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# Towards an Automated Camera Trap Monitoring System with Satellite and Drone Upload Capabilities for Island Invasive Mammal Surveillance

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**ABSTRACT:** Invasive mammals pose a significant threat to native island ecosystems. However, detecting and removing mammals at low densities remains a costly and challenging endeavor. While camera traps (CTs) are effective detection tools they must be manually visited to collect data for analysis, confirmation of target animal detection, and subsequent management action. Deploying CTs in remote, inaccessible, or dangerous areas leads to delayed data collection and processing, hindering timely management efforts. To decrease time, costs, and risks associated with CTs Conservation X Labs developed a prototype automated monitoring system called the Sentinel. The Sentinel plugs directly into CTs, processes sequences of collected images to detect if animals are present using on-board machine learning models. Within several hours of CT the first trigger event, the Sentinel transmits text-based metadata of animal detections, termed insights, via low bandwidth satellite communication protocols to an online dashboard that automatically notifies field staff of events of interest. To further advance the utility of this device in disconnected environments or where CT access is dangerous access, we expanded the transmission capabilities of the Sentinel to include remote upload of CT data to a nearby small Uncrewed Aircraft Systems (sUAS). Here, we report on the first field-test of the prototype Sentinel units for invasive mammal management. We conducted this test on Kaho‘olawe Island, Hawai‘i where island managers face significant challenges in managing feral cats due lack of connectivity, steep terrain, and unexploded ordinance. Our results confirm that remote data retrieval from Sentinels using sUAS effectively addresses current limitations by reducing physical retrieval time by 300-400%. Further, we found that although the deployed ML model achieved an accuracy of >90% in detecting the species of interest, generated insights were limited to text or highly compressed images hindering direct validation of automated satellite-delivered detections by end-users. In use-cases like invasive mammal management, high confidence in data accuracy is required to guide subsequent management decisions, meaning that even with satellite-delivered insights end-users had a strong desire to regularly collect all original CT data to confirm model predictions. We found that combining Sentinel’s close-to-real-time species detection and data transmission capabilities with sUAS remote upload capabilities holds significant promise as an end-to-end rapid monitoring system, especially where human verification of raw data is required and physical access to cameras is costly, dangerous, or could negatively impact animal behavior.

**KEY WORDS:** artificial intelligence, camera trap, conservation technology, data collection, drone, eradication, *Felis catus*, feral cats, Hawai‘i, invasive rodents, island restoration, Kaho‘olawe

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## INTRODUCTION

Kaho‘olawe, one of the eight main Hawaiian Islands, is the only island in the archipelago that is dedicated to one of the major akua (gods), Kanaloa, and is considered both a Wahi Pani (sacred place) and Pu‘uhonua (place of refuge). It is a refuge for many unique Hawaiian species that live on the island, including the ‘Ua‘u Kani (wedge-tailed shearwater, *Ardenna pacifica*) and the endangered

Hawaiian Hoary Bat (*Lasiurus semotus*) (KIRC 2017). Protecting these species is therefore paramount to preserving indigenous and cultural heritage. However, the presence of feral cats (*Felis catus*) poses a threat to these native species, making their removal essential for biodiversity recovery and cultural identity preservation. The eradication of invasive mammals from the island is a demonstrated conservation management tool capable of

cultivating significant ecosystem recovery and protection and representing a high return on investment to protect natural and cultural resources. Detection and monitoring efforts are critical to successful eradication campaigns and represent a sizable portion of the overall cost. It is estimated that one third of the \$4.5 million budget to remove feral cats from Kaho‘olawe would need to be dedicated to these efforts (KIRC 2022).

Currently, monitoring efforts consist of deploying an extensive camera trap (CT) grid capable of passively collecting invasive species demographic and geospatial information over months (Bruch et al. 2014). While this information is essential to directing eradication actions, manual processing and collection of data is costly and time-consuming, and consequently traditional CT-based monitoring limits data-to-action timelines to months or years, leading to insufficient management and protection of ecosystems (Tuia et al. 2022). Moreover, on Kaho‘olawe, monitoring and eradication of invasive mammals is further compounded by the fact that the island was used as a bombing range by the US Navy from 1940 until the 1990s. The landscape contains unexploded ordnance (UXO), making ground-based actions on the island extremely dangerous and costly (e.g., technicians must be chaperoned by UXO specialists when working in the field). Without a safe and cost-effective method of monitoring CTs across the island to ensure eradication success, restoration and reclamation of this island is not viable.

Recently, cellular and WiFi enabled CTs allow for near real-time and cost-efficient data streaming and processing in the cloud. However, such types of connectivity are typically restricted to the vicinity of human population centers and are absent from remote islands such as Kaho‘olawe. Satellite networks provide global coverage but have limited data bandwidths and few solutions exist that allow for near real-time monitoring of remote and disconnected areas (Whytock et al. 2023).

A consortium of stakeholders, including Island Conservation (IC) and the Kaho‘olawe Island Reserve Commission (KIRC), initiated the process of planning for the complete removal of feral cats from the island (KIRC 2015) and in order to address the cost, time, and safety needs for Kaho‘olawe – and global conservation efforts in general – IC partnered with the nonprofit technology organization Conservation X Labs (CXL) to deploy and test their automated CT monitoring system called the Sentinel (Figure 1), aimed at reducing data-to-action timelines and manual intervention. The system consists of (1) a Sentinel automated processing and transmission unit (Figure 2, stage 2) and (2) a remote data retrieval system (Figure 2, stage 3). Sentinel units directly connect to traditional CTs, enabling automatic processing of incoming image data in near real-time via on-board machine learning (ML) models. Processed data is then transmitted via low bandwidth satellite communication protocols within several hours to automatically notify field staff via a text message of target species detections and associated metadata, termed insights, in close to real-time (Figure 2, stages 6, 7, 8). To verify model predictions and collect raw data without the need for physical access to the camera location we modified the Sentinel units to respond to commands from a sUAS and remotely transmit data onto an on-board SD

card and retrieval by the sUAS operator operating within line-of-sight of the sUAS. We show that Sentinel units can be used effectively to automatically classify incoming data and send information about cat detections in close to real-time (hours) from remote locations. Furthermore, using sUAS (Figure 2, stage 4) to retrieve raw data from Sentinel units reduced physical retrieval time by 300-400%. The deployed system provides proof-of-concept of an end-to-end rapid monitoring system, where human verification of raw data is required and physical access to cameras is costly, dangerous, or could negatively impact animal behavior.

## METHODOLOGY

### Framework

Throughout this report, we used the Application Usability Levels (AUL) framework, proposed by Halford et al. 2019. This framework describes and tracks the development of an application from ‘basic research’ (AUL1) to ‘approved for on-demand use’ (AUL9). This report focuses on demonstrating the application in a relevant context (AUL5) to progress to AUL6, which includes the validation of the application within the relevant context, from where a prototype can be developed (AUL7) and validated (AUL8).

### Sentinel and Camera Traps

Sentinel units (Figure 2, stage 2) contain a custom printed circuit board (PCB) including a low-power system operated by a Microchip SAM D21E microcontroller (Microchip Technology, Chandler, AZ, U.S.A) and a high-speed Google Coral System-on-Module (Coral SoM) with integrated Tensor Processing Unit, enclosed in a weather-proof plastic housing. The board optionally includes several communication modules including cellular (Blues Wireless module; Blues Inc., Boston, MA), LoRa, and satellite (Swarm module; SpaceX, Hawthorne, CA) in addition to WiFi. Here, we focus on a version that includes the satellite module connecting to Swarm satellites. The Coral SoM is a single-board computer capable of processing CT images with ML models. The board also contains custom power management components, a camera trigger detection circuit, connections between communication and data processing modules, and a micro-SD slot to store captured images. The Sentinel is powered by rechargeable 18650 lithium-ion batteries and offers the possibility to be powered by an external solar panel.

The Sentinel directly connects to the SD card slot of the CT (Figure 2, stage 1) via a USB-to-SD cable (Spypoint, Victoriaville, Quebec, Canada). The cable connects via the Mini-USB connector to the Sentinel board and replaces the normal SD card in the CT. This architecture allows for basic camera functions such as trigger speed, image quality, and battery life to be unhindered, and eliminates the need to manipulate the CT (Whytock et al. 2023). During this deployment, Sentinels were connected to Bushnell Trophy Cam HD CTs (Bushnell Outdoor Products, Olathe, KS).

### Remote Data Retrieval

A previous case study (Mountcastle et al. 2021) demonstrated that UAS remote download technologies



**Figure 1. The full prototype solution at the end of AUL 5, including a Sentinel drone payload attached to DJI Phantom 4 with receiver mounted to the drone controller. Open Sentinel device next to Reconyx camera trap.**

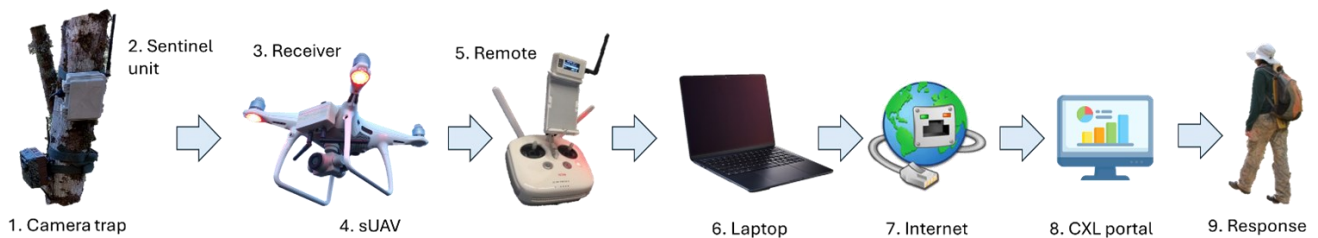


**Figure 2: Infographic outlining the end-to-end AUL 3 concept. Although not expressly depicted, the Sentinel units have the capability to transfer text and small image thumbnails via low band satellite and LoRaWAN directly to the CXL portal as well.**

were effective in reducing data collection times and operational costs in data retrieval, with limited flight times being a major constraint to operational use. To allow full data retrieval from each Sentinel, we developed a sUAS-attachable payload (Figure 2, stage 3) to create a WiFi hotspot in-air, connect to deployed Sentinels on the ground, and remotely collect raw and processed image data from them.

The payload consists of a small, embedded computer (Raspberry Pi Zero W) which broadcasts a WiFi network over 2.4 GHz (802.11g) and a microcontroller with on-board 915 MHz LoRa transceiver (Adafruit Feather M0 RFM95) which transmits a wake signal to the Sentinel and

relays data download progress to the operator. An external USB port allows retrieved data to be stored on a small USB flash drive that can be accessed once the sUAS has landed. The payload is powered by a 3.7v, 2000mAh lithium-ion battery allowing it to operate fully independent of the sUAS. A built-in micro-USB port allows recharging of the payload battery between flights. All components are packaged in a 3D-printed housing designed to match the contour of the sUAS for improved aerodynamics and ease of attachment. The assembled payload weighs 120 grams allowing it to be flown on a wide variety of commercial sUAS.

To control the payload operation while inflight and monitor download progress in real-time, a remote was created to allow two-way communication between the payload and the operator. The remote consists of the same microcontroller and LoRa transceiver as the payload with the addition of an OLED screen and push buttons to allow control input from the operator. The remote is powered by a 3.7v, 400mAh battery that can be recharged through a built-in micro-USB port. A 3D-printed housing encloses all components and allows the remote to be handheld or attached to the sUAS controller.

To enable the payload to retrieve data from each Sentinel device, we added a 915 MHz LoRa transceiver module (RFM95CW) to the Sentinel PCB. The Sentinel briefly activates this module once every two minutes to detect a wake signal transmitted by an overhead sUAS. By utilizing a brief (400 millisecond) radio receive window, the Sentinel can remain in a low-power state without the sUAS upload capability negatively impacting battery life. If the wake signal is detected, the Sentinel device will activate the Coral SoM and then connect to the WiFi network broadcasted by the payload. Once the Sentinel joins the WiFi network, the payload initiates a secure shell connection to the device and begins to download any new data not yet transferred using the rsync file transfer utility, a Linux-based open-source file synchronization program. The payload then monitors the rsync process and transmits download progress and transfer speed statistics which are displayed on the remote (Figure 2, stages 2, 3, 4 & 5). When the download is complete, the payload goes out of radio range for a pre-determined threshold of 60 seconds, or if the operator cancels the download using the remote, the Sentinel device will return to a low-power state to conserve battery until another data download is requested.

### Model Training

To enable automated detections of target species of interest we used a two-stage machine learning process using (1) a general animal detector to determine if an animal was in an image and (2) a species-specific detector trained to determine the probability that a detected animal in an image was a cat. The general animal detector model was adapted from Megadetector an open-source CT specific detection model created by Microsoft trained on millions of images around the world (Beery et al. 2019, Microsoft 2020). Megadetector is known to have >95% accuracy in detecting the presence of animals in images and reducing manual processing time by more than 500% (Fennell et al. 2022). To use the model on the Sentinel we converted the original Megadetector model to the TensorFlow Lite format and quantized its weights to run on the Tensor Processing Unit of the Sentinel device.

The cat detector was trained on a mix of publicly available camera trap images from the Labeled Information Library of Alexandria: Biology and Conservation (<https://lila.science/>) and private from Island Conservation and others. The total dataset contained 234,098 images of a range of species and 12,389 images of cats specifically. The model therefore learned to detect cats while ignoring other species that might be captured by the camera trap. The model was trained using the Pytorch library and was then converted to TensorFlow Lite format followed by a

weight quantization to run it on Sentinel’s Tensor Processing Unit. The inference speed of the model on the device could vary between 0.1-0.2 seconds per image. Versions of the model can be made freely available upon request.

### Metrics

To measure satellite transmission times, we calculated the difference in hours between the time an image was taken by the CT and when the associated insight (detection of the target species) was received by the field staff. Those time differences therefore include data processing time, time until next satellite pass (every ~three-four hours at our field sites), and time until satellite message downlink to a ground station. We therefore do not expect average transmission times under five hours, given the battery optimized settings and trigger frequencies of the deployed devices. However, average satellite transmission times of 1.5-2 hours could theoretically be achieved by compromising battery life.

Images collected to verify model accuracy were manually reviewed to determine cats were in the image or not and marked as either a true positive, false positive, false negative, or true negative as defined below. We chose precision, recall, and accuracy metrics to measure the performance of the object detector (YOLOv5 model) deployed to the Sentinel. Precision is denoted by:

$$\frac{TP}{TP + FP} \quad (1)$$

where TP (true positives) stands for the number of correct predictions for a given class and FP (false positives) stands for the number of incorrect predictions for a given class.

Recall is denoted by:

$$\frac{TP}{TP + FN} \quad (2)$$

where FN (false negatives) stands for the number of class instances missed i.e. negatively predicted by the model. Accuracy is denoted by:

$$\frac{TP + TN}{TP + TN + FP + FN} \quad (3)$$

where TN (true negatives) stands for the number of instances for which both the predicted and actual class values are negative.

### Deployment Setup

Nine Sentinel units and CTs were distributed within a 2km boundary of KIRC basecamp on Kaho’olawe. The locations were selected based on (1) recommendations from KIRC as having a high chance of observing feral cats, (2) the ability to evaluate several different distances from the Landing Zone (LZ) and location types to examine how the sUAS upload system responded.

The nine Sentinel units were placed in several environment types to test the impact of deployment conditions on data transfer speed and distance. Installation locations included in the open, strapped to and under various-sized hardwood trees (all *Prosopis pallida* species), in between

metal and wooden buildings, and under a shipping container situated on a semi-trailer.

During the trial, Sentinel units were deployed for varying time periods (from weeks to months). Sentinel units were equipped with ML models that either detected the presence of animals or the presence of feral cats specifically. Here, we analyzed satellite data transmission times for two Sentinel units (one that detected cats specifically, and one that detected animals in general) deployed in open terrain and ML model performance for two Sentinel units that detected cats.

Remote upload capabilities were installed on all nine Sentinel units and data retrieval experiments lasted for three days, where each unit was visited at least six times by sUAS for remote data upload tests.

## RESULTS

### Sentinel Performance

We observed median transmission times of 33.7h and 32.97h across two (789 insights) devices respectively, with a minimum transmission time of 5.4min and a maximum transmission time of 105.05h.

We analyzed data from two Sentinel units that included an ML model to detect feral cats. During the deployment, Sentinels collected and processed 2586 CT images in total. Upon manual verification we found that the ML model correctly detected and classified 54/66 images containing cat(s) and did not falsely detect cats in any of the remaining 2520 images resulting in a recall of 82%, a precision of 100% and an accuracy of 99%.

Out of 19 insights on one Sentinel unit that operated the cat model (insights here meaning cat detections), and for which we analyzed satellite data transmissions, 14 insights were received by our database (i.e. 74%), all of which were correct detections. Seven cats were not detected by the model, resulting in 59% of human-verified cat images taken by the CT being reported to the field staff. Those insights were received with a median delay of 15.7h.

### Remote Data Retrieval

54 visitation flights over five hours of flying were completed during the three-day experiment. Of these all but one flight successfully downloaded a dataset from a Sentinel unit, resulting in a 98% data retrieval rate. The reason for the failed dataset download is unknown.

The sUAS tests successfully demonstrated Sentinel's remote data upload functionality, reducing average data retrieval time by 300-400%. A 2.8 km long trip to download data from three camera units that would have taken experienced staff 60 minutes by foot or 40 minutes by utility task vehicle (UTV) to complete, took less than 15 minutes for the sUAS download system (Table 1). In addition, data retrieval was able to occur at a significantly increased frequency due to the reduction in safety risk to human personnel by UXO. Since images detected by the ML as containing cats or empty were sorted into separate folders on the device manual data review times were reduced from a typical one to two hours per 1000 images to one to two minutes per 100 images), similar to the level of efficiencies reported using animal detector models elsewhere.

Download speeds ranged from 0.6 - 2.1 megabytes (MB) per second, with an average speed of 1.7 - 2 MB/s. Datasets ranged from 40 - 400 MB and in number from 10 - 100 files. The sUAS was able to wake Sentinel units from 500 meters away and then begin downloading their data within a range of 25 meters from the Sentinel unit. Download performance was optimal when the sUAS was positioned at an angle of 30 - 75 degrees above the Sentinel's horizontal plane, rather than hovering directly above the unit (90 degrees) due to the orientation of Sentinel's on-board WiFi antenna.

Aside from a Sentinel unit situated underneath a shipping container, which required the sUAS to hover to the side of the trailer as opposed to above it, no decrease in download functionality was observed across the nine Sentinel locations. On average, the sUAS payload took three - five minutes to wake the Sentinel unit and then download its complete data set, with 10-20% of this time spent waiting for the Sentinel to wake prior to the data download.

Distances from the payload on the sUAS to the remote located with the sUAS operator ranged from 0.1 - 1.2 km during the tests on Kaho'olawe while previous range testing demonstrated payload remote control range of up to 3.1 km.

On average, the sUAS was able to fly to, wake, and download all data from three - four Sentinel units before exhausting its battery during ~20 minutes of flight time. The longest total distance travelled by the sUAS in one flight to download complete datasets from four Sentinel units was ~three km.

## DISCUSSION

Here, we demonstrated a successful deployment of Sentinel units that provide a practical solution for monitoring hitherto unconnected areas. Using Sentinel units shortened data-to-action timelines from years or months to hours or days, while greatly reducing the need to physically access remote places. This can be crucial to detect the spread of invasive species, estimate changing population densities and allow for timely response. We integrated Sentinel units with a remote data retrieval mechanism to provide a faster and more secure alternative to physical collection of raw data and to allow for rapid human verification of model predictions.

Analysis of ML model performance on a subset of deployed Sentinel units revealed that 82% of all cats were detected by the model while the model never falsely detected a cat in 2586 CT images. On one Sentinel unit with satellite connection, 19/26 (73%) cats on the CT images were detected by the model and 14/19 (74%) of those insights were transmitted successfully via satellite, leading to field staff being notified of 59% of all cat instances on the recorded CT images. After the deployment ended, we identified an error in the insight queuing software on the Sentinel units, causing a fraction of insights to not be transmitted via satellite. Correcting this error will increase transmission success rates in future deployments. Including more data from the actual deployment locations might be used to improve model performance in the future.

It typically took several hours from the time a CT was triggered to when an insight was successfully transmitted

**Table 1. Relative time taken to retrieve data from three camera units on a 2.3-km trip during the test on Kaho‘olawe, Hawai‘i.**

| Method      | Time Taken (minutes) | Distance (km) | Additional Benefits                                           |
|-------------|----------------------|---------------|---------------------------------------------------------------|
| On Foot     | 60                   | 2.8           | None                                                          |
| UTV         | 40                   | 2.8           | None                                                          |
| sUAS System | <15                  | 2.8           | Increased frequency, reduced safety logistics due to UXO risk |

via satellite. A significant portion of this time delay can be attributed to the satellite provider (SpaceX Swarm) as satellite pass windows occurred only every three - four hours. We could consider the Iridium satellite network, which can be used to transmit data at much shorter time intervals (shortening median transmission times to minutes or hours (Whytock et al. 2023)). However, Iridium transmission costs are considerably higher (~20×) and possibly prohibitive for larger scale deployments over longer time spans. Furthermore, messages cannot be queued on the Iridium module leading to increased power consumption and reduced device operational uptime. Importantly, Swarm operates at lower frequencies, enabling Sentinel units to transmit messages from most geographies, including forests and when placed close to the ground, which would not be possible using Iridium.

In its current configuration the remote data retrieval system is optimized for use where there are multiple cameras in a one-two km radius and data is checked every three to five days with an sUAS to keep dataset sizes small. Future improvements in data upload distance and sUAS flight time are needed to operationalize this system for large area deployments or where cameras (i.e. Sentinel units) will be checked at a weekly or monthly frequency and will have larger datasets. To achieve this, the use of a fixed-wing UAS, with longer flight times and distances will be explored. To retain the flexibility, ability to deploy, and usability realized with the multi-rotor sUAS used in the pilot study, a vertical take-off and landing (VTOL) capable UAS is ideal. In addition, a UAS with the capability to fly beyond visual line of sight (BVLOS) would allow coverage of larger islands and increased CT distances. Further software enhancement to automate the flight control would allow the UAS to autonomously fly to the next waypoint on conclusion of Sentinel data transfer.

Sentinel units capable of transmitting text-based insights via satellite networks and uploading raw data to UASs can be highly beneficial to rapid response control actions. For example, if a project focuses on removing remnant target populations during post-eradication efforts, the Sentinel’s satellite insights could provide managers with critical information, e.g., a detection of a remnant target species, which could then be confirmed quickly through an sUAS data visit, and consequential management actions could be initiated faster than via traditional camera trap data recovery and review methods.

Subsequent to this study, the Sentinel system has been tested in real-world operational settings for invasive species management in the Galapagos and New Zealand and more than 280 devices have been deployed in 10

countries for multiple use cases. The transmission capabilities have also been expanded to include low resolution images over satellite networks and expanded to include cellular, LoRa low-power, wide-area networks, and Starlink Direct to Cell service. Additional test after this study suggested that fixed-wing drones could improve the range and performance of the remote upload capability if they had the ability to loiter in a radius less than 100m around a way point and did not conflict with the remote upload transmission frequency.

The successful integration of the Sentinel CT system with UAS data retrieval capabilities represents a significant step forward in developing automated surveillance for invasive mammals. By addressing connectivity challenges and streamlining data collection processes, the solution here presented offers a promising path towards more effective and efficient conservation practices on remote islands and landscapes.

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