Distributed Surveillance and Decision Support Ecosystem for Control of Coconut Rhinoceros Beetle

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To my beloved family,

Nahid, Jafar, Omid, Samaneh, Amin, Lindsey, Ali, Parsa, & Hanissa

Abstract

An introduced population of coconut rhinoceros beetle (CRB; *Oryctes rhinoceros*) was first discovered on the island of Oahu in late 2013. Adults of this invasive beetle feed on a variety of host plants, including palms, bananas, and sugar cane. As the name of the beetle implies, the preferred host is the coconut palm (*Cocos nucifera*). CRB feeding results in large boreholes near the crown, introducing a route for infection by a variety of pathogens. CRB damage can easily be recognized by characteristic cuts and notches on fronds as they grow out, and in cases of severe damage the tree can be completely defoliated and die.

Surveillance efforts to delineate populations and identify spread poses one of the greatest challenges for control. Currently there are almost two thousand CRB panel traps installed throughout the island of Oahu, scaled back from over three thousand before populations spread to every significant part of the island and control efforts were reorganized to focus on ports of entry to prevent accidental export. Each of these traps is visually inspected at regular intervals (approximately once or twice per month, depending on location) by human operators. This manual trap checking is laborious, expensive with respect to personnel and transportation costs, and time-consuming. Intermittency of trap checks and associated manual data entry and processing to understand geographical distributions also result in delays responding to new outbreaks.

Here, we have developed an energy-efficient, automated remote surveillance (CRB-Cam) and data management ecosystem, incorporating machine vision tools to facilitate the monitoring of CRB in highly distributed remote locations. Accurate object detection of beetles in traps, and associated coordinates of traps from on-board GNSS receivers are used to automatically generate maps of daily trap catches which are especially important for rapidly responding to new incipient populations before they can become established in an area. In preliminary field trials with systems uploading trap images hourly, adult CRB exhibited crepuscular behavior, with over 2/3 of observed trap catches occurring at night within 3 hours of civil twilight after sunset, catch rates

trailing off gradually throughout the night, and fewer than 1% of catches occurring during daylight.

Based on these observations and observations from earlier researchers that even with regularly changed pheromone lures panel traps catch only small percentages of CRB in a local area, we investigated the use of nocturnal artificial lighting to improve catch rates. In a field trial rotating programmable LED arrays programmed to illuminate with different color LEDs for 6 hours after sunset, and for 3 hours before sunrise, traps illuminated with ultraviolet (UV) caught significantly more CRB than those without illumination, and traps illuminated with all tested visible wavelengths resulted in significantly fewer CRB catches.

Management of CRB relies primarily on effective green waste management to remove or destroy potential breeding sites in decaying organic matter, and pesticide applications in host trees to kill foraging adults. As a last element of this research we investigated the use of precision aerial application of pyrethroid based pesticides directly into crowns of palm trees as an alternative to or in rotation with the current practice of trunk injection of systemic neonicotinoid pesticides. Crown applications were shown to be effective at killing CRB and protecting the tree for a period of several months, and were also useful for identifying actively infested trees as CRB would emerge and fall to the ground to die. Data from these experiments were used to obtain crisis use exemption for using dilute formulations of Demon® Max Insecticide (25.3% cypermethrin) for controlling CRB on Maui, Hawaii, and Kauai, where it was used to treat an outbreak on Maui that thus far has putatively been eradicated.

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LIST OF ACRONYMS

In alphabetical order.

a.i.	Active Ingredient
ANOVA	Analysis of Variance
AP	Average Precision
API	Application Programming Interface
CRB	Coconut Rhinoceros Beetle
CNN	Convolutional Neural Networks
EPA	Environmental Protection Agency
FN	False Negative
FP	False Positive
GNSS	Global Navigation Satellite System
GPU	Graphical Processing Unit
HBM	High Bandwidth Memory
IoT	Internet of Things
IoU	Intersection over Union
IPM	Integrated Pest Management
LED	Light Emitting Diode
LTE-M	Long-Term Evolution for Machine-type Communication
mAP	Mean Average Precision
PV	Photovoltaic
RP	Raspberry Pi
TCP	Transmission Control Protocol
TP	True Positive
UAS	Unmanned Aircraft System
UTC	Coordinated Universal Time
UV	Ultraviolet
YOLO	You Only Look Once

1. General Introduction

In this chapter, I introduce the target pest of the dissertation, discuss several concepts we have used to enhance the monitoring and control of the pest, and finally, clearly propose the objectives of this dissertation and chapters organization.

1.1. Coconut Rhinoceros Beetle

The invasive pest of this study is coconut rhinoceros beetle (CRB; *Oryctes rhinoceros*), native to Asia, which invaded the Pacific in 1909 at Upolu island, in Samoa (Jackson et al., 2021). Adults of the beetle cause damage to its preferred host (Coconut Palms, *Cocos nucifera*) by boring into the crown to feed on sap. It was first identified on the Hawaiian island of Oahu in 2013 (Marshall et al., 2017). There is an ongoing effort to control this pest and prevent its further spread through an assortment of integrated pest management approaches (Jackson et al., 2021). Proper identification and monitoring is the first step for any effective program to control invasive species. To this end, there are thousands of pheromone-baited panel traps for CRB (Alpha Scent Inc., Sequoia Parkway Canby, OR, USA), as shown in Figure 1.1, distributed throughout the Hawaiian Islands (Paudel et al., 2023). However, given the wide geographical distribution and limited personnel and other resources available, manual trap checking is costly with respect to labor and transportation, and may be inadequate in frequency to mount effective response to new outbreaks. Our first goal in this dissertation is to monitor the CRB traps more efficiently, utilizing novel Internet of Things and computer vision tools.

Figure 1.1. An example of a CRB Pheromone-baited Panel Trap deployed by CRB Response Hawaii. Panel Traps (Alpha Scent Inc.).

1.2. Internet of Things

Internet of Things (IoT) refers to any electronic device (Thing) connected to the Internet. An electronic device equipped with sensors can gather information from the environment and share it to a server where the data is processed (Fang et al., 2014). For example, as shown in Figure 1.2, an IoT weather system (SparkFun Electronics, Niwot, CO, USA), gathers weather information, such as humidity, temperature, wind speed, etc., and communicates the data to a server, where this information is recorded, processed, and monitored.

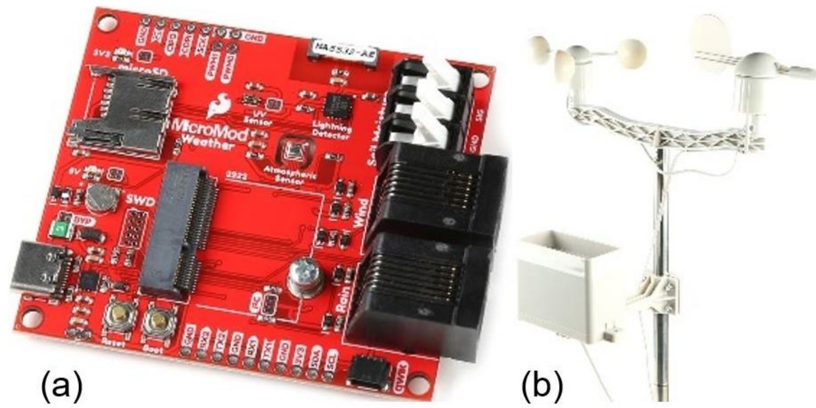

Figure 1.2. Example of IoT: Commercially available Internet of Things Weather Station, SparkFun (a) MicroMod Weather Carrier Board, and (b) Weather meter Kit.

1.3. Computer Vision and Object Detection

Computer vision (or Machine Vision) is a field in artificial intelligence that enables machines to understand visual information in image data from the world. Similar to how mammals use vision by training the brain neurons (Hubel and Wiesel, 1962), computers can train and use neural network models (Voulodimos et al., 2018) to understand images. In computer vision, understanding images is performed by several tasks, including image classification and object detection. The first successful image classification neural network architecture was LeNet5, a convolutional neural network architecture with several convolutional and subsampling neural network layers developed by LeCun et al. (1998) to classify handwritten digits. Further improvements to classification occurred with AlexNet (Krizhevsky et al., 2012) in 2012, with the integration of Graphical Processing Units (GPU) and training of convolutional neural networks (CNN) with larger image datasets (Deng et al., 2009), demonstrating the efficacy of CNNs with more layers to understand complex patterns in large amounts of data, starting the deep learning era (LeCun et al., 2015).

Object detection in computer vision combines classifying and localizing the objects in an image, as shown in Figure 1.3. The first successful real-time object detection model, which performed both class predictions and bounding box location predictions using a single convolutional learning network pass, called "You only look once" (YOLO), was first introduced in 2016 (Redmon et al., 2016).

Figure 1.3. An adult CRB on a rotating stage in a photo studio light box. The rectangular shape around the CRB is called a bounding box, and its coordinates are predicted by a computer vision detection model, localizing the target object.

1.4. Organization of This Dissertation

This dissertation describes the development of innovative tools to enhance the efficiency of CRB monitoring and control efforts.

In chapter two, I consider the main challenges of monitoring CRB with traditional trap checks, and describe the implementation of a new autonomous surveillance system to monitor remotely deployed CRB traps. The system periodically wakes from a low power sleep mode to send trap images and location data using cellular networks to a remote server, which displays these as an image gallery on a public-facing website.

In chapter three, I describe the training and application of a computer vision model and server-based implementation of the model to automate the identification and enumeration of the CRB in traps, and display of these information on a map including the trap coordinates inferred from GNSS receivers on the surveillance system.

In chapter four, I describe experiments with different wavelength artificial lighting to determine their effects on CRB trap catch in pheromone-baited panel traps.

In chapter five, I investigate the efficacy of precision aerial pesticide application using unmanned aircraft systems (UAS) in depressing CRB pressure on infested palm trees to mitigate damage from feeding CRB adults.

Finally, in chapter six, I highlight the novelties, advantages, and limitations of the dissertation work.

To summarize, this dissertation work addresses four objectives:

- Objective I. (Chapter 2): Development of an autonomous IoT surveillance system for CRB panel traps

- Objective II. (Chapter 3): Development of a machine vision tool for automated delineation of CRB geographical distributions

- Objective III. (Chapter 4): Investigating effects of artificial lighting on catch rates in CRB panel traps using a custom programmable LED array

- Objective IV. (Chapter 5): Evaluating the efficacy of precision aerial pesticide application using a UAS for control of adult CRB in palm trees

1.5. Publication Notes

Chapter 2 is edited from a published paper (Paryavi et al., 2025b). Chapter 3 was presented at the International Symposium on Applied Sciences (ISAS-2024), hosted by Ho Chi Minh University of Technology in Vietnam in 2024 (Paryavi et al., 2024). I plan to incorporate retraining of the CRB detection model with more images (that are accumulated daily from deployed trap systems) to enhance the model performance further and publish it afterward. Chapter 4 is edited from a published paper (Paryavi et al., 2025a). Chapter 5 is pending further updates, including the application of machine vision tools to quantitatively evaluate the mitigation of new CRB damage on treated palm trees. We are considering submitting an updated version of this chapter for possible publication in the journal Applied Engineering in Agriculture.

2. Objective I. Autonomous Cellular-Networked Surveillance System for Coconut Rhinoceros Beetle

2.1. Introduction

Coconut rhinoceros beetle (CRB*; Oryctes rhinoceros*), is an invasive scarab beetle native to Southeast Asia and a major pest of coconut (*Cocos nucifera*) and oil (*Elaeis guineensis*) palms throughout the Pacific islands (Bedford, 1980). In the 1960s and 70s, the use of Oryctes rhinoceros nudivirus (OrNV; *Alphanudivirus oryrhinocerotis*) was an effective biocontrol agent, helping prevent CRB spread to new islands in the Pacific (Bedford, 1986). However, in 2007 a new haplotype of CRB (designated CRB-G) was reported that appeared less susceptible to OrNV infection (Marshall et al., 2017; Moore et al., 2017). Subsequently, rapid spread of CRB was observed to new Pacific islands, including Port Moresby, Papua New Guinea in 2009, Oahu in 2013, Honiara, Solomon Islands in 2015 (Marshall et al., 2017), and recently to other Hawaiian Islands of Kauai (HDOA, 2023), Hawaii and Maui in 2023, most likely due to movement of infested compost or other green waste from areas with high population densities (Moore et al., 2016).

Integrated pest management (IPM) is an environmentally informed and sustainable pest management framework aimed at reducing pesticide use and resistance, and mitigating impacts on human health and the environment (Radcliffe et al., 2009). Efficient pest population monitoring is an essential pillar of IPM, enabling the early detection of incipient pest populations, supporting appropriate control decisions, and measuring the efficacy of the control efforts (Barzman et al., 2015).

Pheromone-based capture in bucket or panel traps is a routine tool for CRB monitoring to delineate populations (Marshall et al., 2023; Paudel et al., 2023, 2022). Currently, there are nearly two thousand CRB panel traps baited with the male aggregation pheromone ethyl 4-methyloctanoate installed throughout the island of Oahu, each visually inspected at regular intervals (approximately once or twice per month, depending on location) by human operators. Visual inspection is tedious, expensive both in labor and transportation costs, and requires mundane and time-consuming data entry. Importantly manual trap checking constrains the frequency of monitoring, which could result in significant delays and limited success of control operations (Preti et al., 2021). There is a growing interest in automated pest monitoring technologies, notably through the use of camera-based traps (Preti et al., 2021). However, commercial camera traps commonly have several limitations that restrict their scope of application (Čirjak et al., 2022). The traps are not easily customizable for target pests, and unit prices sharply increase with image quality. There are open-source camera trap approaches which typically use off-the-shelf camera modules, though typically these are operated offline recording images (Schrader et al., 2022; Zhao et al., 2016) or video data (Droissart et al., 2021) locally, requiring traps to be serviced to retrieve data. Remote operation off of the electrical grid and without access to local wireless networks is especially challenging. In some cases developers base designs on high performance single-board computers with incumbent power demands (Adami et al., 2021; Bjerge et al., 2021; Chou et al., 2023; Droissart et al., 2021), restricting use to greenhouses and other settings with extensive electrical and network infrastructure, or else requiring large batteries and other power systems that make setup more difficult and pose increased risks of theft or vandalism (Meek et al., 2019). Automated communication of pest monitoring information increasingly relies on wireless technologies, including textual reporting through relatively long range (a few km) LoRa radio (Varandas et al., 2020) or more commonly, through local Wi-Fi hubs (Rustia et al., 2023), though these approaches are not suited for extensively deployed surveillance systems over a wide geographical area.

In this study, our primary objective was to develop a customized surveillance system for monitoring CRB panel traps with discrete and efficient autonomous power management, and using low power wide area network (LPWAN) technologies (Islam et al., 2021) to enable reporting and image sharing wirelessly from a wide geographical area to a dynamic image gallery on the cloud. Finally, we evaluate data from early deployments of the system programmed to report trap images hourly to better understand the diurnal behavior patterns of CRB adults in the field.

2.2. Materials and Methods

2.2.1. Hardware Design

A completed PCB assembly of one of our surveillance devices (CRB-Cam) is shown in Figure 2.1, and all of the hardware design files are available in the published paper (Paryavi et al., 2025b). The primary design considerations aside from the ability to record images and sound in traps were to enable remote data communication through existing wireless networks, and autonomous operation / power in these remote locations. The system was built around an ESP32-S3 microcontroller module (ESP32-S3-WROOM-1U-N16R8, Espressif Systems, Shanghai, PRC), interfaced to a “2 MP” CMOS imaging sensor (OV2640, OmniVision, Santa Clara, CA, USA) and a digital microphone (ICS-43432, TDK InvenSense, San Jose, CA, USA) similarly as in off-the-shelf camera modules (i.e. ESP32-CAM, Espressif Systems). Communication using Long-Term Evolution for machine-type communication (LTE-M) bands for wide area connectivity was provided through a commercial multi-band LTE-M / Narrowband IoT cellular modem with built-in GNSS engine to enable autonomous geolocation (SARA-R422M8S-00B, u-blox, Thalwil, Switzerland), using an external antenna (W3907B0100, Pulse Electronics, San Diego, USA) connected to a miniature u.fl connector. Reception of GNSS satellite signals occurs through a separate on-board GNSS antenna (SGGP.18.4.A.08, Taoglas Limited, Tainan City, Taiwan). Subscriber management for communication was provided through commercial IoT sim cards (Aeris, San Jose, CA, USA). Energy generation was provided through a USB-output photovoltaic panel with 6 W nominal power output (Soshine, Shenzhen, PRC), charging a 2000 mA-hr single cell LiPo battery through a commercial charging IC (BQ24210, Texas Instruments, Dallas, TX, USA). For efficient delivery of intermittently high current for the LTE module and microcontroller primary 3.3 V regulated power was provided through a buck-boost switching-mode regulator (ISL91107IRTNZ-T7A, Renesas Electronics, Tokyo, Japan), which was in turn stepped down to lower voltages for sensor chips through linear regulation with capacitor and ferrite bead "pi" filters at input and output to isolate these devices from switching noise. Digital outputs from the microcontroller also gated MOSFET switches to deliver nominally 20 mA to a white LED (SPMWH1228FD5WAVMS3, Samsung Electro-Mechanics, Suwon, Republic of Korea) for scene illumination, and to power-down the LTE modem when not in use. As illustrated in section 2.4, circuit boards were mounted in customized enclosures, with extended openings for cables from the photovoltaics (PV) panel and to the antenna to prevent ingress of water, as well as downward facing openings for the camera, microphone, and white LED.

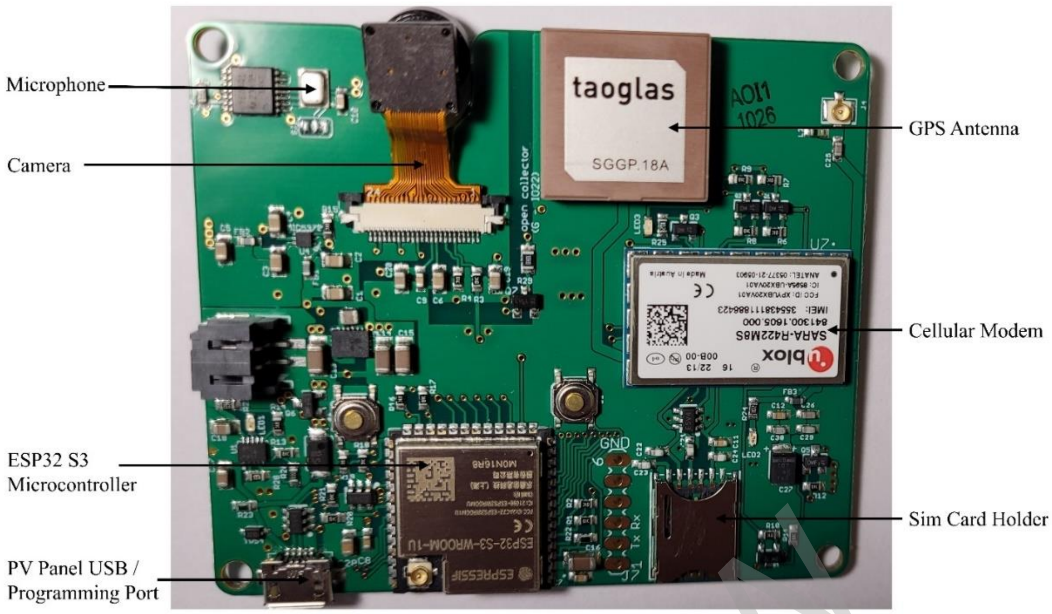

Figure 2.1. CRB-Cam completed circuit board assembly.

2.2.2. Software Design / Algorithm

The surveillance system is controlled by custom firmware running on the deployed camera board in the field, working in tandem with software running on a remote server. The deployed trap camera board runs a sequence of instructions to activate different on-board sensors to retrieve trap data including the trap's unique identification, image of cup contents, and geolocation then connects to a remote server to upload data. The remote server is a remote cloud Linux machine (Linode, Akamai, Philadelphia, USA) with 2 CPU cores, 4GB of RAM, and 80 GB of storage running a virtual Ubuntu 22.04 Linux Operating System. I programmed the remote server with back-end and front-end services. The back-end listens for and handles upcoming CRB-Cam connection requests and receives data (trap name, image, and geolocations), and the front-end displays the data through a publicly accessible website. After data is uploaded directly from deployed CRB-Cams to the remote server, it is instantly available on the server through a website with an image gallery web service. The image gallery allows the CRB Response team and their