FINAL REPORT

Project Title: Electronic sensors to capture spatiotemporal population density of SWD

PI: Joanna C. Chiu
Organization: University of California Davis
Telephone: (530) 752-1839
Email: jcchiu@ucdavis.edu

Cooperators: Eamonn Keogh (UC Riverside, Dept. of computer science and engineering)

Budget: **Year 1**: $31,384

Budget
Organization Name: UC Davis **Contract Administrator: Yang Yeh**
Telephone: (530) 752-3794 **Email address:** ypyeh@ucdavis.edu

Item	2018	2019
Salaries	$16,016	
Benefits	$8,168	
Wages	-	
Benefits	-	
Equipment	-	
Supplies	$5,200	
Travel	$2,000	
Miscellaneous		
Plot Fees	-	
Total	$31,384	**No-cost extension**

Footnotes:
Salaries and Benefits are for one SRAI (technician) for sensor testing and insect collection (33.3% time)
Supplies include funding to construct 20 sensors for testing ($4000) and for insect capture and maintenance ($1,200)
Travel funds ($2,000) are requested for SRAI to travel to Washington or Oregon to conduct field sensor testing

JUSTIFICATION

Sensor technologies and automated insect identification models were developed for the control of insects that spread human diseases. Our cooperator Dr. Keogh, a computer scientist at UC Riverside, has recently developed inexpensive pseudo-acoustic opto-electronic sensors and accompanying classification algorithm that can accurately classify multiple species of mosquitoes that vector pathogens such as Zika and West Nile virus (Chen et al. 2014) by using wing-beat frequencies, daily activity patterns, and geographical distribution. The ability to remotely capture real-time measurements and forecast insect density in a spatiotemporal manner allows for efficient and precise insect control response that could prevent public health crisis. ***The overall goal of this proposal was to adopt and translate this technology to optimize insect pest management programs and benefit agricultural stakeholders.*** We proposed to develop and ultimately deploy opto-electronic sensors that can accurately identify Spotted Wing Drosophila (SWD) and differentiate it from other insect inhabitants of cherry orchards.

SWD is a highly invasive pest species that cause up to $500 million in annual losses in the western United States because they oviposit into marketable, ripening fruit (Goodhue et al. 2011, Wiman et al. 2016). An insect sensor utilizing wing beat frequency for classification can theoretically be applied to identify any flying insect, but the substantial economic loss caused by SWD warrants the prioritization of optimizing this new technology for its control. It is important to stress that the electronic sensor technology we proposed to develop and optimize for SWD was not simply a modernized version of insect traps currently used for population monitoring. Besides supplanting conventional monitoring tools and greatly reducing the time necessary to process trap contents, we anticipated that the capability of the sensors to classify insects in real-time will revolutionize pest management research and lead to developments in precision agriculture. For example, current monitoring tools lack spatial and temporal resolution as conventional traps do not provide time-stamps for insect catches. Our sensors on the other hand can ultimately be connected to a central network and were capable of reporting real-time movement between crop and non-crop host plants, providing opportunities to target SWD for sprays at times when they are at maximum density in non-crop plants. This can reduce insecticide residues on crops, a major concern for export markets.

OBJECTIVES

Objective 1:

Measure wing beat frequency and circadian activity pattern of SWD to improve insect identification algorithm. Opto-electronic sensors will be installed in insect cages that house SWD to measure wing beat frequency and daily activity patterns simultaneously. Since biological parameters, e.g. sex, age, and seasonal morphology, may alter wing beat frequency and activity patterns, we plan to evaluate male and female SWD, different ages of SWD, and summer and winter forms of SWD. Various abiotic factors can also affect wing beat frequencies so we will evaluate recordings in a range of environmental conditions.

Objective 2:

Field recording to assess opto-electronic sensor and insect identification algorithm. We will deploy opto-electronic sensors housed in McPhail traps to assess the capability of the sensors to accurately identify SWD from other inhabitants of Cherry orchards.

METHODS

Objective 1: Refining insect identification algorithm using opto-electronic sensors

Overview: In order to automate the process of insect identification based on wing beat frequency, an algorithm was created and refined to take into account biotic and abiotic factors that may result in changes to insect wing beat frequency and activity pattern. Our cooperators have previously created an algorithm to accurately identify insects down to species and sex using wing beat frequency in controlled environments, which they have tested on mosquito species (Chen et al. 2014). To refine this algorithm for SWD and use in the field, we recorded wing beat frequency of SWD and other insects commonly found in cherry orchards different environmental conditions (temperature, light cycle, humidity, etc.). The data acquired from these species in controlled environments were then incorporated in insect identification models to enable refinement of the algorithm.

Collection of data for insect identification algorithm refinement

Flies of a known species and sex (N=60) were placed into a modified McPhail trap outfitted with an opto-electronic sensor ring and connected to a recording device. This setup was then placed into a Digitherm incubator (Tritech Research) that allowed us to control the environmental conditions. Using this setup, we recorded wing beat frequency data in different temperatures, humidity, light-dark cycles with different photoperiods, etc. as well as wing beat frequency of different species and sexes. The data collected in these controlled environments were visualized using analysis programs using MATLAB (Mathworks). General trends were visualized using these analysis tools. Comparison between SWD and the closely related *Drosophila melanogaster* in controlled conditions showed distinct wing beat frequency patterns. Based on live capture in field in CA, we identified several closely related *Drosophila* species such as *D. simulans*, *D. biarmipes* and *D. tristis*. Recording using these different species and other relevant species present in cherry orchards were generated in order to refine the algorithm and improve identification accuracy.

Refinement of insect identification algorithm

Previously our cooperators have created an insect classification algorithm which they have used to accurately identify disease carrying mosquito species based on wing beat frequency alone (Chen et al. 2014). When more species were added or environmental conditions were changed the classification model was less accurate. Due to the large diversity of species present in the field and the heterogeneity of environmental conditions, it is important to have accurate classification established on a wide range of fluctuating parameters and species to mimic field scenarios. By creating a training dataset using the data we collected from *Drosophila* flies in various conditions, we were able to "train" the classification model to accurately identify insect pests in vastly different environments. We have already "trained" the insect classification model based on geographical and circadian rhythm data to increase the accuracy of the model in identifying mosquitos down to the species level. By "training" the insect classification model to correctly identify insects using a larger number of variables we were able to increase the accuracy of our identification process in the field. This was an iterative process of testing and refinement.

Objective 2: Assessment of insect identification algorithm and field deployment of sensors

Overview: With current monitoring methods, it is extremely time consuming to monitor insect pest species in the field because it requires the presence of a specialist to manually identify individuals. In addition, the time lapse between trapping and identification constitutes an important limitation to initiate a quick and appropriate response to slow down crop infestation. Our goal in refining the insect identification algorithm was to develop an automated identification process that is easier and faster to identify insect pests compared to current pest capture and identification processes. We assessed the ability of the sensors to correctly identify and monitor pest species both spatially and temporally in and around SWD habitats in CA.

Deployment of insect sensors in the field

Once the classification algorithm was found to be highly accurate (>99%), we deployed our system in SWD habitats. We used baited McPhail traps outfitted with sensors in the opening at the bottom to record the wing beat frequency and relevant environmental variables (temperature, humidity, time, etc.) of any insect that enters the trap and identifying them in real time. By deploying multiple trap/sensor setups, we were able to track the movements of SWD throughout the day, e.g. from crop to non-crop hosts. We envision this will allow for the development of more precise strategies of pest management than are possible through conventional monitoring techniques using traps and manual identification. The automated process of insect identification also means that there will be far less processing time required to identify flies allowing growers and researchers to respond to the presence of pests as soon as they arrive and are detected in their fields.

RESULTS:

Objective 1:

Hardware optimization for insect sensors

We successfully went through several iterations of design and testing of the sensors. We have converged on a solution that we feel is robust, maintainable and cheap to produce in large numbers. Briefly, we use IR emitters and phototransistors working at a wavelength of 940nm, which is outside the visible light spectrum. Our emitters (OSRAM SFH 4043) and phototransistors (Everlight PT19-21C) use around ~20mA. There may be some other low power emitters and phototransistors out there that we can used to further improve our design in the future. We are currently using a cortex M4 MCU, which runs at 80Mhz. This chip has 32K of flash and 2K of RAM. It consumes around 5.5mA when running at 8Mhz but we can put it to sleep when there is no activity, in sleep mode it only consumes few micro amps. For transmission we are using Long Range Wide Area Network (LoRaWAN) technology. LoRaWAN is a wireless standard designed for long range communications at a low bit rate on a very low power budget. We use Semtech SX1272 LoRa module which has a range of 2 miles in non-line-of-sight environment and up to 15 miles in line-of-sight environment. It can achieve data rates up to 50 kbps. SX1272 consumes ~15mA while transmitting/receiving and a negligible power (1.5 uA) in idle state. We have started to install solar panel to the sensor unit, so that the sensors can be left unattended in the field for weeks at a time (Figures 1 to 3 and Figure 5).

Development of species ID algorithm

Since the completion of the activity and wing beat frequency recordings for 5 different *Drosophila* species (*D. simulans, D. tristis, D. suzukii, D. biarmipies, D. melanogaster*) at various temperature and photoperiod conditions (Figure 4), we have collected more than one million insect "encounters", in diverse conditions of light, temperature, humidity, life-stage, species, sex. Using this data, we have built the state-of-the-art classification model for insect classification, which is invariant to environmental conditions. For example, we can now train a model say in our dry hot California research station at ten meters above sea level and be confident that the model will generalize to the cooler humid conditions. Just a year ago, this environmental variability would cause our models to fail to generalize, drastically reducing our accuracy. Now the accuracy of the resulting species ID algorithm is easily over 90% accuracy and will continue to improve as we continue to feed the algorithm with data collected in the field.

Objective 2:

Field deployment and testing

For the purpose of testing the power and communication modules, we leveraged a field setup that was already in place to monitor Navel Orange Worm (NOW). We can then easily adopt the same setup for use with SWD monitors. We outfitted the sensors with solar panel and cellular data transmission for remote sensing. A first field trial was performed in an almonds orchard located in CA from May to September 2019 to trap (Figure 5). NOW can be trapped using sticky card loaded with species specific pheromone allowing us to collect and validate information for a given species before increasing complexity by adding more species to the system. During this test we were able to successfully validate:

1) the autonomy of the sensors.
2) the ability of the sensors to remotely send information to the database.

3) the accuracy of the system to match insect counts recorded by the sensor with the number of insects collected on sticky trap.

Indeed, the solar panel efficiently ensured full autonomy of the system as it provided enough power to sustain the sensor during the 4 months of the trial without any intervention required from us to recharge the battery. Data were send remotely using cellular signal to an online database where insect counts as well as environmental parameters associated (T°C, Humidity, Pressure, Light cycles...) were readily accessible. Finally we observed a strong correlation between information collected from the sensor and number of insects on the sticky card attesting of the efficacy of the sensor to detect pest pressure in real time (Figure 6).

Sensors to monitor for SWD (Figure 7) are currently deployed in the UC Davis orchard of Wolfskill. Traps are filled up with yeast-sugar solution, an attractive lure for *Drosophilds* allowing us to validate the capability of the sensor to accurately identify the presence of SWD among other species of fruit flies. Given the current percentage of accuracy provided by the algorithm we are confident that SWD recordings will result in high accuracy identification. Results from this trial are expected to set the stage for field application in the upcoming growing seasons. We hope to offer growers and PCA unprecedent tools to optimize insect pest management programs. Users interested in testing the smart sensor in their own crop are invited to request a demo by contacting the PI Joanna Chiu (jcchiu@ucdavis.edu) or by visiting the Farmsense website (www.farmsense.io).

LITERATURE REVIEW:

There have been some efforts in identifying insects based on recordings of their wing beat frequencies and these attempts date back to the advent of commercially available computers and audio recording devices (Reed et al. 1942, Foster and Robinson 1991, Moore and Miller 2002, Raman et al. 2007). These attempts have not been successful in creating an automated and accurate identification process based on recordings of wing beat frequencies. In most studies, wing beat frequency has been recorded using acoustic microphones, which are susceptible to noise from the wind as well as any ambient noise in the environment (Reed et al. 1942, Mankin et al. 2006, Raman et al. 2007, Villarreal et al. 2017). This made it very difficult to get quality recordings of insect wing beat frequency with acoustic recording devices. Because of this difficulty, wing beat frequency data is sparse, low quality, and typically recorded in unnatural conditions (Moore et al. 1986). Despite the sparseness and low quality of available insect wing beat frequency data, some researchers have attempted to create insect identification models with 300 or less recordings (Moore 1991). It is difficult to create models with such sparse data and this will cause the models to have very low accuracy in identifying insects (Banko and Brill 2001, Halevy et al. 2009). This is compounded by the fact that most attempts at classification of insects by recording wing beat frequency have used just one variable (wing beat frequency). Other environmental factors that cause wing beat frequency to change have also been ignored (Chen et al. 2014). By using pseudo-acoustic opto-electronic sensors, we will be able to record higher quality data. We will also be able to record larger volumes of data in more natural conditions than has been possible in the past, which will allow us to create a highly accurate insect classification model that can be used to identify SWD and differentiate it from other species in the field.

LITERATURE CITED:

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FIGURES

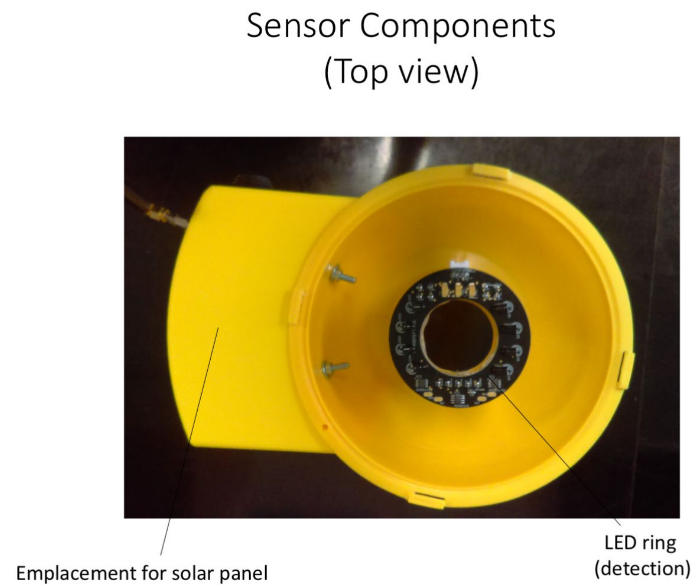

Figure 1: Top view of the modified Mcphail trap outfitted with the LED sensor ring, showing emplacement for solar panel.

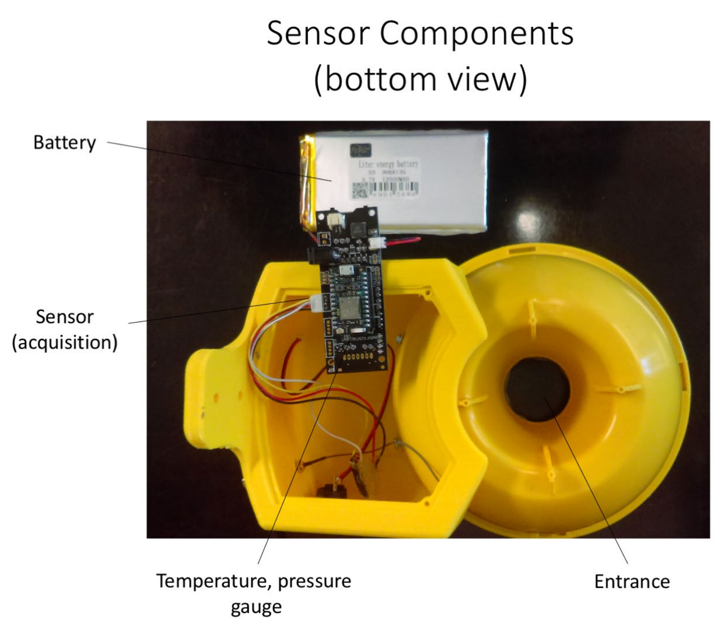

Figure 2: Bottom view of the modified Mcphail trap showing the battery unit, the data acquisition unit, the environmental measurement unit, and the entrance of the trap.

Field deployment

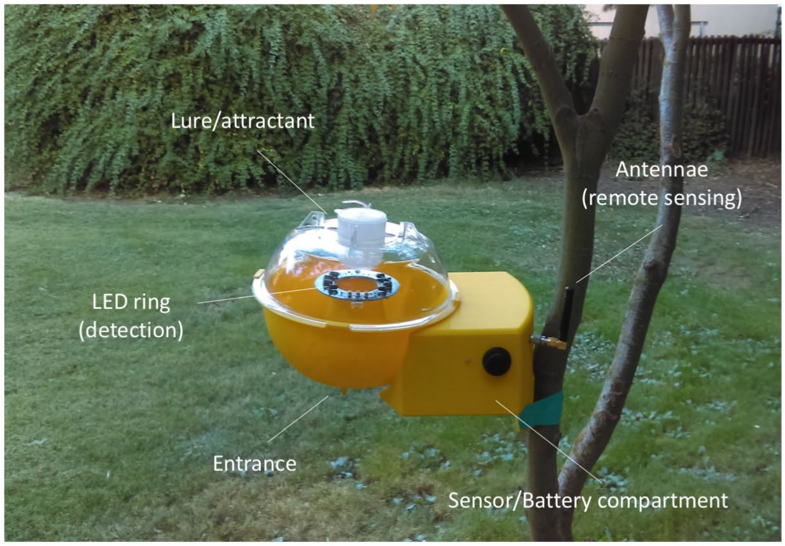

Figure 3: The modified Mcphail trap holding the sensor unit in a field setting. The antennae for transmitting remote sensing data is shown.

Temperature:		20C	25C	30C
D. sim	Male	x	x	x
	Female	x	x	x
D. tris	Male	x	x	x
	Female	x	x	x
D. suz	Male	x	x	x
	Female	x	x	x
D. biar	Male	x	x	x
	Female	x	x	x
D. mel	Male	x	x	x
	Female	x	x	x

Photoperiod		12:12
D. sim	Male	x
	Female	x
D. tris	Male	x
	Female	x
D. suz	Male	x
	Female	x
D. biar	Male	x
	Female	x
D. mel	Male	x
	Female	x

Figure 4: Temperature and photoperiod conditions for wing beat frequency recordings. Conditions marked with pink have been completed. *D. simulans (D. sim); D. tristis (D. tris); D. suzukii (D. suz); D. biarmipes (D. biar); D. melanogaster (D. mel).*

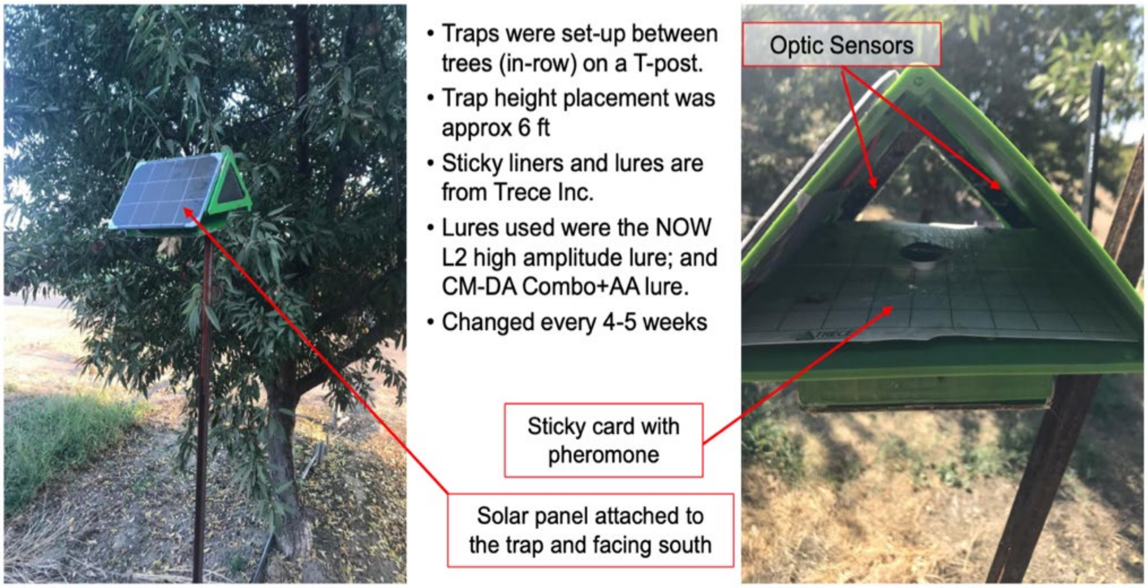

Figure 5: Experimental setup for field testing on NOW

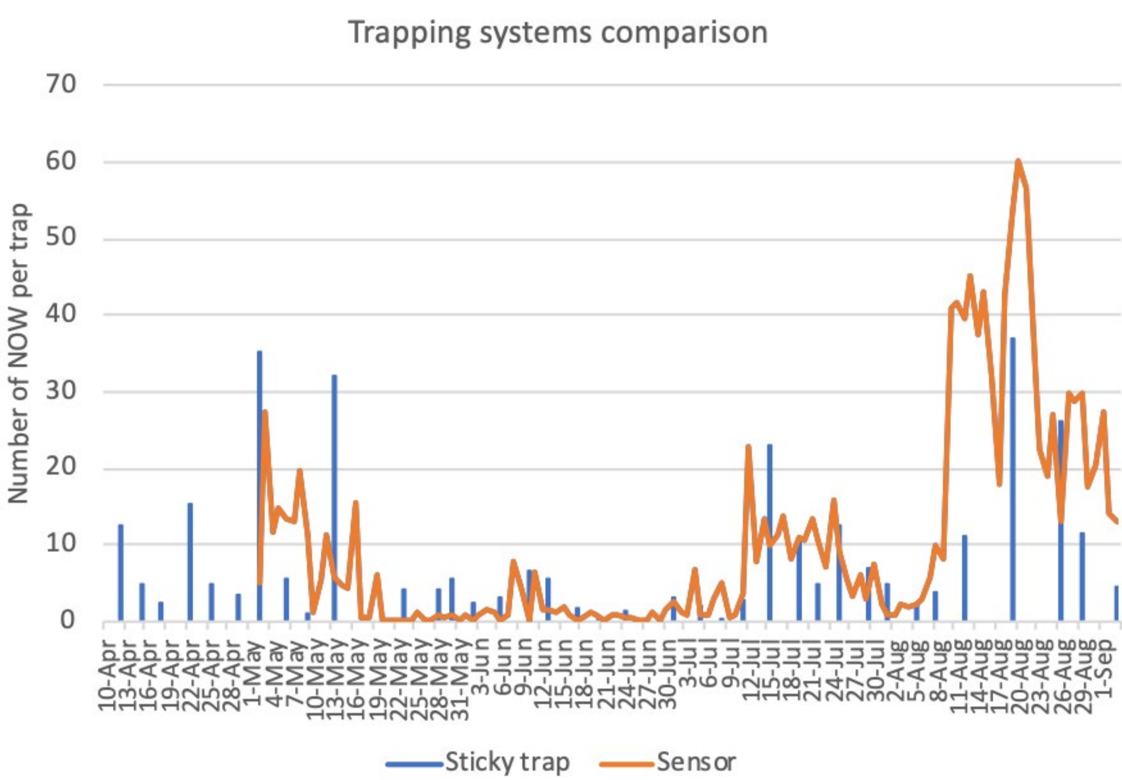

Figure 6: Insect count comparison between Sensor vs Sticky trap.

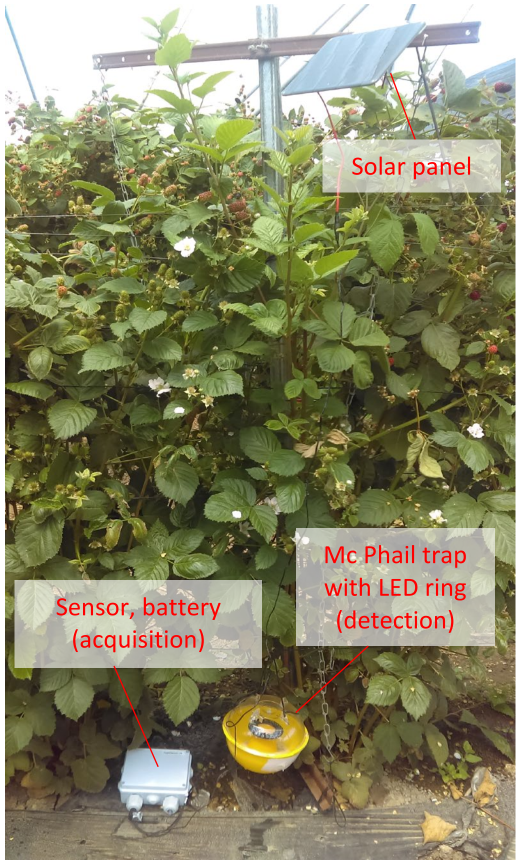

Figure 7: Field deployment of the sensors monitoring for SWD

EXECUTIVE SUMMARY

Project Title: Electronic sensors to capture spatiotemporal population density of SWD

KEY WORDS: Spotted Wing Drosophila, *Drosophila suzukii*, remote sensing, insect identification

Spotted Wing Drosophila (SWD) is a highly invasive pest species that has now established itself as a keystone pest of U.S. fruit crops, including cherries. SWD oviposits into marketable, ripening fruits, leading to significant annual crop and economic losses. ***The overall goal of this proposal was to adopt electronic sensor technologies and develop automated insect identification models to enable remote and real-time SWD identification and monitoring to support management programs and IPM research efforts.*** Our cooperator Dr. Keogh, a computer scientist at UC Riverside, has previously developed inexpensive pseudo-acoustic opto-electronic sensors and accompanying classification algorithm that can accurately classify multiple species of mosquitoes that vector pathogens such as Zika and West Nile virus by using wing-beat frequencies, daily activity patterns, and geographical distribution. An insect sensor utilizing wing beat frequency for classification can theoretically be applied to identify any flying insect. We therefore proposed to optimize electronic sensor technologies for SWD identification. It is important to stress that the electronic sensor technology we proposed to develop and optimize for SWD is not simply a modernized version of insect traps currently used for population monitoring. Besides supplanting conventional monitoring tools and greatly reducing the time necessary to process trap contents, we anticipated that the capability of the sensors to classify insects in real-time will revolutionize pest management research and enable precision agriculture. For example, current monitoring tools lack spatial and temporal resolution as conventional traps do not provide time-stamps for insect catches. Our sensors on the other hand can ultimately be connected to a central network and were capable of reporting real-time movement between crop and non-crop host plants, providing opportunities to target SWD for sprays at times when they are at maximum density in non-crop plants. This can reduce insecticide residues on crops, a major concern for export markets.

<u>*Key products of project:*</u>

1. Software: We have collected more than one million insect “encounters” in diverse conditions of light, temperature, humidity, life-stage, species, sex, and completed the development of SWD species ID algorithm.
2. Hardware: We have successfully validated the solar power and remote communication modules of the sensor.
3. Field trials: We have initiated field testing of the SWD system and will continue repeated iterations of trial and optimization cycles. Measurements of field encounters will continue to improve the species ID algorithm. Demo units can now be requested.