## NEW PROJECT PROPOSAL PROPOSED DURATION: 1 Year

**Project Title:** Smart Orchards Year 2 + Optional Connectivity

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**Cooperators**: Dave Brown [AWN], Bernardita Sallato, Lee Kalcsits, Claudio Stockle

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

**Total Project Request:** **Year 1:** $60,000 + $30,000 optional for connectivity **Year 2:** **Year 3:**

**Other funding sources:** **Requested**
**Amount: $1,000,000**
**Agency Name: USDA-NIFA**

**Other funding sources:** **Requested**
**Amount: estimated value $60,000**
**Agency Name: In-kind donation or discount by sensor/equipment providers –** Tuctronics/AgriNET, Davis Instruments, Teralytic, Green Atlas, Smart Guided Systems, PocketiNet Communications, WSU AgWeatherNet, Microsoft

**Notes:** innov8.ag will work with WTFRC and the above sensor providers (as well as additional to-be-identified providers) to solicit donations, loaners, or discounts for the 2021 growing season. As of time of proposal submission, Davis Instruments has committed to continuing to fund one location, and WSU AgWeatherNet will continue to fund the existing smart orchard location & the second location as part of their WTFRC-funded grant. The additional providers have indicated intent to heavily discount or donate to this project in order to accomplish stated objectives.

**WTFRC Budget:** none

**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)** | **2022** |
|---|---|---|---|
| **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 | 0 |

**Reasons for Extension:** We would appreciate no-cost extension to this project until 9/30/22. The extension will help us: 1) complete data collection from 2021, some of which wasn't uploaded by sensor providers and/or API wasn't provided as agreed; two examples are dendrometers & Dynamax sensors. 2) Analyze & interrelate data sets, including collected drone imagery. We'll gladly deliver a progress report in 2021 to show progress, challenges, and early insights; followed by multiple published papers that are in the pipeline for early-mid 2022. With a 2022 new proposal, our 2021 learnings will inform a highly-focused 2022 – with an emphasis on application of insights to irrigation & nutrition considerations, particularly at the Grandview smart orchard.

**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** | **2022** |
|---|---|---|
| **Salaries** | | |
| **Benefits** | | |
| **Wages** | $23,776 | |
| **Benefits** | $2,378 | |
| **Equipment** | | |
| **Supplies** | $2,000 | |
| **Travel** | $1,520 | |
| **Plot Fees** | | |
| **Miscellaneous** | | |
| **Total** | $29,674 | $0 |

**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).

## Justification

Availability of real-time orchard site information, specifically local weather conditions, soil water and nutrient status, and canopy vigor/tree health, will permit growers to precisely execute timely management decisions and avoid crop losses, thereby enhancing the competitiveness of the Washington's fruit crops. Currently, growers cannot benefit from available or emerging technologies due to a disconnect between our ability to i) conduct reliable sensing and streamlined data transfer through a common interface, ii) computing of big-datasets, i.e. high resolution spatiotemporal aerial & in-canopy imagery and 2D Light Detection and Ranging (LiDAR) point-cloud data, and iii) reliably transfer data products to end-user(s) for immediately actionable insights. This proposal addresses the above gaps by continuing the 'Smart Orchard' project at Chiawana Orchards, as well as selecting a second site with a more varied topography. Overall, we expect to have **two** established Smart Orchard test blocks for research and stakeholder education.

Washington apple industry buy-in of approach is anticipated, as we break down existing data siloes. Through data analytics of collected data, we expect: 1) identification of data products (indicators) that better reflect vigor status in the orchard block and decision aid for water and nutrient management, and 2) increased level of knowledge of data driven technology for practical management execution. The tree fruit industry will benefit from long-term impacts realized by the reduction of use of resources, while improving their production and pack-outs.

## 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.

## Methods

**Objective 1**. Maintaining an array of connected infield sensors as well as through-season high resolution aerial multispectral and thermal imagery collection & analysis.

With the fundamentals in place, we will gather data (**Fig. 1**) from sensor, imagery, management, & resource providers to represent the entire spectrum of data that growers informally consider in their day-to-day decisions.

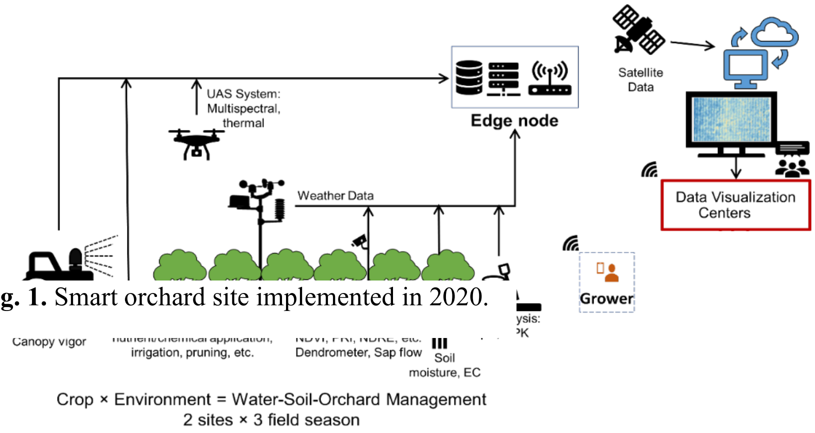

**Fig. 1.** Smart orchard site implemented in 2020.

**Table 1** lists our targeted sensor categories, types, and specification. Associated manufacturers have provided *support* for this project; whereas some sensors (& platforms) are available with WSU researchers. Our on-going pilot project has been using these sensors since April-2020, being powered by DC power packs and solar panels recharging the battery packs. For sensors that haven't integrated to the 'Azure Farmbeats' platform, as well as management & resource-based (chemical, labor) systems, we will work with the participating grower(s) to ingest data from their enterprise reporting systems (e.g. Famous Software) to a SQL database that will reside in a neighboring resource group within Azure. Similarly, some imagery data (satellite imagery from Sentinel, aerial imagery from UAS platforms) will be ingested through Farmbeats. For non-Farmbeats-compatible sources, we will utilize a similar ingest and storage methodology to Farmbeats and will store the reference data in the above-referenced SQL database.

**Table 1.** Details on sensors with key specifications & data products realized from smart orchard project¥.

| Category | Purpose/ location | Instrument | Manufacturer | Specifications* | Data products |
|---|---|---|---|---|---|
| **Weather** | Open-field & In-orchard | ATMOS 41 | Meter Group | 12 weather parameters | Orchard specific Weather/climate variability, Growing Degree Days; Cold/Heat stress indictors |
| | Above canopy, in-canopy at 3' and 6' AGL | Vantage Pro2 6820 | Davis instruments | 5 weather parameters, A: 2% | |
| | In-canopy at 3' AGL | ANTHA | Tuctronics | Temperature, humidity and leaf wetness | |
| **Soil, Water** | Soil moisture at 2' depth | Drill & Drop | Sentek | Measurements every 4" | Soil health;<br>Temporal layers of soil nutrient status, moisture availability & water use |
| | Soil moisture, nutrients and temperature at 4' | AquaSpy probe | AquaSpy | Measurements every 4" | |
| | Soil water potential | Teros 21 | Meter Group | R: 0.1 kPa, A: 90% | |
| | Soil quality at 6", 18", and 36" depths | Soil probe | Teralytic | NPK, moisture, salinity, aeration, respiration, temp., light & RH | |
| | Irrigation monitoring | PS-1 irrigation pressure switch | Meter Group | Set point: 5 psi (± 1) | |
| **Tree/Canopy** | Tree trunk and fruit size | Dendrometer | Phytech | Shrink-swell in µm | Spatial and temporal maps:<br>Tree growth<br>Canopy vigor variation<br>Canopy health/stress<br>Crop water use<br>Crop density |
| | Sap flow measurement | Dynagage Sap flow sensor | Dynamax; Oregon State University | A: 90% | |
| | Leaf wetness | LWS | Campbell Scientific | Measurement time: 10 ms, Output: 250–1500 mV | |
| | Canopy health (NDVI, PRI) | Spectral Reflectance Sensor | Meter Group | A: > 90%; Green-1: 532 nm, Green-2: 570 nm, Red: 650 nm; NIR: 810 nm | |
| | Canopy health (NDRE) | Custom development | PI Brown & Khot | Bands: NIR and RE | |
| | Canopy vigor | 2D LiDAR | Smart Guided Systems LLC | AR: 0.25°, Scan frequency: 25 Hz | |
| | RGB imaging | RGB imager w/ DJI Phantom 4 (in WSU inventory) | | PR: 12.4 Mega Pixels, SR: 5 cm @ 100 m altitude | |
| | Multispectral imaging for canopy vigor/health | 10-band dual camera imaging system | Micasense Inc. | SR: 7 cm @ 100 m altitude<br>Bands: Coastal blue (444 nm), blue (475 nm), green-1 (531 nm), green-2 (560 nm), red-1 (650 nm), red (668), red edge-1 (705), red edge-2 (717 nm), red edge-3 (740 nm) & NIR (842 nm) | |
| | Thermal imaging for canopy temperature and health | FLIR Duo Pro R w/AgBOT quadcopter (in WSU inventory) | | A: 95%, lens size: 13 mm, Spectrum: 7500–13500 nm, SR: 13 cm @ 100 m altitude | |

**AR: Angular resolution, SR: Spatial resolution, A: Accuracy, PR: Pixel resolution; ¥ Ground truthing data details in objective 2 methods; Vegetation indices: NDVI- Normalized Difference Vegetation Index; NDRE-Normalized Difference Red Edge Index; PRI- Photochemical Reflectance Index.*

Finally, our architectural approach will optimize for different personas and associated entities, while optimizing for the grower to have control of with whom their data is shared, what part of their data is shared, and what level of the data may be de-identified [while still holding some value] for certain personas. This is critical, in that according to the Sustainability Consortium (Rhode, 2020), grower trust concerns are an inhibitor to data collection and growers resent unequal financial gain from data sharing by downstream organizations, while also harboring concerns about government and private companies misusing their farm-level data. Thus, we will be sensitive to understand, document and integrate grower concerns and their needs to architect an approach that has potential to be adopted across the industry.

***Expected outcome***: We expect to have two established 'Smart Orchard' test blocks for research and stakeholder education. Washington apple industry buy-in of approach is anticipated, as we break down existing data siloes.

**Objective 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.

***Task 2.1 Data warehouse.*** We will use Microsoft Azure Farmbeats hardware and software layers as core (**Fig. 2**), as their agricultural-centric datahub approach minimizes API integration with sensor & imagery providers, as the partners such as *Davis Instruments, Teralytic, and DJI* have already standardized their APIs to flow data into the datahub instance that will be operated by Innov8Ag.

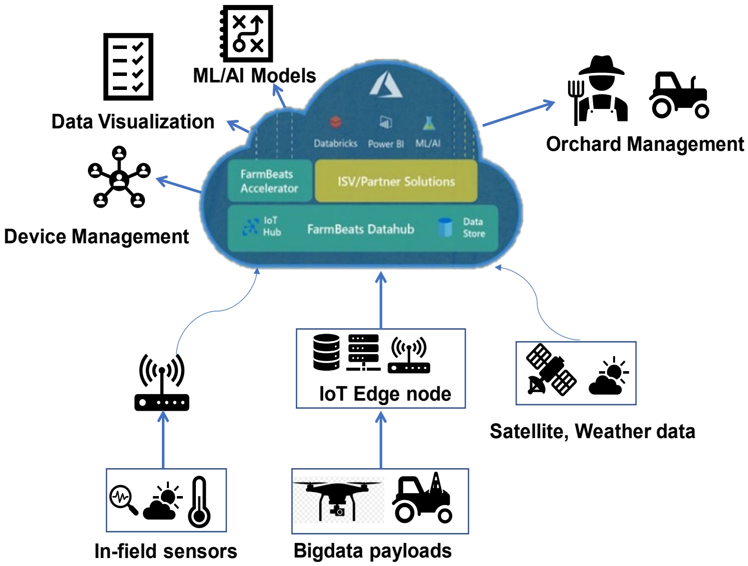

**Fig. 2.** Microsoft 'Azure Farmbeats' platform architecture utilization.

***Task 2.2. Data products*. Table 1** lists the key data products that will be derived for the data collected at each of the two sites. Those include, i) orchard specific weather/climate variability, Growing Degree Days; Cold/Heat stress indicator; ii) Soil health: temporal layers of soil nutrient status, moisture availability & water use, iii) Spatial and temporal maps: Tree growth, Canopy vigor variation, Canopy health/stress, and Crop water use, and iv) Crop density maps. Pertinent to crop density maps, we intend to utilize high resolution ATV-based imagery to quantify variability in crop distribution – at the very least at one point in the growing season; ideally at multiple points throughout the growing season (e.g. blossom to applets to apples) for yield prediction.

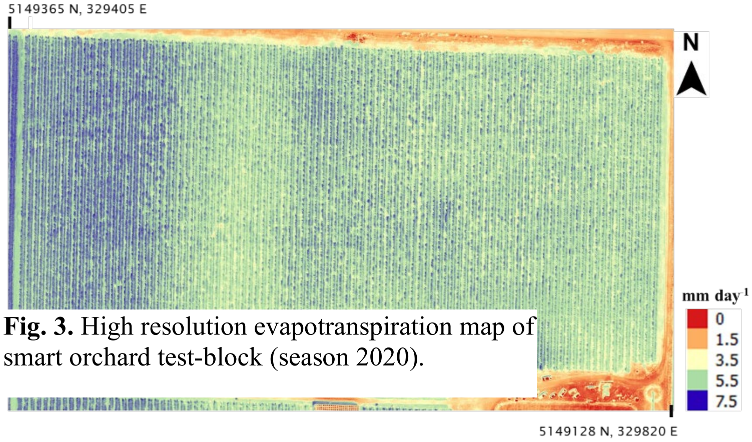

**Fig. 3.** High resolution evapotranspiration map of smart orchard test-block (season 2020).

Pertinent to spatial maps, we will utilize high resolution aerial imagery to extract canopy/soil temperature, crop vigor/stress maps [Green Normalized Difference Vegetation Index (GNDVI), Normalized Difference Red Edge Index (NDRE), Crop Water Stress Index (CWSI)] and crop evapotranspiration (ET) maps (**Fig. 3**). PI Khot's lab has streamlined data quality check and analysis protocols to extract above imagery products (Zúñiga et al., 2017; Chakraborty et al., 2019; Ranjan et al., 2019). Pertinent to high resolution crop ET maps, our team (Chandel et al., 2019; 2020) has successfully modified METRIC (Mapping Evapotranspiration at high Resolution with Internalized Calibration, Allen et al., 2007) model to obtain daily ET estimates at 10 cm/pixel resolution from small UAS imagery data for spearmint, potato, alfalfa and grapevine crops. On this project, we will continue to transfer and validate this and related energy balance models to apple crop ET estimation. Inputs from Dr. Claudio Stockle, who is a Crop System Modeler and collaborator on this project, will be critical in this process.

***Expected outcome***: We expect: 1) Identification of indicators that better reflect vigor status in the block and guidelines for water and nutrient management, 2) Industry members will increase their level of knowledge of data driven technology for practical management execution, 3) Growers will learn about specific technology and management recommendations to manage tree vigor, water and/or nutrients and 4) the tree fruit industry will benefit from long-term impacts realized by the reduction of use of resources, while improving their production and pack-outs.

**Objective 3.** Organize 'field days' for growers, researchers, & other interested parties to learn more about data and how it's being used toward in orchard decisioning.

A 2018 survey developed by Sallato's program has identified that the growers prefer live interaction and hands-on activities during the extension events. This is the most impactful outreach/education method that leads to change in actions and technology adoption. Thus, our extension education efforts will focus on organizing 3 field days per year to share outputs of the project, with the participation of growers, researchers, consultants, and other industry stakeholders.

We will incorporate the outcomes and features of this project through recurring **field days,** similar to 2020 season. Field days will also be recorded and shared through several tree fruit extension avenues: the Fruit Matters monthly newsletter, Facebook, and mailing list with more than 2,900 subscribers. In addition, the team will participate in industry events such as the Washington State Tree Fruit Association Annual Meeting. Frequent newsletters will outline progress toward project objectives and provide information on relevant technology related topics. We will contribute to trade magazines (e.g. Good Fruit Grower, Fruit Grower News, etc.) on data-driven technology for tree fruit management.

**Objective 4.** Implement a high-speed wireless network w/ edge computing for one smart orchard location, to highlight technical & economic viability of addressing orchard connectivity challenges.

A fundamental challenge with imagery & LiDAR point-cloud data is that the data size is substantial. For UAS & ATV-based imaging operators, after flying or driving for the day they take the imagery collected on SD cards, return home, and copy 24+ GB of raw data for UAS, or 1TB+ of raw data for ATV (for 20-acre orchard block) to a local drive on a laptop and/or cloud service for processing. While the intelligent orchard sprayer captures raw LiDAR data to determine the height/width/volume of each tree, the raw LiDAR data itself is 'thrown away' within 4 hours of capture, as the quantity of the data throughout a day of spraying easily reaches Terabytes (TB). It is too much to cache it onto a SD card without distracting the operator from their core role of sprayer operations.

For these scenarios, data transfer is inefficient and problematic, as the transfer from capturing device to processing device involves friction from human process as well as transfer speed limitations. For 1 TB of data, for instance, at 25 Mbps upload speed, an upload for cloud processing could easily take 3 days – assuming the upload is not interrupted. Therefore, we propose to implement an

- **Edge computing** device (**Fig. 2**) for onsite data processing, such as UAS image stitching, LiDAR data analysis to construct a virtual tree canopy, and ideally fusion of UAS imagery (above canopy) with LiDAR (in-canopy) for a detailed rendering of each orchard row for objective 2;

- **High-speed connectivity** component (3GPP-based Private Long-Term Evolution (LTE) / Citizens Band Radio Service (CBRS) or WiFi-6 / 802.11ax) for data transfer;
- **High-speed (100Mbps to 1 Gbps) uplink to cloud services**, enabling public cloud efficiencies for imagery analysis via Machine Learning.

Through Innov8Ag's partnership with Microsoft and PocketiNet Communications, we will design, implement and optimize the above approach. **Step 1** will require Radio Frequency (RF) planning, equipment implementation, and tuning, which we anticipate to be particularly challenging, given that the high density planting style of apple trees and the accompanying, supporting trellis system, causes havoc for RF propagation & interference. It will therefore be important to trial options from beginning to end of the growing season, at various stages of vegetation density. Private LTE and CBRS have great potential, as the FCC is making spectrum available for public use as well as carrier use (through a 3.5 GHz spectrum auction in Summer 2020), which is already driving mobile phone manufacturers to support the spectrum (also known as "Band 48"). It's anticipated that growers and/or local service providers would operate a private network that could provide connectivity to both mobile phones, IoT devices, & equipment such as UAS, tractors, & sprayers, as an alternative to [often] non-existent or marginal mobile coverage by traditional phone operators such as Verizon, AT&T, and T-Mobile. Once the RF planning is complete, we will implement radios and assess transfer speeds, and optimize accordingly. The Private LTE/CBRS option has different approaches for fixed (non-moving) devices vs mobile (moving) devices, potentially introducing operational and regulatory barriers, which may limit scenarios as to how we can collect the data (e.g. sprayer & UAS can only connect and upload data when they return to "home base", vs in real-time while they're still deployed in the field). As an alternative, we will evaluate WiFi-6/802.11ax, which may provide more flexibility and less complexity, as our goal is to model an architecture that will be repeatable across other orchards and various perennial cropping systems in the future.

**Step 2** will comprise Innov8 Ag working with Microsoft to obtain, implement, and configure a "Azure Stack Edge" device, which enables the large raw dataset to be transferred close to the source of data capture, while also taking advantage of local Graphics Processing Unit (GPU) capabilities to process the data & run ML models on raw data, then just uploading the processed data (or simply upload ML models) via the link established in step 3. **Step 3** will comprise Innov8 Ag working with PocketiNet and the Public Utilities Department to connect via fiber and/or microwave to the Internet.

**Timeline.**

| Activity/Year | 2021-22 | | | |
|---|---|---|---|---|
| | Q1 | Q2 | Q3 | Q4 |
| *Objective 1* | * | * | | |
| *Objective 2* | * | * | * | |
| *Objective 3* | | * | * | * |
| *Objective 4* | * | * | * | |
| *Reports and Publications* | | | * | * |

## Literature Review

**Crop losses in tree fruit production:** To promote agriculture sustainability and address agricultural challenges for tree fruit production, growers need to implement innovative management practices to deliver quality produce in a highly competitive industry, while reducing their production costs to maintain profitability. Climate change, environmental and human safety awareness demand precise and efficient management. In eastern WA, the largest tree fruit-producing region in the country, growers seek to adapt to these challenges through the use of data and sensor technology and automation to ensure an economically sustainable industry.

Labor costs have been indicated as the most important challenge for economic viability, thus all efforts in new technology needs to aim at reducing labor costs. The most labor-intensive activities include harvesting, pruning, thinning and training. The last three tasks are fundamental for fruit quality and productivity. **Tree vigor**, which can be managed via water and nutrients, has a direct impact on pruning efficiency/need, thinning and tree training. Tree vigor also affects tree's susceptibility to biotic and abiotic stressors, sprays needs, and fruit quality. Given the inherent variability in apple and other tree fruit crop growing conditions, vigor variability within the orchard block reduces management efficiencies, and affects pruning needs, monitoring, spray coverage, precise nutrient management, among others. Thus, prospects of developing innovative technology and data analyses could help growers to identify vigor differences, at a block level, and reduce tree to tree variability through, for example, variable water and nutrients management.

Improving pack-outs (number of boxes of fruit packed for fresh market delivery) by reducing fruit defects will improve grower profitability and efficiency. Sunburn in apples, caused by excess heat and sunlight, accounts for 30% of losses (Prengaman, 2017). Sunburn damage occurs annually in many US and global growing regions and causes multiple problems – structural and morphological changes, alterations in pigment composition, inhibition of adaptive mechanisms, and impairment of photosynthesis (Racsko and Schrader, 2012). Existing technologies for sunburn protection involve the use of overhead sprinkler irrigation to change the orchard micro-climate, sun-protectant sprays and shade nets, either alone or in combination. However, there are negative effects associated to overhead cooling, such as over watering and its influence on vigor and fruit quality, increased human and food safety risks depending on the water quality, and unknown effects on nutrient balance, while the use of netting can be expensive. Adequate prediction of sunburn risk conditions, targeting plant/fruit monitoring, can reduce the use of water and its negative side effects. Tree vigor, water, nutrient management and access to site-specific weather data would thus help reduce losses due to sunburn.

Another mayor loss in high value apples is due to calcium (Ca) related disorders such as bitter pit. According to Rosenberg et al. (2004), bitter pit can account for up to 50% of marketable losses in apple. Bitter pit has been associated to Ca deficiency or its relation to other nutrients at a cellular level (Marschner, 2002). According to De Freitas and Mitcham (2012) environmental conditions can impact the development of the disease in genetically susceptible varieties. Successful practices include **vigor management** (through water, nitrogen or crop load), fruit size, **and adequate nutrient balance in soils** (De Freitas and Mitcham, 2012, Sió et al. 1999). However, these practices have not always worked in all growing conditions. As a preventive measure, growers spray Ca products, in some cases twice a week during the growing season. Even such an aggressive approach does not always translate in bitter pit reduction. PI Sallato is currently leading a WSDA – Specialty crop block grant in collaboration with Kalcsits and Whiting to identify root growth management practices to reduce Ca related disorders such as bitter pit. Preliminary data suggest that limiting factors that can lead to bitter pit vary between orchards, and need to be evaluated and diagnosed at a block level. Most limiting factors have been associated to soil water movement, excess nutrient levels of potassium leading to nutrient imbalance, high vigor and lack of Ca in excessively drained soils. Thus, the ability to monitor and manage water, nutrient and tree vigor at a tree to tree basis, especially under variable soil conditions, can reduce crop losses due to bitter pit, while reducing the excessive spraying of Ca.

**Soil, canopy and weather monitoring:** Weather is one of the major uncertainties affecting the management and performance of agricultural systems, and methods to mitigate weather risk have been a focus in the scientific community over the past two decades (Barros et al., 2012; Gobin et al., 2013; Ranjan et al., 2020). This is particularly relevant to perennial specialty crop producing regions in the U.S. and to WA State, which rank # 1 in several fresh market tree fruit crops (e.g. apple, sweet cherry and pear) production (USDA NASS, 2017). Tree fruit growers rely extensively in weather stations to predict disease and pest infection probability in their orchards and to program their spray applications. Fire blight has been identified as the most harmful disease in apples (Gaganidze et al., 2018) with losses of $100 million USD annually (Norelli et al., 2009). The disease, caused by the bacteria *Erwinia amylovora* can be spread by rain, insects, agricultural tools (Johnson and Stockwell, 2000). Standard management practices rely on weather station prediction of favorable conditions for the disease development in relation to susceptible tree stages, monitoring and timely removal of blighted trees or branches and frequent sprays. Monitoring requires skilled workers driving up and down the rows to observe and spot diseased trees, to reduce the spreading. *Because higher air moisture levels and warm temperatures (above 60 ℉), favor bacteria development (Johnson and Stockwell, 2000), growers opt to cut the water during bloom time, which can affect tree vigor, fruit development and size.* Excessive vigor has also been associated to increased susceptibility. Growers have strongly expressed their interest to utilize sensors and aerial imaging to help monitor conditions, disease development and to guide management practices (shoot removal, sprays, water and nutrient management).

Overall, **vigor variability and vigor management** within the orchard has numerous impacts on labor needs, automation potential, fruit quality, spray coverage, fertilizer use. For example, weak trees are associated with nitrogen deficiency, leading to nitrogen application as an instinctive solution. PI Sallato evaluated 97 apple blocks in 2019 and observed that lack of vigor in apple orchards in the Yakima and Columbia Basin region were related to water management, infiltration or drainage and the presence of a calcium carbonate layer, prominent in many soils in the Yakima valley, rather than lack of nitrogen supply. None of these tree growth stunting conditions can be solved by nitrogen applications. Thus, accurate sensing technology can help with adequate orchard diagnostic to reduce fertilizer waste, nitrogen leaching, spray needs, while improving tree health, vigor and ultimately fruit quality.

**Internet of Things in Agriculture and Related: Precision farming** is key to attaining sustainable development of agriculture and addressing food security at a global scale. Wireless Sensor Networks (WSNs) are an integral component of precision farming and have previously been applied to **precision irrigation** (Kim et al., 2005; Zhou et al., 2009; Greenwood et al., 2010; Zhang et al., 2011; Casdesus et al., 2012; Coates et al., 2013; Dong et al., 2013; Gutiérrez et al., 2014; Nikolidakis et al., 2015), **biotic and abiotic stress management** (Das et al., 2009; Liao et al., 2013; Datir and Wagh, 2014; Tripathy et al., 2014), and **crop micro-climate analysis** (Morais et al., 2008; Tripathy et al., 2014; Ranjan et al., 2020).

**Internet of Things (IoT)** primarily encompasses the concept *"connect everything and everyone everywhere to everything and everyone else"* (Atzori et al., 2010). IoT, as an extension of WSNs, are bring effectively deployed for providing intelligent solutions for *smart* concepts such as e-health, e-home, and smart farms (Akyildiz et al., 2005; Son et al., 2006; Kun-kun et al., 2013; Gent, 2014; Maia et al., 2014; Ramamurthy and Serrat, 2014; Sebestyen et al., 2014; Fadi et al., 2015; Vasisht et al., 2017; Tzounis et al., 2017). The agriculture sector could similarly benefit from IoT technologies by enabling an optimization of crop inputs amidst the high variability of in-field conditions. This can be achieved by making machines smart enough to undertake timely management decisions without human interference. The use of WSNs for precision farming is primarily limited by long-distance data transmission and initial costs (Aldabbagh et al., 2015). Various efforts from our group and others have used WSNs for real-time measurement of micro-climate parameters (Stafford et al., 1989; Walker et al., 2004; Phillips et al., 2014; Werner, 2015; Chandel et al., 2018; Ranjan et al., 2020). WSNs now collect sensors data which is then sent to a control unit wirelessly (Srbinovska et al., 2015; Ranjan et al., 2020). Most of these WSN applications consist of a dense network of sensor nodes distributed throughout the field. However, existing WSNs have been designed for doing a specific thing or two and do lack scalability and wider compatibility to realize the full-scale adaption and utilization by growers to manage orchard inputs through one ecosystem.

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