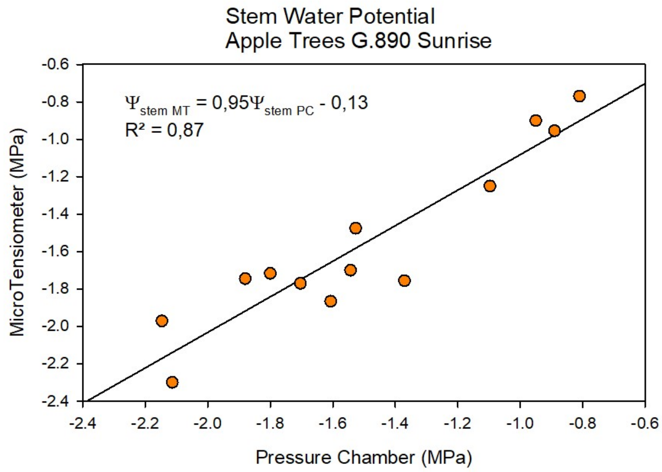


Figure 10. Comparing stem water potential measurements made using the continuous microtensiometer measurements (y-axis) or traditional pressure chamber methods (x-axis).

Extension programming

Smart Orchard Field Day. We organized and participated in a field day with the purpose of providing firsthand information of the plant sensors installed and described in the previous section. The target audience were growers, and farm-making decision individuals in the tree fruit industry. Ninety-four participants attended the event. Overall, from the participants that completed the evaluation of the field day, 95% valued the information presented as excellent (60%) or good (35%).

With the purpose to evaluate the effectiveness of the field day to transfer the information about sensors, we assessed the level of knowledge before and after this event (Figure 4A). The participants gained knowledge about the use of plant sensors in the orchards, as most of them reported to have little knowledge prior to the event but higher after the field day.

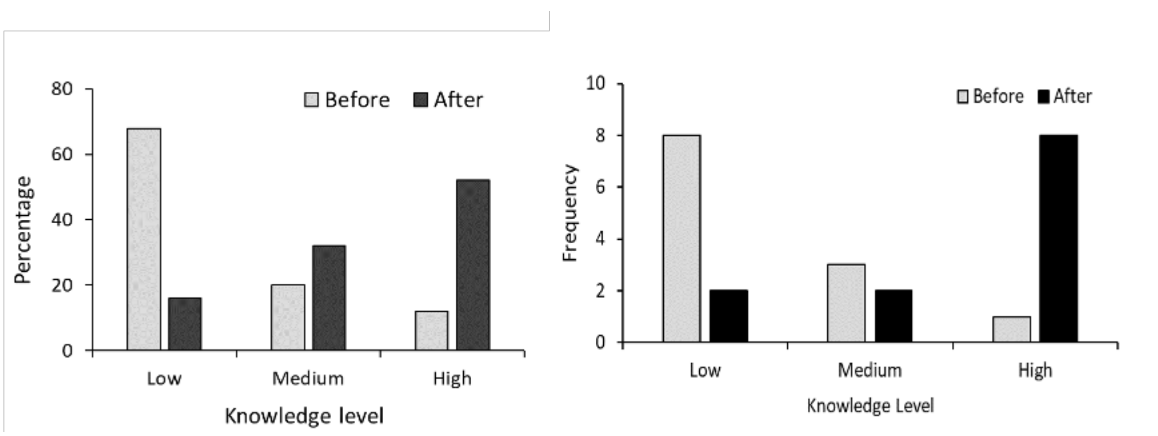


Figure 11. Percentage of participants and knowledge level before (gray bars) and after (solid bars) attending Field days. **A** Smart Orchard- Plant based sensors section. (n = 30). **B.** Field Day at the Roza in Spanish. (n= 15)

***Field day in Spanish*.** During a field day in Spanish organized in the experimental orchard the Roza-WSU – IAREC, we presented basic information related to the use of dendrometers in the apple industry, and we also prepared and shared an infographic about this topic. The event was attended by 15 farmworkers from the south area of the state. Similar to the Smart Orchard event, the evaluation of the field day shows that the participants understood the information provided, and gained knowledge related to the dendrometers. (Figure 4B).

2022 Plans

1. Continue with data collection and comparisons between different plant-based sensors at smart orchard site and at Sunrise Research Orchard

2. Integrate different layers of data into a soil-plant-atmosphere response model as part of the AI Institute agriculture thrust

3. Test the reliability of sensors through the winter

4. Publish Extension fact sheets on each type of plant-based sensor tested for this project. All the extension resources will be provided in a bilingual format.

5. Organize a field day in Spanish at the smart orchard site to provide information about the sensors to the Spanish speaking community in the industry.

6. Publish a peer-reviewed article validating the use of these sensors for accuracy and precision in measuring stem water potential in pear and apple.

Project/Proposal Title: Decision Support Tool for Precision Orchard Management

Primary PI: Joseph Davidson
Organization: Oregon State University
Telephone: 541-737-7171
Email: joseph.davidson@oregonstate.edu
Address: 204 Rogers Hall
Address 2: 200 SW Monroe Avenue
City/State/Zip: Corvallis, OR 97331

Co-PI 2: Cindy Grimm
Organization: Oregon State University
Telephone: 541-737-2600
Email: grimmc@oregonstate.edu
Address: 204 Rogers Hall
Address 2: 200 SW Monroe Avenue
City/State/Zip: Corvallis, OR 97331

CO-PI 3: Ashley Thompson
Organization: Oregon State University
Telephone: 541-296-5494
Email: ashley.thompson@oregonstate.edu
Address: 400 E Scenic Dr Suite 2.27
Address 2:
City/State/Zip: The Dalles, OR 97058

Co-PI 4: Manoj Karkee
Organization: Washington State University
Telephone: 509-786-9208
Email: manoj.karkee@wsu.edu
Address: WSU Prosser – IAREC
Address 2: 24106 N. Bunn Road
City/State/Zip: Prosser, WA 99350

Cooperators: Dave Allan (Allan Brothers Fruit Co)

Report Type: Continuing Project Report

Project Duration: 3 Year

Total Project Request for Year 1 Funding: $73,569
Total Project Request for Year 2 Funding: $77,335
Total Project Request for Year 3 Funding: $71,596

Other related/associated funding sources: None

Budget 1
Primary PI: Joseph Davidson
Organization Name: Oregon State University/Agricultural Research Foundation
Contract Administrator: Charlene Wilkinson
Telephone: (541) 737-3228
Contract administrator email address: charlene.wilkinson@oregonstate.edu

Item	2020	2021	2022
Salaries[1]	$31,331	$32,271	$26,622
Benefits	$8,311	$9,206	$8,162
Wages			
Benefits			
Equipment			
Supplies[2]	$2,986	$4,000	$4,000
Travel[3]	$3,000	$3,000	$3,000
Miscellaneous			
Plot Fees			
Total	$45,628	$48,477	$41,784

[1]Salaries includes a Graduate Research Assistant on a 12-month, 0.49 FTE appointment in years 1 and 2, and a 9-month, 0.49 FTE appointment in year 3. Salaries also include 0.25 months per year for Joe Davidson and Cindy Grimm.
[2]Leaf samples are included in the supply budget.
[3]Travel budget is requested to support mileage and lodging for data collection and field experiments.

Budget 2
Co PI 2: Manoj Karkee
Organization Name: Washington State University
Contract Administrator: Katy Roberts
Telephone: 509-335-4564
Contract administrator email address: katy.roberts@wsu.edu

Item	2020	2021	2022
Salaries	$17,840	$18,554	$19,296
Benefits	$5,101	$5,304	$5,516
Wages			
Benefits			
Equipment			
Supplies	$4,000	$4,000	$4,000
Travel[1]	$1,000	$1,000	$1,000
Miscellaneous			
Plot Fees			
Total	$27,941	$28,858	$29,812

[1]Travel budget is requested to cover the mileage for field experiments.

PROJECT OBJECTIVES

The current standard practice of broad-acre management does not result in targeted actions that are optimal for individual trees – this reduces the impact of management decisions and wastes resources while falling short on achieving the yield and quality potential of individual blocks. Our team's overall goal is to improve fruit quality and yields by managing individual trees through a combination of automated sensing, learning algorithms, decision support tools, and precision application with variable rate technology. While for this project we focus on matching nitrogen fertilizer to nitrogen demand, our long-term vision is to extend this framework for farming at the tree level to other orchard management decisions (e.g. plant growth regulators, root pruning, tree pruning, chemical thinning). The conceptual framework that we have developed for precision nitrogen application is shown in Fig. 1 and includes the following sequence of activities:

1. Build a site map of individual trees (performed once at the beginning of the project)
2. Use non-contact sensing to estimate tree nutrition (performed annually)
3. Recommend tree-specific fertilization plans using decision support tools incorporating machine learning
4. Apply variable rate nitrogen using real-time vehicle localization and precision technology
5. Use historical data to improve the performance of the decision support tool

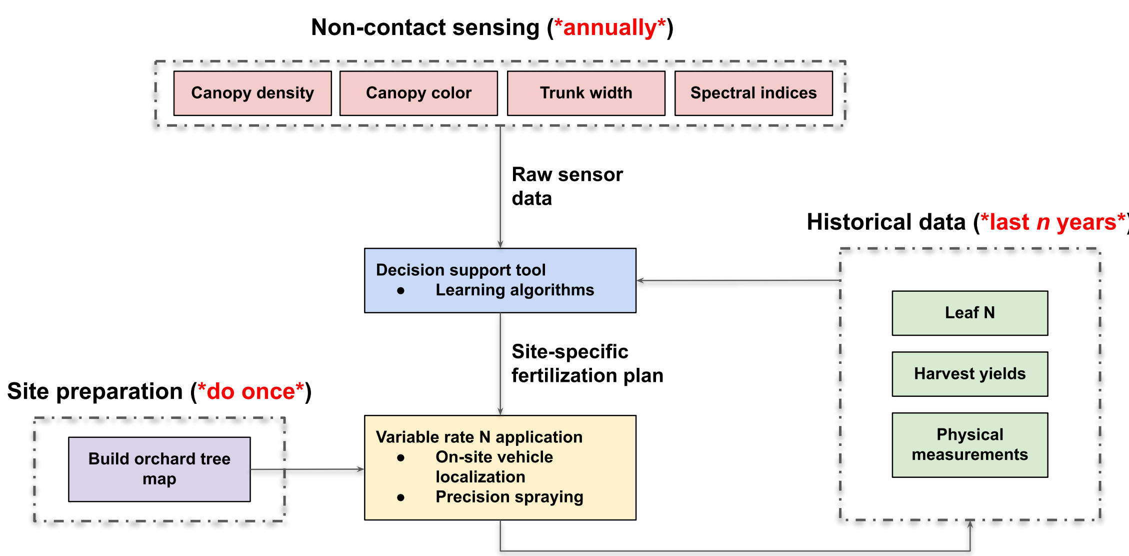


Figure 1. Project framework. A detailed tree map is developed for the site at the beginning of the project. Raw sensor data on various orchard parameters is used as input to a learning algorithm that provides precision fertilization plans. Onsite vehicle localization is used to execute precision application of nitrogen. Historical data on destructive leaf N measurements, horticulturalists measurements, harvest yields, etc. is used to tune the learning algorithm.

We describe integration of these activities in greater detail throughout the remainder of this report. To implement the framework shown in Fig. 1, we have created the following three specific research objectives:

1. Develop a ground vehicle-mounted sensor system that *i*) maps the geographic location of individual trees within an orchard block; and *ii*) measures plant parameters (e.g. shoot vigor, trunk cross-sectional area, and fall leaf color) to estimate the nitrogen status of individual trees
2. Develop a decision support tool that recommends nitrogen application levels per tree and tracks the tree's long-term response

3. Develop and demonstrate a proof-of-concept precision spray system that localizes the vehicle with the orchard map, identifies the neighboring trees, and then selectively applies the desired level of nitrogen within the root zone

This continuing report summarizes research progress for the performance period of November 2020 – October 2021.

Objective 1: Orchard Mapping & Nitrogen Sensing

In July 2021 we collected another large sensor dataset at the project site in Prosser. The types of data collected are similar to what we gathered previously in July and October 2020, consisting of RGB images, depth images, inertial measurement unit (IMU) data, and GPS data. There were two notable changes we made to the data collection process. First, since we are developing methods for automatically measuring trunk cross-sectional area, we angled the RGB-D camera to point more towards the ground so that the graft unions would be visible in the image (see Fig. 2 for an example image). The second change is that we collected GPS data from a low-cost GPS in addition to the more expensive model used in 2020. Details of the findings are described in Task 2.

Task 1 – Tree trunk detection (OSU lead, WSU participant)

The goal of this task is to detect tree trunks from an Intel RealSense D435 RGB-D camera feed. Detecting the trunk and then estimating the coordinates of the trunk in the pixel frame is necessary for both *i*) creating an initial map of the orchard, and *ii*) real-time localization at the time of N application. A map can be created by combining the detected trunk, its depth data and the vehicle's GPS coordinates. We wanted to have a detector that could be used in real-time during nitrogen application, thus we needed a fast and accurate detector.

We selected the YOLOv3 Convolutional Neural Network (CNN) object detector for trunk detection. Using the available datasets, we manually labelled the trunks with bounding boxes that correspond to the tree in the row closest to the camera. A sample result of the trunk detection is shown in Fig. 2 with the confidence of detection noted by the bounding box. The additional data collected in 2021 proved critical to improving the detector's performance. A detector trained on images from only October 2020 performed poorly at detecting trunks in July 2021 images. By expanding the training set to include additional image variability (e.g. season, lighting conditions, leaf color), the retrained network (i.e. trained on 2020 & 2021 images) was able to generalize and robustly detect trunks from both years. Table 2 summarizes network performance.

Figure 2. Output of trunk detection using a YOLO network trained on images from 2020 and 2021.

Table 1. Evaluation of network performance.

	Accuracy	**Recall**	**Precision**
2020 October (490 images)	94.32%	94.65%	99.38%
2021 July (523 images)	84.22%	83.75%	98.05%

Findings:

- YOLOv3 is fast enough to use in real-time and shows robust performance.
- A network initially trained only on 2020 October data showed poor performance when tested on 2021 July data; this was resolved by retraining the network with data from 2020 and 2021.
- The network occasionally detected background trees even though we only trained it with foreground trees.
- As shown in Table 2, the current network still shows worse performance on July 2021 test data which had more leaves covering the trunks and higher illumination conditions compared to 2020 data.

Methods: An object detector's performance is substantially affected by the similarity of the object's features in the training and testing images. Tree features vary by season and weather conditions at the time the images are collected. There are a couple of methods to improve or maintain a consistent performance; one of them is applying image histogram equalization on the data that are being fed to the network. This method involves adding/subtracting certain values to the R, G, B channels of real data so its histogram aligns with the training images' histogram. The second method is to train the network on data that are collected under a variety of conditions, thus the network learns the features of trunks in various conditions. We will continue to expand the training set to improve the ability of the trunk detector to generalize across conditions.

Task 2 – Orchard mapping (OSU lead, WSU participant)

In our previous data collection trials, we collected GPS data using the Trimble GPS. While we generally observed high-quality results with it, the Trimble GPS is expensive, bulky, and difficult to set up. We recently acquired a lower cost RTK-GPS (a Reach GPS), which costs less, is lightweight and self-powered, and relatively easy to set up. As such, for this data collection run, we collected data using both the Trimble and Reach GPS setups to see if the Reach GPS could provide adequate GPS performance. One comparison of the two GPS systems for a single orchard run is shown in Figure 3.

Findings:

- Overall, the Reach GPS (shown in blue) had very similar performance to the Trimble GPS (shown in red), separated by a very small, nearly-constant offset.
- The results from Fig. 3 are from our second day of data collection. On the first day, the Reach GPS sometimes lost the RTK fix and ended up jumping around the map. However, since the status of the GPS message changed when this happened, we should be able to ignore these readings and fall back to dead reckoning methods as necessary.

Methods: Our next step for creating a map is to combine the processed data from trunk detection (Task 1) with the GPS data. We extracted the depth information of a detected trunk and were able to identify the tree's location with respect to the vehicle's location by reading the depth information and GPS data. However, we still need to work on instance tracking to avoid multiple tree counting. Theoretically, there will be clusters of multiple points that correspond to each tree, and we plan to set a distance threshold for the clusters. We then average the coordinates of all the points in a cluster, which will be the final estimated location of the corresponding tree.

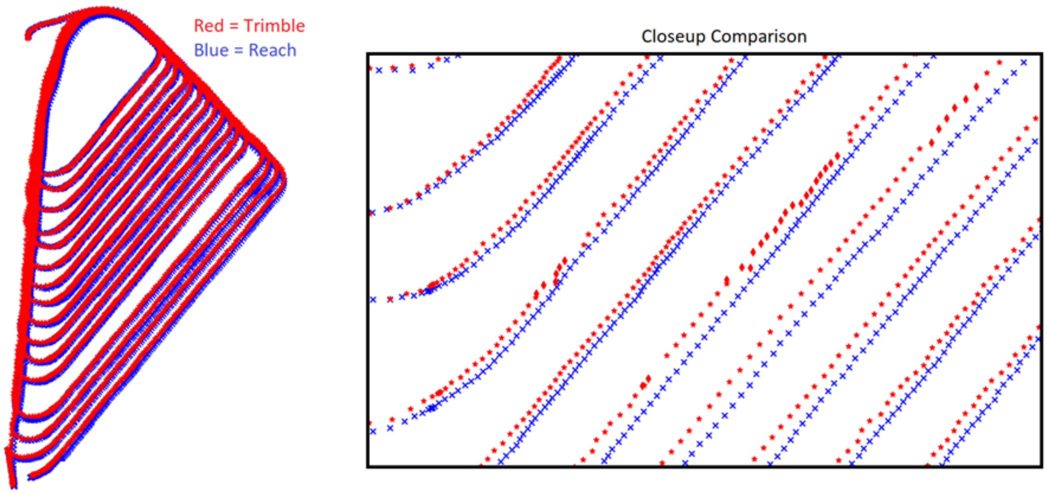


Figure 3. A comparison of GPS readings from two separate sensors during traversal of the test orchard.

Task 3 – Nitrogen measurements and non-contact sensing (WSU lead, OSU participant)

Tracking the growth of canopy shoots over the season can be a good indicator of the nitrogen status of the tree. We collected images towards the end of bloom during May 2021 using an RGB-D sensor (Zed camera). Fifty shoots at different positions in the canopy were chosen at random from thirty-five trees at various locations to obtain the ground truth data for the shoot length. We drove the camera assembly through seventeen rows to get the images of all tagged trees. The tagged shoots were tracked and measured using the depth images and compared against the ground truth. This approach for obtaining the shoot length through depth data was limited due to constraints of the depth sensor as it did not provide depth values for all positions in an image and tracking the shoot and their orientation in the image was challenging.

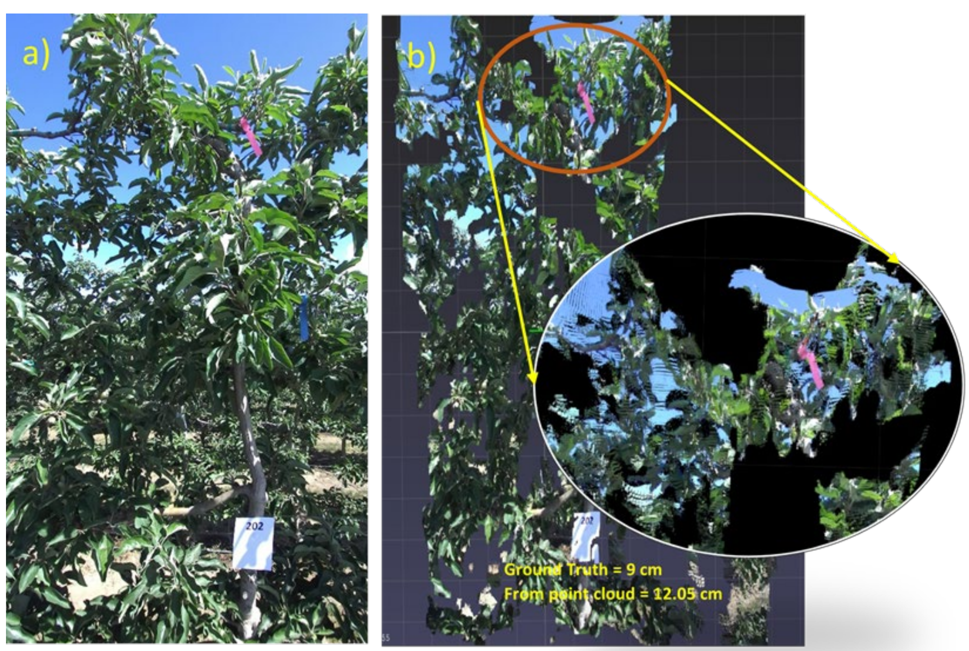


Figure 4. a) RGB image and b) point cloud showing the tagged shoot.

Canopy density and canopy color are other potential indicators of the nitrogen status of the tree. We captured images using the Zed camera from an offset distance where the overall canopy was visible (~1.5 m). Our working assumption is that trees higher in nitrogen will have a denser canopy and more vegetative growth than trees lower in nitrogen. The first task in obtaining the canopy density was segmenting the desired tree in the foreground from the trees and other objects in the background. We applied a *K*-means segmentation with two clusters followed by depth thresholding from the depth data to obtain the segmented image for each tree. The segmented image from one of the instances is shown in Fig. 5. The segmentation task will be useful for both canopy density and canopy color estimation. We are also interested in the color change of the trees throughout the fall season as the trees start to change colors and shed leaves. We have already started and will continue taking images throughout October and November 2021 each week to track the change in color of leaves for each tree. We can obtain a time series data for color change throughout fall and potentially relate that to the nitrogen content of each individual tree.

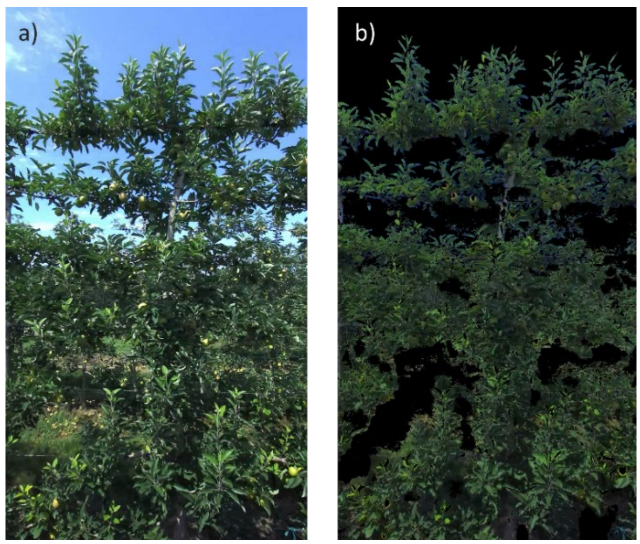


Figure 5. a) Initial and b) segmented image of a tree after clustering and depth thresholding.

Findings:

- Estimating shoot length from point clouds is not accurate using existing techniques and will require further investigation.
- Leaf samples were collected during July 2021. However, results from Ward Labs were not available at the time this report was submitted.

Methods:

For canopy density estimation, we plan to generate a bounding box for each tree in the segmented image. The area occupied by pixels other than the background (black) will be divided by the total area of the bounding box to obtain an estimate of the canopy density of each tree. The obtained number will then be compared against the nitrogen level of each tree obtained from the ground truth (i.e. destructive leaf sampling) to see if there is a correlation between leaf nitrogen and canopy density.

For canopy color estimation, we also start with the segmented image for each tree. After equalizing the image's histogram, we will cluster pixels based on color into 4-5 classes so that the fraction of each color in the canopy can be quantified. By the end of this analysis, we will have a time series data of the color of leaves for each tree that we can compare against the nitrogen content of the tree.

As mentioned earlier, we also plan to develop a method for automatically calculating trunk cross sectional area using RGB-D data. A YOLOv4 network will be trained to detect graft unions. The graft union detection will then be used to find the pixels that are an appropriate distance from the graft union for cross sectional area calculations. These pixels will be sampled to find the distance of the tree from the camera. Next, the width of the tree at this height (in pixels) will be found using Hough transforms and edge detection. The tree width, distance, and camera lens angle will then be used to calculate cross sectional area. This calculation will assume circular trunks.

Objective 2: Decision Support Tool (WSU/OSU joint lead)

We have only started preliminary investigations on the Decision Support Tool at this stage of the project. Our main effort to date has been collecting extensive datasets from multiple seasons and developing the algorithms required for the various components of the project. Our focus over the next year will be to use sensor data, horticultural measurements, and historical data on yields to develop learning algorithms for creating precision N fertilization plans. We plan to start with relatively simple statistical techniques such as nonlinear regression or logistic regression to classify individual trees as 'N-low,' 'N-satisfactory,' or 'N-high'. Based on the classification performance with regression, we may need to consider more sophisticated learning algorithms. We will start with two to three variables such as trunk diameter and leaf color and progressively add new variables such as NDVI and canopy density as they become available.

Objective 3: Variable Rate N Application

<u>Task 1 - Vehicle localization (OSU lead, WSU participant)</u>

Vehicle localization within a known map is a well-studied problem in autonomous systems. For this project, we are using a navigation system that combines two vehicle sensors, an inertial measurement unit (IMU) and camera. For a precision N application, the vehicle starts from a known location at the beginning of the first row of the orchard. As the vehicle begins to traverse a row, sensors provide feedback on detected trunks and vehicle kinematics. By fusing the sensor information with a Particle Filtering algorithm, a standard technique for state estimation and localization in autonomous vehicles, we can use dead reckoning to continuously track the spray vehicle's position, heading, and velocity inside the orchard block without the need for GPS. To fine tune the algorithm for localization, we simulated the orchard environment and vehicle movement in python and tested the convergence of the ground truth vehicle position and estimated vehicle position (Fig. 6).

<u>Findings</u>:

- A particle filtering system shows potential as a method to localize work vehicles using camera and inertial data only (i.e. no GPS required)

<u>Methods</u>:

We are using a particle filtering algorithm for localization. The basic principle is that we initialize a few thousand particles around the sensed vehicle location. One of these particles would be the ground truth position of the vehicle. We find this position by filtering these particles using landmarks. Here, we are using the trees as the landmarks. We get the closest tree to the vehicle from sensor readings and find the particles that are at the same distance to this tree from the vehicle. These particles are given higher weights and as the closeness of the particle-tree distance to vehicle-tree distance decreases, the weights given to the particles also

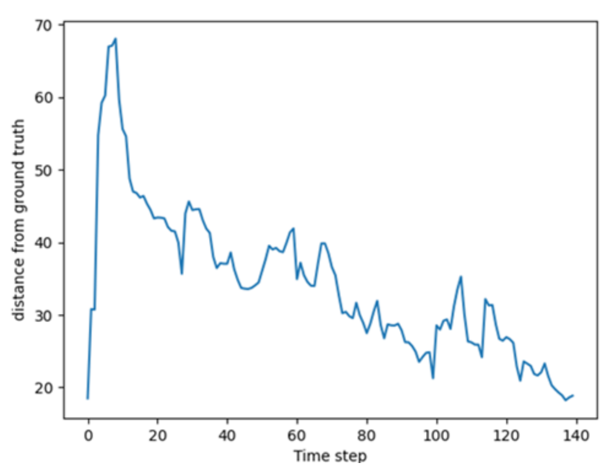


Figure 6. Convergence graph between ground truth position of the vehicle and localized position versus time step.

decrease. These weights are distributed as a function of negative powered exponentials. Finally, we create a cumulative weighted distribution of the particle weights and pick particles for the next time step using this distribution. Thus, higher weighted particles are picked at a higher frequency. The localized position is taken as the mean of these particles. We iterate the process for a few time steps and the localized position converges with the ground truth.

DISCUSSION

Table 1 shows the project's original objectives, subtasks, and current schedule (an **X** marker indicates an activity in progress). During the first 18 months of this project, we have focused on collecting extensive datasets (i.e. sensors, horticultural measurements, and yield/quality at harvest) and developing computational techniques for trunk detection, non-contact N estimation, and vehicle localization. During the upcoming year, we will dedicate additional resources to using the collected datasets to develop a Decision Support Tool for precision fertilization plants. We will also begin working on some of the hardware required for an initial prototype of a variable N application system. While we will make the datasets and algorithms open-source and freely available to the community, we anticipate that the Decision Support Tool will have the most long-term value to the industry. Also, while it was not an original objective of this project, we have determined that a low-cost, open-source portable sensor box that could be used for vehicle localization may be of widespread interest. We will explore the development of such a sensor system over the next year.

Table 2. Original project objectives and schedule**.**

Objective	Research Activity	Year 1		Year 2		Year 3	
1	Develop methods & algorithms for tree trunk detection	X	X	X			
	Discussions with experts and N data collection (e.g. leaf samples, physical measurements, N applied)	X	X	X	X		
	Map the orchard block with RTK-GPS		X	X			
	Develop methods & algorithms for vehicle localization		X	X	X		
	Develop methods & algorithms for N sensing: geometric, color, and spectral characteristics	X	X	X	X		
2	Create a collaborative decision-making framework for recommending fertilizer plans						
3	Design and develop a variable rate, proof-of-concept sprayer						
	System integration with limited field trials demonstrating variable rate N application						

Project Title: The Next Fruit 4.0

PI:	Peter Frans de Jong	Co-PI (2):
Organization:	Wageningen University & Research	Organization:
Telephone:	+31 4884 73744 (voicemail) +31 (0)6 30475029 (SMS/Whatsapp)	Telephone:
Email:	peterfrans.dejong@wur.nl	Email:
Address:	Lingewal 1,	Address:
Address 2:	Droevendaalsesteeg 4,	Address 2:
City/State/Zip:	Randwijk, Gelderland, 6668 LA	City/State/Zip:
City/State/Zip2:	Wageningen, Gelderland, 6708 PB	

Cooperators: Manoj Karkee and Lav Khot (Washington State University), Joseph Davidson (Oregon University)

Project size
Amount: 3,156k€ for 4 years
Agency Name: Dutch ministry of Ministry of Agriculture, Nature and Food Quality
Notes: Total project size is 3,156k€ for 4 years, the other half (1,578k€) is financed by Dutch growers and companies (in cash/in kind) and the Washington Tree Fruit Research Commission. The part that is financed by WTFRC is stated below.

Item	**2021**	**2022**	**2023**
Salaries	$54,000	$54,000	$54,000
Benefits			
Wages			
Benefits			
Equipment	$5,000	$5,000	$5,000
Supplies			
Travel			
Miscellaneous			
Plot Fees			
Total	$59,000	$59,000	$59,000

Objectives overall project

Making fruit cultivation more efficient, intelligent, sustainable, and future-proof requires us to be able to monitor, manage, and make decisions at the level of individual trees. **Smart Technology** will enable getting the most out of an orchard through the targeted, efficient use of crop protection agents, plant hormones and fertilizers, while saving on labour and minimizing food waste. This all contributes to the creation of a sustainable fruit cultivation system.

The project has therefore three key objectives in relation to technology development:

1. Improving the sustainability of cultivation and the supply chain by:
   a) developing ways of applying crop protection agents, plant hormones or fertilisers to individual trees (or parts of trees) based on new ways of detecting stress, pests, and diseases (using sensors and new algorithms) and
   b) by combining data to develop new decision support models using AI. This will, for example, give decision support in storage duration and conditions to prevent loss and waste of the fruit, or help to determine the optimal dose of crop protection agents, growth regulators and fertilisers.
2. Maximising yields by optimising cultivation and storage through the optimisation of individual tree growth.

3. Minimising costs by developing multifunctional robots to replace human labour and ensure the efficient use of inputs.

The need to achieve these objectives has led to the project being organised in four cases. A brief description of the four case studies is provided below, including an explanation of how they mutually reinforce each other.

Case study 1: Further development of precision sprayer
The former project Fruit 4.0 demonstrated that precision spraying at the level of individual trees is possible. In The Next Fruit 4.0 we want to further develop and broaden the application of precision spraying by controlling it down to individual nozzles and by using sensors to detect pests and diseases and apply sprays in response. Being able to control sprays at the level of individual nozzles also optimises the use of regulators for growth and fruit setting, resulting in a more uniform orchard. Hot spots of insect infestation can also be controlled without spraying the whole orchard.

Case study 2: Advanced crop management and yield registration
This case study is based on the use of sensors to collect data and translate it into decision support models visualised as clear dashboards. This will involve making the sensor platform from the Fruit 4.0 project applicable to more than just apples. The wide range of data and information gathered will also be distilled into clear insights around cultivation management. With help from experts and the use of modern AI algorithms, decision models will be created that can contribute to optimising and improving the sustainability of fruit cultivation.

Case study 3: Cool data
Apples and pears are often stored for a long time, even up to the following harvest. Storing the fruit for any length of time often leads to substantial losses due to a lack of clear, objective information on how long a particular batch can be stored. This case study will focus on maximising the use of data derived from the cultivation phase (climate, crop, and soil) and the focused application of new technology (sensors), leading to decision models that deliver better risk assessments and storage strategies. This will help reduce loss and waste during storage.

Case study 4: Multifunctional robot
Finally, The Next Fruit 4.0 will also work on expanding the functionality of existing robots which are already in development (e.g. by adding a gripper for picking pears, or for pruning and removing suckers) and which could perform more efficiently through technological improvements and better orchard design. All of this will help solve the problem of increasingly limited availability of seasonal labour.

Project kick-off was the first of May 2021. The results presented are from the last 6 months. Results are presented per case.

Case study: Precision sprayer

Objectives
A validated prototype precision sprayer for several fruit crops, which is directed at nozzle level on the basis of smart algorithms and decision models and combined with stress, disease and pest detection.

Significant Findings

- Laser scanner data can be processed into tree height and volume
- First steps are made to translate laser scanner data into spray actions

Methods

The first year of the project will concentrate on:

- Building an improved sensor platform with lidar and GPS.
- Data collection in the orchard.
- Processing data into usable data for spray decisions at nozzle level
- Build 2 sprayers with laser scanner that can spray at nozzle level and that can adapt dose on tree volume

Results and Discussion

In Fruit 4.0 (former project) and The Next Fruit 4.0 we have been busy mapping the crop in recent years by means of a Lidar (LIght Detection And Ranging) system. This is a system of project partner Pepperl + Fuchs. The Lidar can be mounted on a sprayer of sensor platform. Three dimensional information is collected by driving through the orchard as is explained below.

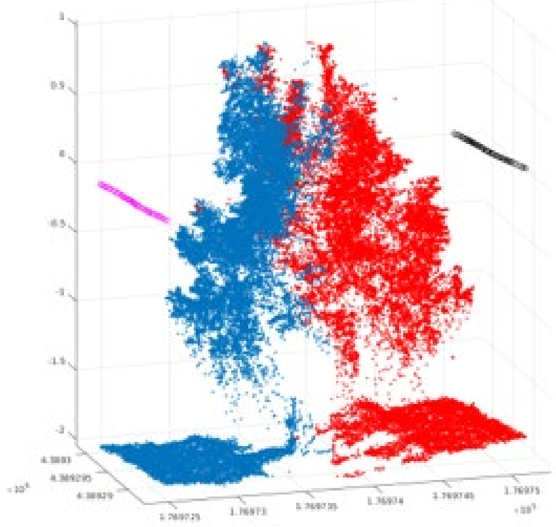
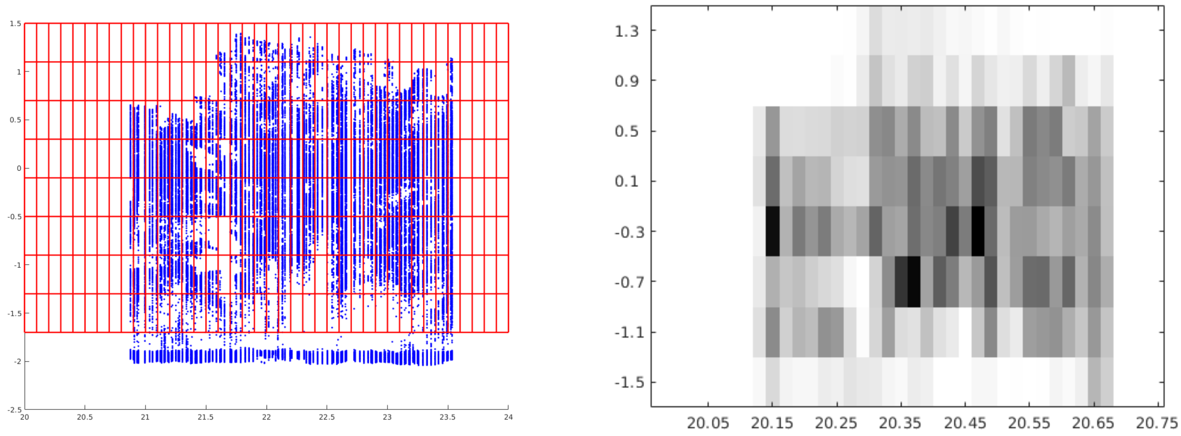


Figure: Lidar data from both sides of the tree merged into one.

A Lidar system gives pulses with an infrared light and rotates at high speed, the pulses are collected again and in this way it is determined which objects are closest. If you then know the location of the sensor, through GPS, you can reconstruct the shapes of the objects around the sensor. We then also merge the data from the two sides of the row of trees together and in this way you can arrive at a fairly complete tree structure. The advantage of the system is a fairly good resolution (1440 measuring points in the round, 50x per second) and that it is not affected by sunlight. We are currently at the stage where we can estimate the height and volume per tree and we are working hard on how we can control a sprayer based on this data. The height and volume can mainly be used to get an overview of the crop/field, but other input is needed to control a sprayer. One possibility is 'ordinary' gap detection, we define blocks based on the nozzle positions, and we then check whether something is present in these blocks, the nozzle can then be controlled accordingly.

The next step is to look at tree volume, so that the amount of spray liquid is adjusted if there is more or less volume in one spot. This is not yet applied to the available orchard sprayers in the Netherlands. Yet another route is to decide on the basis of data in the time, how has a tree developed in recent times and should fruit growers therefore, for example, do a growth-inhibiting or stimulating treatment. The Lidar data could also be used for this. In the coming period, there will be consultations with spray machine manufacturers KWH, Munckhof and ABB to see how the Lidar can be integrated into their orchard sprayer (robot).



Left side: laser scanner data of several trees with an grid overlay, right side: translation data into spray volume based on number of laser points per grid (light-low amount to dark-high amount)

Within this work package, there is regular contact with our colleagues in the US of the Washington State University about the precision sprayer. A research budget has been requested there to record the blossom with sensors, just like in the Netherlands, and to link it to a spraying action.

Case study: Advanced crop management and yield registration

Objectives

- Validated sensors and algorithms to collect physiological and phytopathological characteristics of apple and pear.
- Validated decision models developed on the basis of collected data and expert knowledge; targeted on production optimization.

Significant Findings

- New sensor platform with RGB camera's, laser scanner, chlorophyl sensors and GPS that successfully was used to collect data at different grower sites. The new interface made it possible to use the platform with little background knowledge.
- Laser scanner data has a good relation with tree vigour. This gives the potential to regulate growth at tree level with root pruning, growth regulators or leaf fertilizers.
- First results of field trials that show the potential of management on tree level with blossom and fruit thinning.

Methods
The first year of the project will concentrate on:

- Building a new sensor platform that can be used by non-professionals and is easy to transport. Sensor used are: RGB camera, laser scanner, chlorophyl sensor and GPS
- Data collection in the orchard and ground truth measurements on tree vigour, number of blossoms and fruits.
- Processing data into usable data for tree vigour, pear blossom and fruit detection
- Building data models and dash boards for growers for presentation and management at tree level
- Setting up trails on thinning based on sensor input

Results and Discussion

After building the new sensor platform, data was collected at different sites during the growing season. Also ground truth data was collected.

In addition to collecting data, the first hand has also been laid on developing models that can directly translate data input (from the sensor platform or drone flights) into a precision spray application. The first step is by giving each tree an identity (tree ID). Each Tree ID data has information on orchard structure such as planting distance, planting system, age, etc. And in addition the amount of flower clusters, the amount of wood in a tree and the type of wood on which the flower clusters are located. This provides information about the tree's energy balance, which strongly influences the natural June drop.
The next step is that each tree can be treated separately. Such as inhibiting by means of root pruning or growth regulators or stimulating by fertilization or, among other things, gibberellins. But the biggest opportunity is in chemical fruit thinning. The model combines vigour with blossom and analyses to achieve the desired applications in practice. It is often seen that there are four scenarios: too much blossom/little growth, too much blossom/much growth, too little blossom/little growth, too little blossom/much growth. Each of those 4 scenarios has its own applications. By combining this with precision spraying, the data management can be converted into direct practical applications and therefore added value for the grower.

To test the potential of management at tree level, experiments were set up in which parts of the orchard has been treated completely and other parts treated on a task card. Fruit counts were done just before harvest. The results are now being worked out, but the first results are promising.

Case study: Cool data
Objectives
The focus for this year was to select and evaluate tools for non-destructive quality assessment of fruit both preharvest and postharvest. Observed differences between batches of fruit should be related to relevant quality characteristics of the fruit. Not only aiming at quality assessment of freshly harvested fruits but also related to storage behavior of the respective batches.
In order to perform proper evaluation of the selected tools, a selection of batches that supposedly differ in (storage) quality is needed. This season was used to arrange different batches of Conference pear that can be used to evaluate the tools.

Results and Discussion
First the tools to evaluate the fruit have been selected. Non-destructive measurements using new tools are being related to common (destructive) quality assessment methods.

<u>Common quality assessment</u>

- Firmness, Brix, Weight
- Photographic analysis (color, shape, percentage russeting)

Nondestructive assessment

- Near Infrared – both a hand held sensor from the project partner Kubota and hyperspectral imaging from our in-house facility
- Microwave based – a hand held sensor from the project partner Vertigo

Both the hand held sensors (from Kubota and Vertigo) have been used in one of the selected orchards, pre-harvest (Figure 1).

Figure: Quality assessment of fruits in the orchard. On the left picture using the Microwave based sensor, on the right, the portable NIR sensor

Variation in fruit quality was arranged using fruits from:
Two high risk for *Cadophora* spp. orchards
An experimental orchard where four different irrigation regimes have been applied
Two commercial orchard that supposed to differ in storability characteristics
Next to that one of the high risk for Cadophora orchards has been used for 1-MCP (Fysium) treatment.

Fruits from these orchards were stored under optimal conditions (ULO) in a commercial storage facility. Besides part of the fruit is stored under suboptimal conditions at the WUR facility in Randwijk.
Quality of the fruits will be evaluated after two different storage duration in 2022.

Furthermore activities to analyze pictures from regular storage bins, on location and shortly after harvest were started. This aims at providing the fruit grower with quantitative information (size, shape, russeting, other aberrations) upfront storage and sorting.

Future plans
In 2022 after storage quality of the pears will be assessed and correlated with original quality data gathered before storage. Furthermore different other sources of orchard data will be studied and possibilities for discrimination of batches upfront storage will be explored.

Case Multifunctional robot

Objectives
The main objective of the multifunctional robot case is to expand the functionality of existing orchard robots and of orchard robots currently under development in parallel research projects. The focus of the work is on two topics, namely the development of a sensing system and a gripper for picking pears and on a sensing system, robot control and end-effector(s) for robotic pruning of fruit trees and red currant bushes. On the longer term additional tasks such as automatic thinning, removing weeds and precision spraying will be targeted.

Significant Findings

- For robotic harvesting pear the detection system needs not only to be able detect the position but also the orientation and some key points of the fruit.
- The required motion to detach a pear from a tree is significantly different from that to detach an apple.
- Robotic pruning of fruit trees is exceptionally challenging due to the complex and dense structure and also due to the different pruning rules applied at different growers.
- Extensive knowledge and expertise on automatic pruning and fruit harvesting is present at Washington State University and Oregon State University. Close cooperation and knowledge exchange between Dutch and US researchers will be of mutual benefit.
- For the pruning of red currant bushes clearly defined rules are available. In consequence the project will target this crop first.

Methods

The first year of the project will concentrate on:

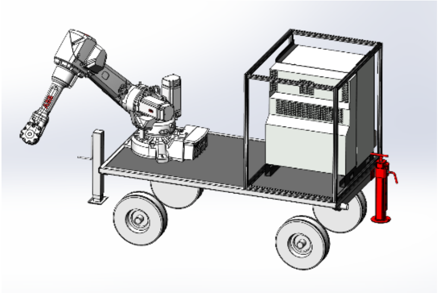
- Building up knowledge on the current state-of-the-art.
- Extracting the brief of requirements for the targeted applications.
- Drafting first concepts and designs.
- A first round of data collection in the orchard.

Results and Discussion

The multifunctional robot case of the Next Fruit 4.0 project explores two different robot concepts. The first concept is based on the apple picking robot that is currently being developed in the parallel on-going project "Handsfree Robotics" that started in 2020. In this project the Dutch companies Munckhof Fruittech Innovators and RIWO Engineering cooperate with Wageningen University and Research. The base of this concept is a Munckhof Pluk-O-Trak harvesting aid.

The Munckhof Pluk-O-Trak harvesting aid (source: https://www.munckhof.org/en/machine/pluk-o-trak-junior/)

Multiple robot units will replace the human workers on the Pluk-O-Trak. It will therefore become in the future an apparatus with several smaller robotic arms. In the second concept only one, but much larger robotic arm will be used. This arm can reach an entire apple or pear tree on either side of the corridor from one fixed robot position. The participating robot company ABB makes the arm available for this. WUR will realize a mobile set-up for this that will be located in the experimental orchard from WUR in Randwijk.



Concept with one large robotic arm on a mobile carrier

For both the topics (harvesting pears and robotic pruning) a literature study is currently carried out. Input from stakeholders and end-users will be collected for setting up a brief of requirements.

Harvesting pears

For the topic of harvesting pears research on different camera systems and on image analysis methods for fruit pose detection is carried out. First sensor data was collected just before manual harvest takes place. Next to images also video recordings were collected that allow a detailed study on the motion needed to detach a pear in the correct way. Based on the collected images a deep-learning based pear detection and pose estimation system is under development.

Furthermore, for red current, a camera system is currently being worked on that can map the 3D branch structure of the plants. During the manual pruning of the red current in upcoming winter season first data will be collected. The ability to distinguish between 1-year-old and 2-year-old shoots on the basis of colour or spectral properties is also being investigated. A first hyperspectral analysis of red current branches showed good possibilities to do so.

Work is also being done on realizing a realistic indoors robot test environment. This setup will contain tree trunks with plastic twigs, leaves and fruits. Such an arrangement will enable us to carry out experiments year round.

Red Currant

Within the topic multifunctional robot there is contact an a regular base with researchers in the US from Washington State University and Oregon State University about autonomous pruning with robots. First data sets have been shared already. Possibilities for mutual visits (once Covid allows) and the exchange of students/visiting researchers have been discussed.

As the project kicked-off just little more than half a year ago the activities scheduled for the first year are all still in progress and are not finalized at the time writing this report. It is not expected that significant deviations from the original project plan and from the scheduled milestones will occur in the first year.

Economic Validation & Innovation Adoption

Working on new technology without also investigating whether the practice ultimately also wants to invest in this technology is not smart. That is why in this part of the project, together with technical companies and fruit growers, we will map out the added value of the new technology. The first case study to work on is the precision spray technology.
We look at both the added value in the short term and the value in the longer term. In addition, an overview is given of what can contribute to a rapid implementation of new technology in practice.

An interactive workshop was held on the 11th of October in which a group of suppliers for parts of the precision sprayer, manufacturers of the precision sprayer, growers, cultivation consultants and sales organisation jointly mapped out (1) what added value the precision sprayer already has for end users. and (2) what the additional added value could be in the future.

CONTINUING PROJECT REPORT **YEAR**: 4

WTFRC Project Number:

Project Title: Multi-purpose Robotic System for Orchards

PI: Avi Kahani **B.Sc.**
Organization: FFRobtics Ltd
Telephone: +972 5456 15020
Email: avikahani@ffrobotics.com
Address: 1b Yitzhak Rabin Street
City/State/Zip: Qadima Zoran Israel 4282300

Co-PI (2): Yoav Koster, M.Sc.
Organization: FFRobtics Ltd
Telephone: +972 5287 37271
Email: yoavkoster@ffrobotics.com
Address: 1b Yitzhak Rabin Street
City/State/Zip: Qadima Zoran Israel 4282300

Co-PI: Manoj Karkee
Organization: Cetr for Precision & Automated Ag Systems, Washington State University
Telephone: 509-786-9208
Email: manoj.karkee@wsu.edu

Co-PI: Qin Zhang
Organization: Cetr for Precision & Automated Ag Washington State University
Telephone:
Email: qinzhang@wsu.edu

Cooperators: Columbia Fruit Packers, Auvil Fruits Inc.

Total Project Request: **Year 1:** 248,058 **Year 2: 250,780** **Year 3:** 255,692

Percentage time per crop: Apple: 100% Pear: Cherry: Stone Fruit:
(Whole % only)

Other funding sources

(*If no other funding sources are anticipated, type in "None" and delete agency name, amt. request and notes)*

Agency Name:
Amt. requested/awarded: **(retain either requested or awarded and delete the other)**
Notes:

Budget 1
Organization Name: FFRobotics **Contract Administrator: Avi Kahani**
Telephone: +972 545615020 **Email address: avikahani@ffrobotics.com**

Item	2018	2019	2020	2021 NCE
Salaries	$59,400	$63,000	$66,150	
Benefits	$5,940	$6,300	$6,615	
Wages	$30,450	$31,500	$33,075	
Benefits	$3,045	$3,150	$3,308	
Equipment	$25,000			
Shipping (**)		$10,000	$10,000	
Supplies	$12,000	$8,000	$6,000	
Travel (*)	$20,000	$21,000	$22,000	
Plot Fees				
Miscellaneous (***)	$10,000	$25,000	$25,000	
Total	$167,950	**$167,950**	$172,148	

Footnotes: Footnotes: (*) Travel budget is requested to cover the travel and accommodation (Travel from Israel)
(**) Shipping product to field experiments (***) Equipment

Budget 2
Organization Name: Washington State University **Contract Administrator:** Katy Roberts
Telephone: (509) 335-4564 **Email address:** katy.roberts@wsu.edu

Item	**2018**	**2019**	**2020**	**2021 NCE**
Salaries	$53,522	$55,662	$57,889	
Benefits	$5,101	$5,304	$5,516	
Wages	$6,000	$6,240	$6,490	
Benefits	$600	$624	$649	
Equipment				
Supplies	$12,000	$10,000	$8,000	
Travel *	$5,000	$5,000	$5,000	
Plot Fees				
Miscellaneous				
Total	$82,223	**$82,830**	$83,544	

Footnotes: *Travel budget is requested to cover the mileage for field experiments and to visit collaborators/co-PIs

1. OBJECTIVES

The following are the project objectives that remained same as the ones proposed in the original proposal.

1) Optimize camera configuration for multi-arm operation of our robotic harvesting machine
2) Integrate and demonstrate multi-arm harvesting robot to cover entire tree height
3) Evaluate the performance of the harvesting robot while in motion
4) Demonstrate integration of the harvesting robot with fruit conveying and bin filling system
5) Investigate machine vision and robotic end-effectors for blossom and green fruit thinning

1.1 Timeline of the Project Activities

Obj. #	Research Activities	Time						
		Year 1		Year 2		Year 3		Year 4
1	Develop a robotic system with multiple cameras							
	Optimize camera locations and create fruit map for harvesting based on accessibility				(1)			
2	Develop and evaluate a robotic harvesting system with multiple arms for entire tree							
3	Develop a control system for automated forward motion control							
	Evaluate the machine for automated operation during motion							
4	Integrate multi-arm robot with a harvest aid platform							
	Evaluate the performance of the machine for harvesting, conveying and bin filling						(2)	(3)
5	Develop machine vision system for flower and green fruit detection							
	Preliminary evaluation of a robotic system for flower and green fruit thinning							

2. SIGNIFICANT FINDINGS

The most important accomplishment of this project is that we were able to build a full-scale integrated system and evaluate it in Washington, which shows that the robotic apple picking is technically and economically viable. The trials in Washington also exposed us to new apple varieties including Ambrosia, Honeycrisp, and Kanzi, which added a substantial and significant amount of data in our continuing efforts to improve the FFRobot.

- The fruit detection algorithm developed based on a deep learning technique worked properly. The technique and technology used also showed promise for detecting obstacles such as branches and trellis wire.
- The multi-arm system was working correctly with minimum interferences between the different arms.
- The current robotic system is now able to work in 10-14 foot rows.
- The analysis of robot limitation and the description of suggested setting of the fruit is underway; we will work with the tech committee to distribute the document.

- Results with the blossom detection algorithm showed great promise for accurate detection of blossom clusters and estimation of blossom density in orchard environment. A number of end-effectors technologies assessed for effective, robotic blossom thinning.

3. METHODS

Harvesting Objectives 1 to 4:

3.1 Obj.# 1: Optimize camera configuration for multi-arm operation of robotic harvesting machine

Introduction: Our team has been developing and evaluating a robotic apple harvesting machine over the past several years (www.ffrobotics.com). Until 2017, field tests have been conducted with one robotic arm (simple, linear actuation) with a single picking hand in conjunction with a single camera attached to the platform.

Our teams from FFRobotics and WSU found that, in a modern fruiting wall orchard, more than 95% of apples can be detected (e.g. Silwal, 2016). Adding additional robotic arms (12 arms by now – tested in Washington) made it necessary to evaluate whether the location of the camera on the platform will yield the same results, and investigate the alternative of attaching camera to the base of the robotic arm to achieve best data acquisition results. WSU team lead this objective in collaboration with FFRobotics team.

Materials: The current vision system has been modified to facilitate placement of the required hardware on the base of the robotic arm which is attached to the platform frame. Field data was collected to determine the percentage of apples detected by the vision system from different locations. The system was evaluated in different kinds of orchards including -

(A) An orchard with fruit thinning to singles and pruning tree growth to approximately 10 inches beyond the trellis wires.
(B) An orchard with mechanical pruning
(C) Different canopy architectures including V-shape and Tall Spindle system.

Procedure: The entire image acquisition process began by scanning the canopy directly in front of the initial multi-arms robot position. Some apples were blocked by other apples, leaves, branches, trunks and trellis wire, which were difficult to be accessed and picked using a robotic hand. A deep learning-based image processing technique was used to identify different parts of the canopy and other objects as potential obstruction to apples for robotic picking. The image processing technique was able to detect apples that are not obstructed by other fruit, branches, trellis wire and trunk. These fruits are identified as completely visible and accessible fruit, which were picked by robotic hands. After the initial picking cycle was completed, the same section was re-scanned to see if more fruit are exposed with desired level of visibility and accessibility. The process was repeated until no accessible fruit are available in the canopy. The picking system then moved down the row and the process was repeated (as discussed in the following sub-sections). Missed apples were hand counted and compared to the number of detected apples. For vertical trees, this process was repeated from other side of the canopies to maximize the fruit harvesting percentage. The technique has been also extended to process videos collected by moving machine, which allows understanding the potential improvement in fruit detection through different viewing angles.

3.2 Obj.# 2: Integrate and demonstrate multi-arm harvesting robot to cover entire tree height

Introduction: As discussed in Obj. #1, our prior prototypes were based on one arm which limited the ability of the robot to pick the entire tree. It was proposed to investigate and introduce hardware and software changes to enable the dynamic structure of several robotic arms to gain the full range of 3 feet width, 3 feet depth, and 12 feet height canopies. We built such a system and evaluated (preliminary) in Israel during 2018 harvest season and an improved machine was evaluated in Washington in 2019 and 2021 seasons (2020 season was missed due to pandemic). FFRobotics led this research activity in collaboration with WSU team.

Fig. 1: Multiple robotic arms supported by one frame

Materials: Hardware and software was modified to support the multi robot arms (6 robotic arms on each side) in the same frame allowing dynamic movements along the height axis of the tree (Fig. 1). The new software algorithms controlled the entire system to allow best performance with dynamic coordination between arms in term of their work-space.

Procedure: The image acquisition and processing system (described in Obj.#1) provided coordinates of linearly accessible fruit in the entire work space of the machine (which is roughly 3ftx3ftx12ft). Optimization techniques were employed to provide sequence of fruit to be picked by each arm of the multi-arm robotic system. To optimize the system, more experiments were carried out by sending, but not picking apples, the robotic arms to the desired fruit. This experiment allowed evaluating several techniques of sequencing fruit picking pattern in the same location.

3.3 Obj.# 3: Evaluate the performance of the harvesting robot while in motion

Introduction: We have introduced both hardware and software changes to our current picking system to automatically move down the row in optimal steps as per the progress in fruit picking estimated by the camera system. FFRobotics team ledi this research activity in collaboration with WSU team.

Procedure: The entire system began by scanning the canopy to detect the fruits, which then started the picking process and automatically moved to the next stop. During the field evaluation, machine capacity, percentages of picked and bruises apples, time between the consecutive locations and the time to stabilize the robotic frame to be ready for the next picking session has been collected. The picking system was then move down the row by certain distance (e.g. 1 meter) and the process was repeated.

3.4 Obj.# 4: Demonstrate integration of harvesting robot with fruit conveying and bin filling system
Introduction: Picking system and the Harvesting Aid system were integrated and evaluated to demonstrate bruise-free end-to-end, fully functional harvesting solution.

Materials/Procedure: There are 6 robotic arms in the same frame allowing dynamic movements along the height of the tree as an add-on for an existing Harvesting Aid System (Automated Ag. Platform). The integration of Harvesting Aid machine and multi-robot conveyer system presented end-to-end solution from fruit harvesting from the trees through to conveyance all the way to the bin. FFRobotics team lead this research activity in collaboration with WSU.

Blossom and Green Fruit Thinning Objectives 5:
3.5 Obj. #5: Investigate machine vision and robotic end-effectors for blossom and green fruit thinning

Introduction: Once harvesting is automated, blossom and green fruit thinning will be another crucial step requiring automation or robotic solution. In this project, while fully developing and evaluating an integrated robotic harvesting system, some efforts was placed on robotic blossom and green fruit thinning. Our hypothesis was that, in the long term, all the manual operations in the field need to be automated and the machines need to be multi-functional with plug and play capability. WSU team lead this objective in collaboration with FFRobotics team.

Materials: A multi-camera system was developed and used in Obj.#1 of this proposal for detecting accessible fruit for harvesting. We used the same cameras and sensors to collect images from apple orchards during bloom and green fruit stages. The images were analyzed to detect and localize flowers and a robotic system was used to approach targeted flower clusteres for destroying or removing desired amount of flower (no efficacy analysis was performed in this work).

Procedure: In this work, the deep learning algorithm developed in Obj. #1 has been revised and improved to detect flowers during the bloom stage, which is als expected to be easily adopted to detect green fruit (future work). Flower and green fruit locations was estimated using a stereo-vision system, which consisted of two cameras (as a part of sensor like RealSense camera). The locations of flower or green fruit in the given work space was provided to a robotic machine for reaching and removing unnecessary flowers. Various end-effector technologies has been evaluated for precision and effectiveness in removing desired amount of flower from target canopy regions, which include pressure hose, waterjet, electrically actuated brush system.

4. RESULTS & DISCUSSION

4.1 Obj.# 1: Optimize camera configuration for multi-arm operation

Images and videos have been collected and were processed for improved detection and localization of apples for fruit harvesting. Data were collected using an Intel RealSense 435 camera (Intel, USA) mounted on top of a robotic arm moving across its workspace.

In addition, the machine vision system, developed using a Mask RCNN (one of the latest deep learning techniques), was expanded to detect additional parts of tree canopies, including branches and leaves along with fruits, so that important orchard characteristics such as branch obstruction, occlusion and pseudo-pendulum effects can be detected, Fig. 2.

The proposed method detected fruit parts with a mean average precision (mAP) value of 87% on a test dataset. The binary mask obtained for each class from Mask-RCNN output was further analyzed to provide safe (avoiding apples that are occluded or not safe to pick for the given view) and reliable (providing right picking orientation by considering the fruits immediate surrounding) harvesting decision to the robot. With this proposed approach, the system was able to identify apples that were safe to harvest with 92% accuracy and was able to predict the fruits challenging to harvest with 91% accuracy compared to ground truth data. Though the current robotic system for picking may not utilize the variable approach direction, new capability of the vision system provides an opportunity to improve the overall harvesting system in the future.

Fig. 2: The row data for harvesting based on MaskCRNN

In addition to branches and other fruit, trellis wires also presented significant obstacles to robotic picking and thinning. Trellis wires were only partially visible (in segments) in images due to their thin size, and occlusion due to branches and leaves. A trellis wire detection technique was developed utilizing binary line descriptors and Haar-like features were combined at the decision level. Segments of the trellis wires detected by the vision system were combined using Hough Transform so that wire location could be estimated in the occluded regions as well. Preliminary analysis showed the trellis wire detection F1-score of 83% (Fig. 3). This technique can be integrated with the current robotic harvesting system to avoid robot collision with trellis wires.

Fig. 3: Trellis wire and trunk detection to avoid end-effector and trellis wire collision. Even though only parts of the trellis wire are visible, the algorithm can reliably estimate the occluded part of the trellis wire assuming a linear geometry.

The additional information gained with the improved algorithms, and the improved mechanism (additional degree of freedom – controlling the twist of the gripper), allowed us to catch the fruit based on the stem orientation and to twist each fruit based on its specific/particular orientation. Based on the tests and improvements over 3 years of this project, we reached a good result of picking fruits. Some challenges we faced in picking included picking with spurs or small brunches (7%-15%), and bruising rate of 6%. "Blocked Apple" - an apple which we identified as one we cannot pick, are left behind in the sections we picked (Fig 4)

Fig. 4: Sample of before and after harvesting by the machine

We took more than 20,000 images to train the system with a better understanding of the 3D location of trellis wire and the fruits, which were used in the algorithm discussed earlier for trellis wire detection.

<u>*Objective 2,3 and 4: Full-scale, integrated robotic system development and evaluation*</u>

As discussed before, we designed and improved a full-scale robotic harvesting systems (Fig. 5) and manufactured two versions of those (the latest improvement was completed in Sep 2021). The commercial-ready mechanical prototype was used in the field trials in Washington and Israel. The robotic picking mechanism was integrated with a dedicated platfrom from Automated Ag Systems and a dedicated convey system and Bin Filler from Maf Roda Industries, for evaluating the completed (end-to-end) harvesting process. Based on the feedback from the growers, we added a sorting/clipping station ("table") before the bin filler to enable the growers to implement the sorting /clipping manually before we automate this task in the future.

Due to the delays, the performance of the entire system was not tested in 2021. A quick video demonstrating the latest machine and its operation in a commercial orchard in WA can be found at https://youtu.be/NjPgO4VnmN8.

Fig. 5: End-to-end system developed for robotic fruit harvesting, conveying and bin filling.

In 2021, we also completed an initial evaluation of the full-scale harvesting robot in a V-traillis canopy architecture to assess the practical usefulness of the same Robot frame for varying canopy architectures. We will need further studies to come up with a improved system for such applications (Fig 6).

Fig 6. V shape harvesting using the lower two self total 4 robotic arms

<u>*Obj. #5: Investigate machine vision and robotic end-effectors for blossom and green fruit thinning*</u>

Blossom Thinning: Flowers are densely located in clusters making individual flower segmentation highly challenging. Furthermore, for the robotic system to operate efficiently, it would be sensible to estimate the number of flowers in each cluster and other orchard parameters such as trunk diameter, branch diameter, and cluster spacing to thin a portion of excess flowers en masse instead of localizing and removing individual flowers. The proposed approach involves segmenting the flower clusters, counting the number of flowers per cluster, and removing a proportion

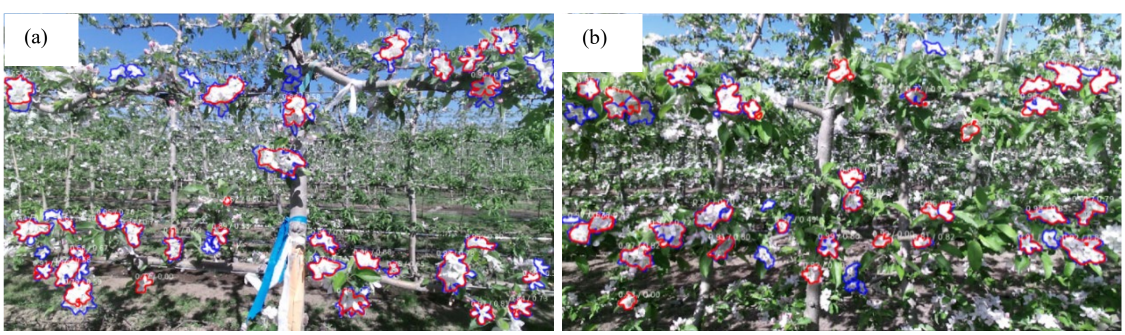


Fig. 7: Detection result achieved by Mask R-CNN algorithm compared with ground truth dataset. Objects inside blue, and red polygons indicate ground truth and detection results respectively; (a) Scifresh apple blossoms; (b) Envi apple blossoms. Mask R-CNN was robust enough to detect true blossoms that are even missed by humans during manual labelling procedure.

of flowers. The effectiveness of automated/robotic thinning heavily depends on blossom detection and estimation of spatial distribution of blossoms under varying background and lighting condition.

To detect flower clusters, a deep learning (Mask R-CNN) based unified semantic segmentation architecture was used. The algorithm takes single image as an input and returns all the instance of flowers/blossoms at pixel level for precise localization of blossoms. Additional images were collected from commercial apple orchard in WA during hand blossom thinning in daylight condition without background manipulation. The image dataset constituted more than 200 images with ~10,000 blossom instances. Mask R-CNN based deep learning algorithm was powerful in learning features of blossoms and was capable of correctly performing pixel level detection of blossoms in images that were never seen by the deep learning model before. Fig. 7 shows the comparison between the human labelled ground truth (blue polygons) and detection results (red polygons) achieved by Mask R-CNN algorithm. Furthermore, with the additional dataset, it was observed that blossom detection in deep learning algorithm was minimally affected by background sky which happens to have similar appearance as blossom. The system achieved a mean average precision (mAP) of 0.86 in detecting blossoms in apple trees.

In addition to flower cluster segmentation, efforts were made to estimate the flower distribution in canopies. We developed and implemented an end-to-end attention-guided regression-based deep learning network to estimate flowers' spatial distribution and count leveraging a point annotation. The proposed approach works on simple point annotation and bypasses the individual object detection, and segmentation, making the spatial distribution and count estimation problem simpler and computationally lighter. The algorithm generated a heatmap identifying the highly probable flower regions. Fig. 8 shows the result of the proposed algorithm where the density map (heat map) is overlayed on the top of the canopy image. Each image is divided into grids to compute flower distribution and count in a localized region. The proposed deep learning-based network showed a promising result with an accuracy of 87.2% to count flowers in images with an average of 89 flowers. The achieved density map can also be easily combined with the cluster segmentation results discussed earlier to compute number of flowers/clusters, which can then be used to develop thinning rules for automated flower thinning.

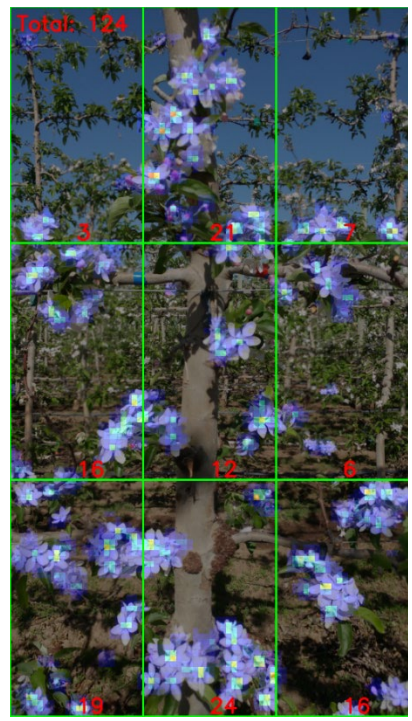


Fig. 8: Flower spatial distribution and count estimation using deep learning based algorithm using point annotation. Heatmaps show the highly probable flower regions which can be used to

Furthermore, in 2020 we investigated and evaluated the performance/efficiency of multiple off-the-shelf end effectors for blossom removal. We tested the operation of pneumatic hose (pressurized air), Waterjet (high-velocity pressurized water), electrically actuated brush system, and commercially available bloom thinner (Bloom bandit/Buster; Fig. 9). The pneumatic hose and Waterjet were ineffective, often dragging the remaining blossoms in the water/airflow direction and badly affecting surrounding flowers that need to be saved. While effective on some occasions, the electric brush system did not easily engage with the blossoms, often rotating and weakening the stem during operation. The commercially available handheld bloom thinner was able to perform targeted thinning. Since the accompanying end-effector (spindle-string configuration) was of fixed size, different end-effector configurations such as varying spindle length, string length, string spacing were developed and tested. The end-effector with shorter strings achieved better control over thinning.

Fig.9: (a) Pneumatic hose end-effector; (b) Waterjet end-effector; (c) Electric wire brush; (d) Commercially available bloom thinner.

Learning from the experiments in 2020, in 2021, a miniature spindle-string end-effector was developed and tested in a commercial apple orchard. The system consisted of custom-designed end-effector connected with a variable speed electrically actuated motor. Experiments were conducted varying the rotational speed, spindle string length, and approach direction to the flower cluster. The custom-designed effector was effective in mechanically removing a proportion of flowers.

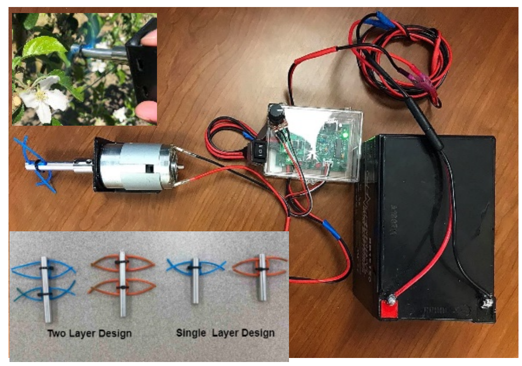


Fig.10: Setup for actuation mechanism for costom-designed end-effector system

Green Fruit Thinning: Upon analysis of RGB images for green fruit detection, it was found that segmentation of green fruit from apple orchards would be challenging in visible spectrum. Green fruits happen to have similar appearance as apple leaves hence limiting the number of features that can be useful for segmenting green fruit. This year multispectral image data were collected during green fruit thinning season. Multispectral images have clear advantage over RGB image as more spectral information are available. This work will continue in the future.

FINAL PROJECT REPORT

Project Title: Towards automated canopy and crop-load management in tree fruit

PI: Manoj Karkee
Organization: Washington State University Center for Prec. & Automated Ag. Systems (WSU CPAAS)
Telephone: 509-786-9208
Email: manoj.karkee@wsu.edu
Address: 24106 N Bunn Rd
Address 2:
City/State/Zip: Prosser, WA 99350

Co-PI (2): George Kantor and Abhisesh Silwal
Organization: Carnegie Mellon University Robotics Institute
Telephone: 412-268-7084
Email: kantor@ri.cmu.edu
Address: 5000 Forbes Avenue
Address 2:
City/State/Zip: Pittsburgh, PA 15213

Co-PI(3): Mathew Whiting
Organization: Washington State University Center for Prec. & Automated Ag. Systems (WSU CPAAS)

Cooperators: Dave Allan, Allan Brothers Fruits; Karen Lewis, Washington State University; Joseph Davidson, Oregon State University.

Total Project Request: **Year 1:** $115,904 **Year 2:** $80,740 **Year 3: 0** **Year 4: 0**

Percentage time per crop: Apple: 80% Pear: Cherry: 20% Stone Fruit:
(Whole % only)

WTFRC Collaborative expenses: None

Budget 1
Organization Name: Washington State University **Contract Administrator:** Katy Roberts
Telephone: (509) 335-4564 **Email address:** katy.roberts@wsu.edu

Item	2018	2019	2020
Salaries[1]	$27,653	$28,759	
Benefits[1]	$ 2,303	$ 2,395	
Wages	$13,500	$14,040	
Benefits	$2,448	$2,546	
Equipment			
Supplies[2]	$3,000	$3,000	
Travel[3]	$1,000	$1,000	
Miscellaneous			
Plot Fees			
Total	$49,904	$51,740	$0 (no cost extension)

Footnotes:
[1]Salary and benefit for a PhD student
[2]Cost to purchase sensors, metals, and other supplies for lab and field tests
[3]Travel cost for field data collection, and testing; and travel cost for cooperative meetings

Budget 2
Organization Name: Carnegie Mellon University **Contract Administrator:** Patricia Clark
Telephone: 412-268-3483 **Email address:** pclark@andrew.cmu.edu

Item	2018	2019	2020

Salaries[1]	$0.00	$5,000.00	
Benefits[1]	$0.00	$1,170.00	
Wages	$0.00	$0.00	
Benefits	$0.00	$0.00	
Equipment	$66,000.00	$18,454.11	
Supplies[2]	$0.00	$1,300.00	
Travel[3]	$0.00	$3,000.00	
Miscellaneous	$0.00	$75.89	
Plot Fees	$0.00	$0.00	
Total	$66,000	$29,000.00	

Footnotes:

[1]A part of salary and benefit for a project scientist

[2]Cost to purchase sensors, metals, and other supplies for lab and field tests

[3]Travel cost for field data collection, and testing; and travel cost of cooperators

1. OBJECTIVES

1. Formulate objective pruning rules by integrating pruning strategy desirable for robotic/automated harvesting and the strategy currently used by growers in fruiting wall apple (e.g. formally trained) and cherry (e.g. UFO) orchards;
2. Develop a machine vision system to locate pruning branches in those two crop architectures.
3. Integrate and evaluate a robotic pruning machine.

Originally Proposed Timeline of Project Activities

Objectives#	Research Activities	Time (Calendar Years and Quarters)							
		2018		2019				2020	
		Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2
1	Develop pruning rules								
	Identify pruning branches								
2	Acquire canopy images and create 3D structure of trees								
3	Evaluate integrated pruning robot								

2. SIGNIFICANT FINDINGS

1. Professional pruners/managers consider formal guidelines when identifying pruning branches in dormant apple canopies. In practice, however, the branches pruned by professional pruners were inconsistent with stated guidelines and demonstrated substantial amounts of variability.
2. Deep learning techniques are capable of analyzing canopy images to estimate various parameters such as size and location of branches.
3. Our integrated pruning system is capable of reconstructing trees in 3D, identifying cutting points, safely navigating to cutting points, and executing pruning. Future efforts will focus on making our system more robust in complex orchard environments.

3. METHODS

3.1 Objective #1: Pruning Rules and Pruning Branch Identification (Carnegie Mellon – Lead; WSU - Participant; OSU - Collaborator)

In the past it was found that, for the tall spindle tree architecture, the pruning process can be captured by four basic rules (Karkee et al., 2014); *i) remove diseased or dead wood/branches; ii) remove branches longer than a specified length; iii) remove branches larger than a specified diameter; and iv) remove branches to maintain a specified spacing.* Lehnert (2015) proposed eight rules for pruning tall spindle apple trees, some of which were similar to four different rules proposed by Karkee and Adhikari (2014). It was also claimed that two major rules; i) remove two to four largest limbs, and; ii) remove all vertically growing limbs (40 degree or less); will cover more than 90% of pruning job in tall spindle apple orchards. These previously developed rules are essential for the automated pruning of tall spindle apple orchards.

However, more work was necessary to develop and apply pruning rules to identify pruning branches in other tree architectures including formally trained apple architectures. Engineers, horticulturists and growers have been working together to explore pruning methods for the proposed canopy architectures. Special consideration was given to the desired limb and fruit distribution for robotic apple harvesting that include the need of presenting fruit individually and without any obstruction by the branches, trunks, or trellis system.

Similar to Karkee et al. (2014), the pruning rule formulation process included observation and analysis of the work of experienced pruners and supervisors. Experienced pruners were selected from commercial orchard crews. They were asked to individually tag pruning branches on randomly selected fruit trees using unique color tags. To keep tagging independent between workers, tags were removed from the tree before another worker was asked to tag the pruning points on the same tree. Video and color images of each tagged tree were captured.

Pruning branches identified by workers as well as the total number of branches were located and counted for each tree. Videos and still images were analyzed to look for the pruning patterns and process each worker follows. A set of objective pruning rules are being defined using; i) expert's knowledge captured from engineering team based on their need for robotic harvesting; ii) horticulturists and growers based on their understanding of training practices, tree architectures, and physiology; and iii) from experienced workers based on pruning processes they follow. We visited with different collaborators to get their input on the pruning strategies to support the process of pruning rule identification.

After objective pruning rules are defined, the 3D tree structure created in Objective 2 and pruning rules can be used to identify branches for pruning. For this task, novel deep learning-based methods were used to distinguish trunk, main branches and sub-branches or laterals of a tree. Geometric parameters of tree canopies including branch size (diameter), branch length, and branch spacing can be estimated using 3D measurements and corresponding color images. Once all the topological and geometric parameters of trunks and branches are estimated, decisions can be made using pruning rules to determine which branches need to be pruned.

3.2. Objective #2: Machine Vision System (WSU and Carnegie Mellon – Co-Lead; OSU - Collaborator)

Under this objective, we focused on creating 3D structures of apple and cherry trees trained in modern fruiting wall architecture (e.g. formal training for apples, UFO architecture for cherries). Images were acquired using a novel stereovision system developed by Co-PI Silwal. This stereovision system features a synchronized camera flash and shutter (called active lighting) to improve point cloud generation from stereo image pairs. Six stereo image pairs were collected with each triggering, and point clouds from each stereo-pair are fused to create a dense point cloud.

A complementary vision system (called Coordinated Depth Cameras) has also been developed that generates 3D point clouds directly using multiple coordinated time-of-flight cameras. The system is mounted on the end of the UR5e robot and can function alone or in tandem with the stereovision system. The Coordinated Depth Cameras concept relies on a global camera, a local camera, and a position tracking camera. An initial image of the entire tree is taken with the global camera. The global camera could be Co-PI Silwal's stereovision system or a dedicated global time-of-flight or stereo camera. This initial image serves as a framework of points for the local camera. The UR5e then begins to "scan" the tree at close range with the local camera along a planned trajectory. The local camera generates a series of high-resolution point clouds that are mapped to the global point cloud as the tree is scanned. This mapping of local points to the global framework is made possible through the tracking camera. The tracking camera continuously estimates the relative position of the local camera to the global camera. Finally, the iterative closest point algorithm is used to complete the mapping of local points to the global framework. Once the scanning is complete, we are left with a very detailed 3D point cloud of the tree structure that can be analyzed to make autonomous pruning decisions.

After image acquisition and 3D point cloud generation, a state-of-the-art object detection algorithm (Faster R-CNN) proposed by Ren S., et al. (2015) was used to identity branching points from color images. These branching points are strong visual ques that detect branch occlusion necessary to segregate individual branches. The link between the detected branching points was associated using the skeleton image generated by the Generative Adversarial Network (GAN). The output of the GAN is a binary image with an array of connected binary pixels that traced the mid-section of branches in the color images. A multi-channel GAN was used to generate a skeleton image for branches and main trunk. Once the skeleton was identified, the curvature of the branches and trunk was warped using the depth information obtained in the previous steps to reconstruct the 3D models. Using this info, the length and size (diameter) of each branch can be estimated. Length can be estimated using the starting and end points of the branches. To estimate diameter, the skeleton of the tree can be overlaid on top of the color images taken from the same perspective. Then, the number of pixels in the orthogonal direction of the branch skeleton can be counted at the base of the branch (2 to 5 cm from the branch-trunk junction). The resulting 3D skeleton and geometric parameters can be used in identifying pruning branches as discussed in Objective 1.

A complementary machine learning approach has also been developed that generates a 3D tree skeleton directly from point cloud data (as compared to first using images). A point cloud from Co-PI Silwal's stereovision system or the Coordinated Depth Cameras system is processed to create a graph of "superpoints" and "edges." Each edge in the graph is processed by a neural network to determine its validity. Valid edges are used to determine the tips and trunk of the tree. The tips and trunk of the tree are input into an evolutionary algorithm that "grows" the tree structure between the trunk and the tips. The output of the evolutionary algorithm is a tree skeleton with trunk, support, and leader labels. Secondary branches can be identified using the leader labels. This tree skeleton can then be used for autonomous cutting point selection.

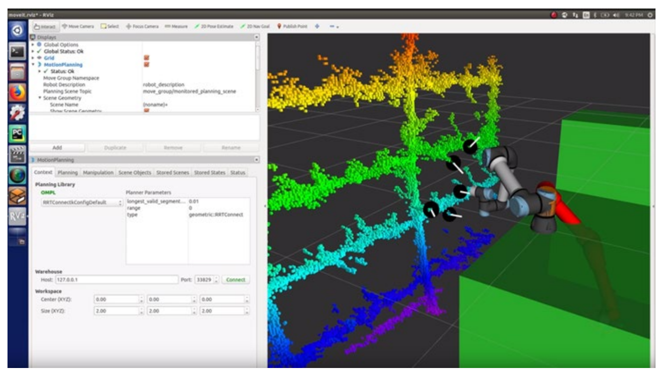


Fig. 1. Simulation of branch pruning in Gazebo. A 3D OctoMap of an apple tree has been created from a 3D point cloud. Five cutting points were selected randomly. The UR-5e traces a collision free path.

3.3. Objective #3: Integrated Robotic System Evaluation (WSU–Lead; CMU Participant; OSU Collaborator)

In the proposed work, two pruning shear end-effectors were developed and integrated with a robotic manipulator to carry out pruning tasks. The machine vision system was integrated with the hardware system for complete system evaluation in the lab and field environments.

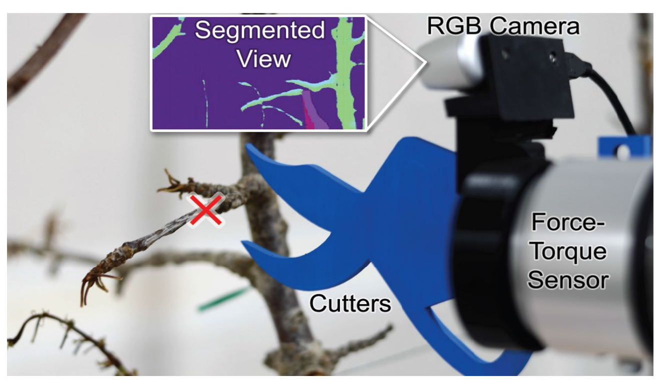


Fig. 2. To complete the final approach to a cutting point, the UR-5e uses a hybrid image/force controller instead of 3D point cloud data.

A UR-5e robot arm from Universal Robots was used for developing an automated fruit tree pruning system. This manipulator demonstrated good speed, reach and maneuverability, and was acquired at both Collaborator Davidson's and PI Karkee's labs in addition to the similar system available at CMU. This facilitated collaborative system development, integration, and evaluation. Developing an integrated software stack for robot control is key for a successful pruning system. Our approach included the following:

1) Create a 3D point cloud of the orchard environment
2) Generate collision free paths to the identified cutting points using FREDS-MP (Fig. 1)
3) Execute a controlled approach to the cutting point using inverse kinematics
4) Cut the identified branch

The planning framework we utilize is called FREDS-MP, which aims to increase the planning speed and overall throughput of the robotic system. FREDS-MP works by precomputing a database of optimistic trajectories offline, utilizing these trajectories during the online phase as effective priors, and ordering the cutting points more effectively. Additional controls have been developed to increase the accuracy of the UR-5e's approach to the cutting point while minimizing risk to the robot and the environment. Oftentimes, the 3D point cloud of the tree is not a perfect reconstruction due to a variety of environmental or technical factors. These inaccuracies could cause unintended collisions during the UR-5e's approach that cause damage to the tree, the UR-5e, or both. As such, a hybrid controller has been developed to increase the accuracy of the UR-5e's final approach (15-30 cm) to cutting points using images and force data instead of 3D point cloud data (Fig. 2). Segmented images of pruning branches and the end effector were generated using another GAN to enable robust vision-based control. The vision-based controller navigates the end effector to the pruning branch until contact is made. Once contact is made, a force-feedback controller was developed using the UR-5e's force torque sensors to navigate the end effector to the pivot point in the shears without creating high forces. This hybrid controller was trained in simulation using proximal policy optimization.

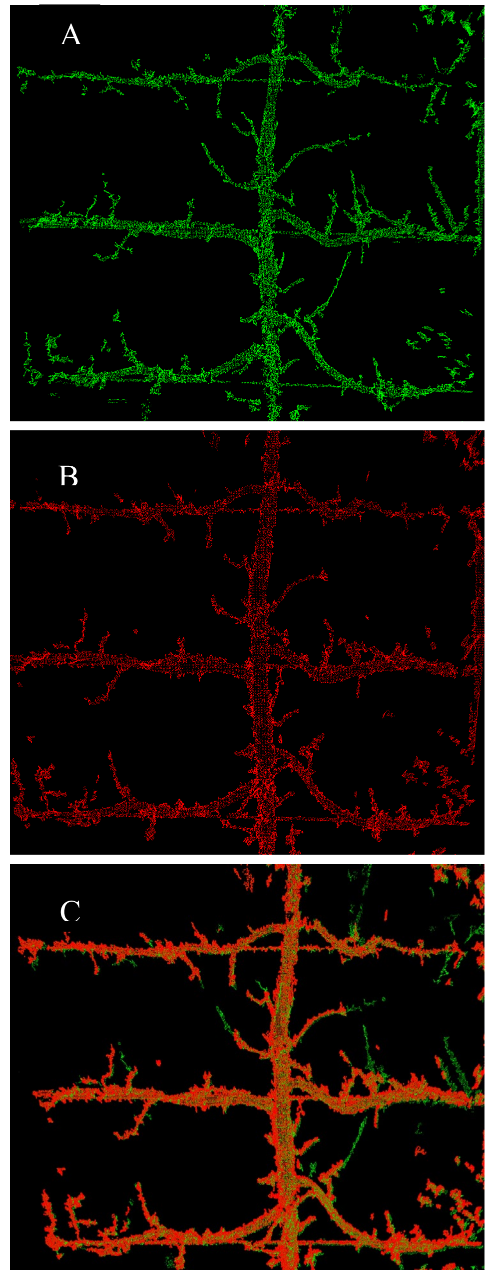


Fig. 3. Pre/post pruned point cloud overlay. (A) pre pruned point cloud. (B) post pruned point cloud. (C) overlaid point cloud. The intersections of green and orange points indicate cutting points.

4. RESULTS & DISCUSSION

4.1 Objective #1: Pruning Rules and Pruning Branch Identification

Our hypothesis for automated pruning rule generation was that the observation of commercial pruning operation and analysis of images/3D models captured before and after pruning could lead to objective pruning rules. To test this theory, we assigned professional pruners to follow commercially adopted pruning rules and prune forty dormant apple trees. For these canopies, the camera system was placed in a stationary location approximately one meter in front of the canopy and we collected before and after pruning wide angled stereo images. Later, point clouds from the two pre/post pruning datasets were overlaid to identify individual cutting points. Figure 3 shows this underlying concept.

A summary of the critical components of the ideal pruning rule for dormant apple trees are listed below for discussion. A detailed description of the pruning rule practiced by professional pruners is included in our 2018 annual report (submitted on Jan 16, 2019).

- Use of a BCA tool to optimally determine the appropriate number of fruiting location per unit length of the lateral branches.
- Fruit spacing was considered an important parameter. Minimum fruiting zone spacing was approximately 4 inches as anything closer might lead to clusters of fruit during harvest season.
- Length of fruiting laterals was another important factor. Laterals longer than 8 inches were trimmed.
- Considerations were also made to remove vertical fruiting sites and those right over or under the horizontal branches.
- Selectively remove smaller buds from a cluster. Remove buds too close to the trellis wire, shoots under the branches, and vertical fruiting zones.
- Remove dead and diseased branches and tie shoots closer to the edge of the branch to fill gaps if lateral branches are short.

The analysis of the pre/post pruning data revealed inconsistency in following the strict guidelines for pruning apple canopies. In practice, branch diameters were assessed visually and intuitively without the use of the BCA tool. This led to suboptimal selection of number of fruiting location per unit length of the lateral branches. Additionally, the minimum gap between fruiting locations were estimated using the width of the palm as a unit of measurement which varied from one pruner to another. These differences between the ideal and practiced manual pruning created large amounts of variation in the data for training a machine learning agent. As such, these revelations led us to focus on synthesizing a pruning rule by just utilizing the geometric measurements and topological parameters. We realized the most important aspect of pruning is the uniform distribution of fruit, therefore we implemented the following simplified pruning rule that prioritizes fruit distribution.

1. Estimate diameter and length of lateral branches and use the BCA equation to determine optimal number of fruiting locations per unit length of the lateral branches.
2. Count and measure the length of secondary branches and only keep secondary branches with minimum of 4 inches gap.

Fig. 4. A multi-view stereo camera system imaging dormant apple canopies. Camera system includes a linear slide.

Fig. 5. A 3D point cloud of the tree structure generated by the Coordinated Depth Cameras system.

In UFO cherries, pruning rule was highly simplified (based on the experts knowledge) to ‘remove all lateral branches on upright fruiting offshoots'.

4.2 Objective #2: Machine Vision System

Secondary branches protruding towards and directly away from the camera are missing in the 3D tree structure when only one viewpoint is used. To mitigate this limitation, Co-PI Silwal from CMU designed a new camera system that images the canopy with two stereo cameras systems (Fig 4).

The new camera system has two stereo pairs, one at a lower height for front view of the canopy and another at a higher and angled position for the top view. Both the top and bottom cameras travel along the linear slide to three different locations and provide a total of six different views of the canopy. The fused point clouds from six different locations provided a more detailed 3D structure of the canopy. In addition to multi-view stereo, like its predecessor, this new camera system is also equipped with active lighting that generates consistent image quality regardless of ambient lighting condition. Additionally, our Coordinated Depth Cameras system can operate alone or further improve the quality of the point clouds obtained by Co-PI Silwal's stereovision system. A sample point cloud obtained by the Coordinated Depth Cameras can be observed in Figure 5.

To implement any pruning rule, the vision system should be able to estimate key aspects of tree canopies such as branch and trunk shapes and sizes. Currently, we have implemented a variation of a deep learning technique called Generative Adversarial Network (GANs) that directly outputs a 2D skeleton image of just the secondary branches. This is advantageous over conventional computer vision algorithm as it bypasses several intermediate processing steps such as pre-processing, multi-class segmentation, and post-processing steps that could potentially add more inaccuracies.

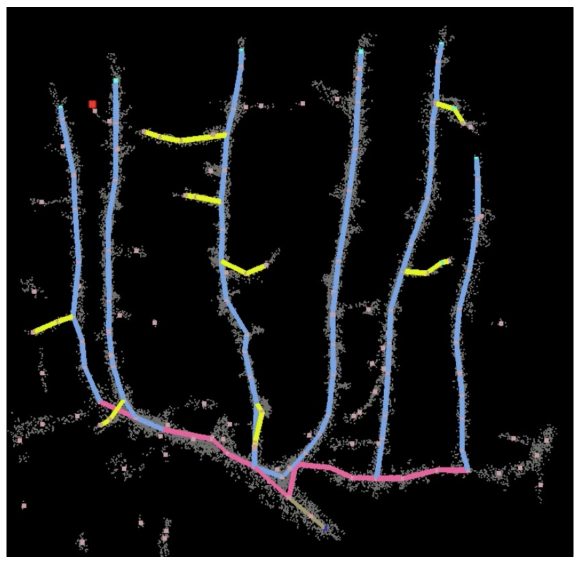


Fig. 6. Labeled tree skeleton output from the skeletonization algorithm.

Our complementary skeletonization algorithm has demonstrated the ability to label point clouds directly and generate a 3D tree structure identifying tree trunk, supports, leaders, and secondary branches. The output of this algorithm can be observed in Figure 6. This tree skeleton can then be used to autonomously determine cutting points for pruning. Further work is going on to estimate desired geometric and other parameters of trees.

4.3 Objective #3: Integrated Robotic System Evaluation

In 2019, we developed an integrated pruning system and evaluated its planning and execution performance in a lab environment. The pruning system is shown in Figure 7, consisting of the UR-5e equipped with an end-effector and an in-hand Intel RealSense D435 camera. The end effector consisted of a pneumatically actuated four-bar linkage with custom-ground blades. Initial tests showed the

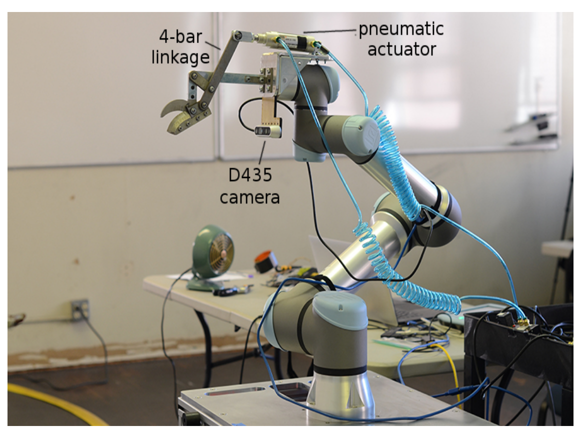


Fig. 7. Our initial pruning robot setup, consisting of a UR-5e robot arm, an Intel RealSense D435 camera, and a custom pneumatic pruning end effector.

end-effector could consistently cut branches up to 10mm in diameter near the pivot point of the blades. Cutting points could be manually selected on a 3D point cloud, and the UR5 could successfully navigate the end effector to manually selected cutting points.

In 2020, our pruning robot was further optimized. A battery-powered, electrically actuated pruning end effector was modified to interface with the UR-5e and support remote actuation. This new pruning end-effector is capable of pruning branches up to 25mm and has no need for compressed air. The UR-5e was mounted on the linear slide with Co-PI Silwal's stereovision system to add an additional degree of freedom for FREDS-MP. Additionally, the Coordinated Depth Cameras system was mounted on the end of the UR-5e with the improved end effector. The refined prototype was further evaluated in labs using actual trees collected from commercial orchards.

In 2021, we integrated all the components of an autonomous pruning robot (Fig 8). The Coordinated Depth Cameras system was capable of creating detailed 3D point clouds, and our machine learning skeletonization algorithm was capable of autonomously selecting cutting points. FREDS-MP was capable of navigating our pruning end effector to the autonomously selected cutting point, and our end-effector was capable of autonomous actuation to cut the pruning branch. The system was brought to field evaluation in a commercial UFO cherry orchard. However, only limited test cuts were performed because of new challenges faced in the complex orchard environment and practical issues on robot operation caused severely cold weather. We outlined the steps we needed to take to have a successful demonstration and have been working towards these goals. Our Coordinated Depth Camera has been optimized since the attempted demonstration, and our vision-based controller GAN is being further trained for robustness in complex orchard environments. We have identified a more efficient mounting orientation for the UR-5e, and we are optimistic our next demonstration will be a success. We will continue to evaluate the system through additional funding provided by USDA to our team.

Fig. 8. The final pruning robot used for our 2021 evaluation, consisting of the UR-5e robot arm, the stereovision system, the Coordinated Depth Cameras system, and a custom electric pruning end effector.

EXECUTIVE SUMMARY

Project Title: Towards automated canopy and crop-load management in tree fruit

Key words: Pruning robot, automated pruning, deep learning, machine vision, robotics

Abstract: The widespread adoption of robotic harvesting systems requires deliberate canopy management to grow fruit in easily accessible locations. Therefore, it is necessary to automate canopy management in tree fruit so that labor use can be minimized throughout the entire production process. Specifically, this project focused on the automated pruning of fruit trees. The objectives of this project were to: i) Formulate objective pruning rules by integrating pruning strategy desirable for robotic/automated harvesting and the strategy currently used by growers in fruiting wall apple (e.g. formally trained) and cherry (e.g. UFO) orchards; ii) Develop a machine vision system to locate pruning branches in those two crop architectures; and iii) Integrate and evaluate a robotic pruning machine. To develop objective pruning rules, 3D point clouds were collected of 40 dormant apple trees before and after pruning by professional pruners. We found that, although professional pruners consider formal guidelines, in practice the branches pruned were inconsistent with the stated guidelines and demonstrated substantial amounts of variability between pruners. As such, we adopted two simple rules that prioritize the uniform distribution of fruit. Two complementary machine vision systems were developed to capture 3D tree structure. An active lighting stereovision system was developed consisting of two stereo pairs that utilized a linear slide. The stereo pairs would take images from three positions along the linear slide to provide a total of six perspectives of the tree to minimize branch occlusion in the resulting 3D point clouds. Additionally, we developed a Coordinated Depth Cameras system that directly generates 3D point clouds without taking images using multiple time-of-flight cameras. The Coordinated Depth Cameras system could be used alone or in tandem with the stereovision system. These machine vision systems produced highly detailed 3D point clouds that were used to make autonomous pruning decisions. Again, two complementary approaches were developed to autonomously identify cutting points. One approach utilized a deep learning technique called a Generalized Adversarial Network to output 2D skeleton images of secondary branches that could subsequently be used to measure branch length and diameter. A complementary approach utilized an evolutionary machine learning algorithm to operate directly on 3D point clouds instead of images. The evolutionary algorithm produced a 3D tree skeleton with labels for the tree trunk, support, leaders, and secondary branches. The information from these tree skeletons could be used to autonomously identify pruning branches and cutting points. A motion planning algorithm called FREDS-MP was used to navigate our UR-5e robotic manipulator and our custom pruning end-effector to the desired cutting point. A hybrid vision-based/force-feedback controller was developed to increase the accuracy of the final approach to cutting points without causing damage to the robot or the environment. The pruning branch could then be automatically cut by our pruning end-effector. In 2021 winter, a fully integrated pruning robot was evaluated at a limited scale in the field, but the orchard environment posed new challenges that our team is currently addressing. An improved and more robust robotic system will be evaluated in the orchard environment in recent future using additional funding our team (led by collaborator Joseph Davidson) have secured from USDA.

FINAL PROJECT REPORT

Project Title: Novel automatic crop health observer

PI: Curtis Garner

Report is forthcoming.

FINAL PROJECT REPORT

Project Title: Novel on-the-fly variable-rate air flow & distribution sprayer

PI: Curtis Garner

Report is forthcoming.

PROJECT PROGRESS REPORT

Project Title: Smart Orchards Year 2 + Connectivity (no-cost extension approved to 2022)

PI:	Steve Mantle	**Co-PI (2)**:	Lav Khot
Organization:	Innov8 Ag Solutions	**Organization**:	WSU
Telephone:	509-795-1395	**Telephone**:	509-786-9302
Email:	steve@innovate.ag	**Email**:	lav.khot@wsu.edu
Address:	103 E Main St Ste 301	**Address**:	WSU IAREC, 24106 N Bunn Rd.
Address 2:		**Address 2**:	
City:	Walla Walla	**City**:	Prosser
State/Zip:	WA 99362	**State/Zip**:	WA 99350

Cooperators: Columbia Reach/Chiawana Orchards – Shawn Tweedy / Chris Hammond (area), Martin Ramirez (ranch); Washington Fruit & Produce - Gilbert Plath & Aylin Moreno (area), Ramon Cuevas / Orlando Joaquin (ranch); WSU – Lav Khot (weather, imaging, data interpretation), Bernardita Sallato (root nutrient uptake), Lee Kalcsits (tree physiology w/ microtensiometers & dendreometers), Jenny Bolivar-Medina (extension). Sensor providers – Arable (weather, soil moisture), Ceres Imaging (fixed-wing imagery), CropVue (insect traps), Davis Instruments (weather), DynaMax (soil, plant, & weather sensors), Green Atlas (fruit & canopy mapping), MeterGroup (weather station API access), Predictive Nutrient Solutions (soil lab testing), SmartGuided Systems (spray mapping), SoilOptix (soil nutrients), Thingy (weather, soil moisture), Tuctronics/AgriNET (weather, soil moisture, water pressure, PAR).

Percentage time per crop: Apple: 100% Pear: Cherry: Stone Fruit:

Total Project Funding: $90,000 expenses

Budget History:
Budget 1
Organization Name: Innov8 Ag Solutions **Contract Administrator:** Steve Mantle
Telephone: 509-795-1395 **Email address:** steve@innovate.ag
Supervisor or Station Manager name and email address (if applicable):

Item	2021	2021 (optional connectivity add-on)
Salaries		
Benefits		
Wages		
Benefits		
Equipment	3,000	10,000
Supplies		
Travel		
Miscellaneous "as a service"	27,000	20,000
Plot Fees		
Total	30,000	30,000

Budget 2
Organization Name: WSU-CAHNRS **Contract Administrator:** Katy Roberts
Telephone: 509-335-2885 **Email address:** arcgrants@wsu.edu
Supervisor or Station Manager name and email address (if applicable): Samantha Bridger, Grant Coordinator, prosser.grants@wsu.edu

Item	2021
Salaries	
Benefits	
Wages	$23,776
Benefits	$2,378
Equipment	
Supplies	$2,000
Travel	$1,520
Plot Fees	
Miscellaneous	
Total	$29,674

Footnotes: Wages of $23,776 plus $2,378 benefits will partially support two graduate students during field season ($29.72/h x 20/week x 32 h [GRA-1] and x 16 h [GRA-2]) who will work closely with the PI-Khot in field data collection, data analysis and reporting. Supplies include replacement drone spare parts (Propellers, Batteries, Landing gears, etc.; $1,200) and subscription to a Pix4D software ($750) used for geospatial data analysis. Travel ($1,520) includes smart orchard data collection trips (110 miles/trip x 10 trip x 0.58/mile x 2 vehicles x 2 sites) and field day travel for the crew ($128).

Original Objectives:

1. Maintaining an array of connected in-field sensors as well as through-season high resolution aerial multispectral and thermal imagery collection & analysis.
2. Maintaining a data warehouse and provide access to raw data and layered data products to end user via a web and/or app interface.
3. Organize ‘field days’ for growers, researchers, & other interested parties to learn more about data and how it’s usage toward in orchard decisioning.
4. [Optional] Implement a high-speed wireless network w/ edge computing for one smart orchard location, to highlight technical & economic viability of addressing orchard connectivity challenges.

Progress Report:
The focus in 2021 was fine-tuning the Chiawana Auburn Ranch [gala] Smart Orchard, and deploying the Washington Fruit Grandview Ranch [honeycrisp] Smart Orchard.

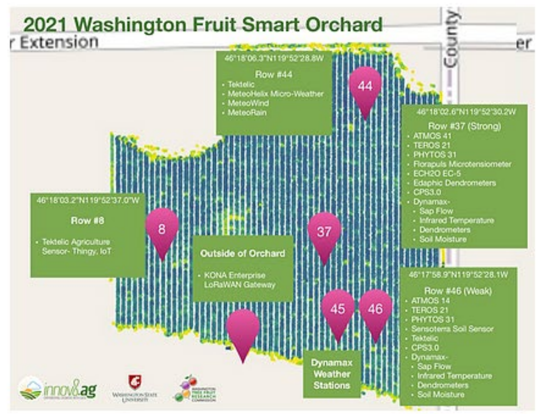
The Chiawana Auburn Ranch location continued operating AgWeatherNet stations in/above/out-of orchard, Davis Instruments temp/RH/wind/PAR in & above orchard, Tuctronics/AgriNET in-canopy temp/RH + soil moisture + water pressure; while removing Phytech dendrometers + water pressure, AquaSpy soil moisture, and Teralytic soil nutrient probes. Through-season drone imaging was maintained year-over-year (and also expanded to Grandview).

For both locations this season, we introduced Ceres fixed-wing imagery, SoilOptix 10' x 10' soil mapping, and GreenAtlas fruit & canopy mapping.

The Washington Fruit Grandview Ranch installation was deployed with the sensors as depicted on the below map, with sensor grouping locations selected by strong vs weak vigor based on GreenAtlas blossom mapping at the beginning of the 2021 growing season.

WASHINGTON STATE UNIVERSITY

WSU
- ATMOS 41 micro climate weather
- ATMOS 14 in-canopy weather
- TERROS 21 soil water potential
- PHYTOS 31 leaf wetness
- Florapulse- Microtensiometer
- Meter Group- ECH20 EC-5
- Edaphic Scientific Dendrometers
- WSU Drone Imagery



THINGY IoT

Thingy, IOT
- Kona Enterprise Gateway-LoRaWAN Connectivity
- MeteoHelix IoT Pro- Micro Weather Station
- MeteoWind IoT Pro
- MeteoRain IoT Compact
- Tektelic Agriculture Sensor
- Sensoterra 6 in. Soil Sensor

Dynamax

Dynamax
- SGEX-19 – 19 mm & 25mm Sap Flow Sensors
- SapIP-IRT – Infrared Temperature Sensors
- DEX100 – Dendrometers
- SM150T – Soil Moisture Sensors
- MICRO2 – Weather Station

Aker

Aker Ag
- Drone Imagery with Aker TrueCause™

ARABLE

Arable
- Arable Mark 2

ceres

Ceres
- Irrigation Management using Aerial Imagery

This year we focused on foundational elements of soil & tree/fruit variability across the blocks, so that we could better measure inputs (via sensors) against outcomes. Detailed [SoilOptix] soil & [GreenAtlas] tree/fruit variability reports are published at:

- Chiawana Auburn Ranch – www.innov8.ag/smartorchardv1
- Washington Fruit Grandview Ranch – www.innov8.ag/smartorchardv2

These reports were provided to the growers, researchers, & participants tied to this project. Additional 'raw' data will be made available with the sensor data as we work to consolidate the data from the season, which is the reason for the no-cost extension into 2022.

Summarizing the soil data, both blocks now have early & late-season soil data available at a granular 335 points/acre, to complement the ground-truthed soil data collected by Bernardita Sallato. When mapped, it's clear that the Grandview block - in particular - has as much as 82% sand at the top of the block, ranging down to 19% at the bottom of the block. While this has implications for soil nutrient distribution (as covered separately in Bernardita Sallato's report), it also has implications to consider for 2022 irrigation system design & scheduling – especially given that the sandy soils at the top of the block/hill perpetuate water flow down to the 50' silty clay at the bottom. The grower & stakeholders also have the ability to view the soil texture & nutrient data interactively in a dashboard/app (available on web browser, Android & iOS apps) – as show in the below figure 2. As the sensor data is ingested from the various sensor providers, we're working toward overlaying that as well – with the below figure showing Meter Group sensor data.

Figure 2 – Soil nutrient & texture data available in the AgriNET dashboard/app, complemented by sensor data.

With the canopy/fruit mapping, we're now able to identify sections of trees where canopy vigor and fruit count/sizing are variable. This provides the opportunity to explore the relationship between soil attributes & vigor/yield elements, as highlighted in figure 3.

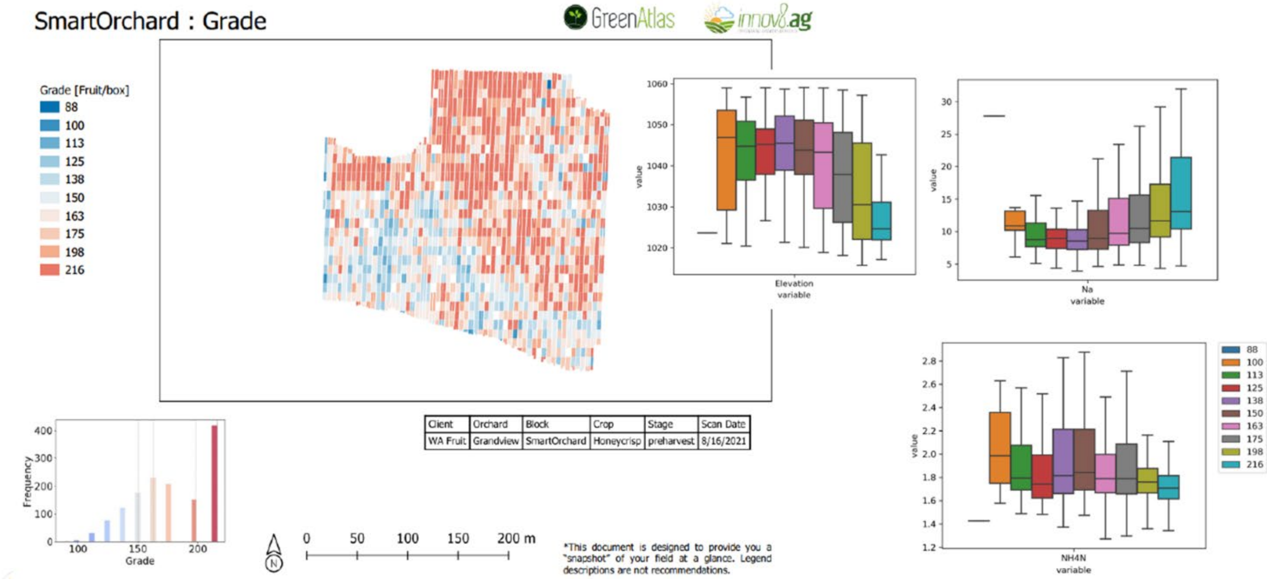
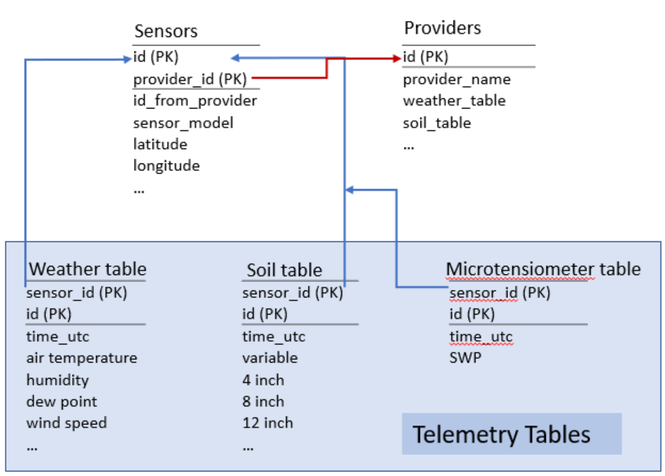


Figure 3 – Exploring the relationship between fruit size and soil attributes.

Further, the detailed canopy/fruit mapping correctly predicted yield in bins/acre for both blocks, while also identifying areas within each block where there is unrealized potential. As we wrap up sensor data collection for the year, we now have focus areas for researchers and researchers-in-the-making (with intent to make this data available for the 2022 WSU Digital AgATH0N, comprised of ag & computer science students from WSU & other schools).

From a data warehousing perspective, sensor data is ingested into a SQL database. Telemetry table example is listed in figure 4. As of November 2021, data is ingested for Tuctronics/AgriNET, Davis Instruments, Meter Group, and FloraPulse. As we extend into 2022, we're continuing to focus on ingesting data that wasn't provided by sensor partners via API, and plan to have the broader dataset ready for the WSU AGATH0N in the Spring, if not sooner.



Chiawana

Source	Tables
Dimensions	ColumbiaReach.providers ColumbiaReach.sensors
Tructronics (AgriNet)	ColumbiaReach.tuctronics_weather ColumbiaReach.tuctronics_soil
Davis Instruments	ColumbiaReach.davis_weather
Meter Group	ColumbiaReach.meter_weather ColumbiaReach.meter_soil

Grandview

Source	Tables
Dimensions	Grandview.providers Grandview.sensors
Florapulse	Grandview_florapulse_microtensiometer
Meter Group	Grandview.meter_weather Grandview.meter_soil

Grandview.providers

id	provider_name	weather_table	soil_table	other_table
1	Meter Group	meter_weather	meter_soil	NULL
2	Florapulse	NULL	NULL	florapulse_microtensiometer

Grandview.sensors

id	provider_id	sensor_model	id_from_provider	port	type	table_name	variables	inside_canopy	height_depth	latitude	longitude
153	1	ATMOS-14	Device z6-12154 port 4	4	weather	meter_weather	AirTemperature(°C) ,VaporPressure(kPa) ,AtmosphericPressure(kPa) ,VPD(kPa)	yes	0.75	46.30	119.87
157	1	TEROS-21	Device z6-12159 port 3	3	soil	meter_soil	MatricPotential(kPa) ,SoilTemperature(°C)	yes	20	46.30	119.88

Grandview.meter_weather

time_utc	sensor_id	AirTemperature(°C)	---	VPD(kPa)
9/27/2021 21:20	153	13.02	---	0.17
9/27/2021 21:25	153	12.86	---	0.16
9/27/2021 21:30	153	12.76	---	0.15
---	---	---	---	---

Grandview.meter_soil

time_utc	sensor_id	variable	20cm	40cm
9/3/2021 21:15	157	MatricPotential(kPa)	-8.26029	NULL
9/3/2021 21:30	157	MatricPotential(kPa)	-8.3521	NULL
9/2/2021 14:15	157	SoilTemperature(°C)	15.6	NULL
9/2/2021 14:30	157	SoilTemperature(°C)	15.58	NULL
---	---	---	---	---

Figure 4 – Telemetry example relationships within database ingesting smart orchard sensor data.

We had one primary field day that was promoted by WSU Extension, with strong attendance of > 70 attendees from across the growing industry, and participation by many of the sensor providers. Feedback was very positive, and the remark was made that this was the first field day in many years where > 1/3 of the attendees were < 35. Additionally, we had field visits from a NY grower, Washington Department of Agriculture, and the WTFRC.

As a result of data collected throughout the year, we've seen multiple research papers submitted for publication. Publications thus far are listed at www.innov8.ag/smartorchard, and include two papers by Dr Abhilash Chandel on ET mapping; with a pipeline of additional papers by Dr Chandel (submitted to IEEE) as well as high school student Maya Sharma (submitted to Regeneron competition).

For wireless connectivity, the Grandview orchard location was selected for an upgrade. The ranch was historically serviced by a CenturyLink DSL connection at ~ 1Mbps. We looked at several options to address the speed issue, including provisioning a Starlink downlink (which was unavailable at this location for now). We partnered with PocketiNET to creatively provision 100Mbps Internet connectivity via a wireless link, and deployed WiFi coverage throughout the shop/office area – a 100x speed upgrade. We also enabled infrastructure for WiFi connectivity across the orchard, deployed LoRAWAN across the orchard – connecting environmental sensors from Thingy. T-Mobile's executive office showed strong interest to provide enhanced mobile connectivity at one or both of the blocks for the 2022 growing season. And finally, we creatively deployed a "mobile ag datacenter" from innov8.ag to provide on-demand edge computing at both locations, which processes the ~ 1TB of photos/LiDAR data collected at each site when GreenAtlas canopy/fruit mapping is performed.

<u>Remote sensing of Orchard -1 and -2</u>

High resolution remote sensing data was collected using two platforms (1) a small unmanned aerial system (UAS) aka drone, and (2) a manned aircraft. The drone (Figure 5) was mounted with a five-band multispectral imaging sensor (RedEdge3, Micasense Inc., Seattle, WA) with Blue, Green, Red, Red-Edge, and Near-Infrared wavebands and a radiometric thermal imaging sensor (Flir DUO Pro R, Flir systems, Wilsonville, OR). The drone also had a skyward facing light sensor (DLS, Micasense Inc., Seattle, WA) to embed the solar irradiance data during flight mission into the multispectral imagery. A calibrated reflectance panel (CRP, Micasense Inc., Seattle, WA) was imaged before and after each mission. The CRP imagery and light irradiance was used to correct the multispectral imagery for any changes in natural light conditions. The imaging missions were configured using a ground control software (Mission Planner, Ardupilot, Open Source Project) to fly drone at an altitude of 100 m (330 ft) above ground level (AGL) and capture multispectral imagery at a spatial resolution of 7 cm/pixel (2.8 in/pixel) and thermal imagery at 13 cm/pixel (5.1 in/pixel). The drone based flight missions were conducted on 157, 98, 62, 26, and 13 days before harvest (DBH) and 11 and 54 days after harvest (DAH) at Smart Orchard-2 (Grandview Orchards, Grandview, WA). Similarly, on 83, 61, 47, and 14 DBH, and 9 and 75 DAH at Smart Orchard-1 (Columbia Reach Chiawana Orchard, Pasco, WA). The collected imagery for respective campaign was stitched in a photogrammetry and image stitching software platform (Pix4D mapper, Lausanne, Switzerland) to obtain seamless orthomosaics of the study site. Resulting orthomoasics were analyzed in QGIS ver.2.18.16 and R ver.3.6.3 software packages as detailed in 'Data Analysis' section.

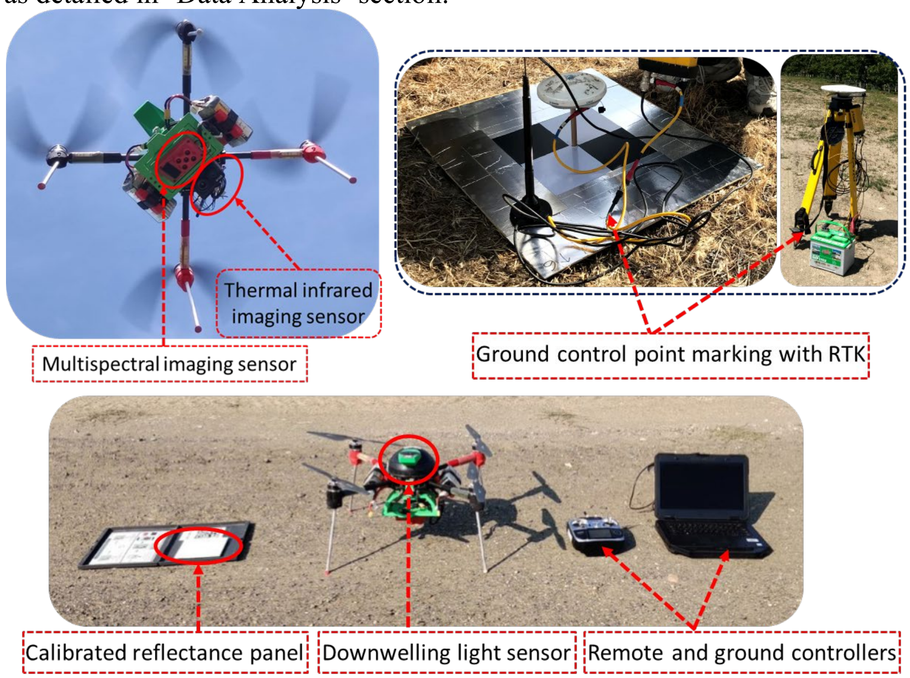


Figure 5. Small UAS based imaging and georeferencing hardware used for high-density apple orchard mapping (RTK: Real time kinematics).

Our industry collaborator, CERES imaging (Oakland, CA) also collected the manned aircraft based imaging missions at both sites. The aircraft had a customized multispectral imaging sensor with Red, Green, Red-Edge, and Near-Infrared wavebands and a thermal imaging sensor. The flight missions were conducted at an altitude of 1000 m (3280 ft) AGL to capture multispectral imagery at 20 cm/pixel (7.9 in/pixel) and thermal imagery at 27 cm/pixel (10.7 in/pixel). The collected imagery was stitched and radiometrically calibrated to obtain the reflectance orthomosaic maps of the site. The manned flight missions were conducted on 98, 82, 72, 62, 56, 41, and 26 DBH for Smart Orchard-2. Three of those campaigns coincided with the drone imagery campaigns. Similarly, for Site-1 the flights were conducted on 61, 47, and 10 DBH.

In addition to the drone and manned aircraft-based imagery, our team also downloaded imagery data from Landsat 7 and 8 satellites, with overpass on 157, 98, 26, and 13 DBH, and 11 DAH. The spatial resolution of the satellite imagery was 30 m/pixel (118 ft/pixel).

Imagery data analysis

All the collected drone imagery was processed to obtain spatial maps of evapotranspiration (ET) and canopy vigor (e.g. Normalized Difference Vegetation Index, NDVI) of the imaged high-density apple orchard blocks. The evapotranspiration was mapped using the multispectral imagery, thermal imagery, digital elevation model, and weather data inputs. The weather data inputs logged at 15 min interval for the 24 h period of the day of imaging were acquired from an all-in-one open-field weather sensor installed outside the orchard at 1.8 m AGL. All these data were processed using an energy balance model; Mapping ET at High Resolution with Internalized Calibration (Allen et al., 2007) modified for aerial imagery data (Chandel et al., 2020; 2021). Similar approach was followed to develop canopy ET and vigor maps from the manned aircraft imagery data. The Landsat 7 and 8 satellite-based imagery data was processed through the standard METRIC model to develop the spatial ET maps.

The above data products are being analyzed to assess the spatial and temporal variability in canopy vigor and water use (ET) within the orchard blocks. The spatial ET mapped using remote sensing data will also be compared with the crop water stress and water use measurements collected at the ground for selected regions of interests (ROIs). This will help to identify the best suited platform, or combination and suitability of the energy balance approach to estimate crop water requirements. For the same ROIs, the canopy vigor derived from remote sensing data will be contrasted and evaluated with the ground measurements of soil properties. This will help to understand the effects of soil nutrient variability on canopy health and resulting yield variability.

Research findings

Usefulness of imagery resolution for crop mapping: Small UAS and manned aircraft imagery could map the vigor variation (Figure 2) and crop water use (Figure 3) by apple canopies at high spatial resolution (7–20 cm/pixel) unlike the Landsat 7/8 imagery that had relatively low spatial resolution (30 m/pixel). The ET mapped using manned aircraft imagery was relative higher for some imaging campaigns (e.g. 98 DBH). This could be due to the overlapped imaging during the operation of the overhead sprinkler cooling systems that wetted the canopy, thereby lowering their temperature and overestimating the instantaneous ET values. The small UAS based imaging was strictly conducted before the overhead sprinkler system actuations to ensure quality of collected data.

Pertinent to canopy vigor mapping, the overhead sprinkled water on the canopies could have increased the reflectance values in the red imaging waveband which eventually reduced the estimates of canopy vigor (NDVI) from manned aircraft imagery. Again, the drone-based imagery might aid in better capture of the canopy vigor. Landsat 7/8 imagery derived attributes of ET and NDVI could account for relatively very low spatial variation. This resolution was not sufficient to segment or separate the tree rows from the inter-rows or the soil background. For the heterogeneous canopies such as the apple orchards, spatial resolution is critical to identify site-specific variations in crop and thereby to guide specific crop management practices.