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Real-time island biosecurity surveillance: evaluating a wireless camera network for AI-assisted early detection of invasive mammals on Santa Cruz Island, CA

Lara J. Brenner[1,*], Nathaniel Rindlaub[1], Juliana Matos[1], Scott Meyler[1], Sue Pollock[1], Falk Schuetzenmeister[1], and Nick D. Holmes[1]

[1]*The Nature Conservancy, San Francisco, CA 94111*

Abstract.—Early detection of nonnative mammal incursions enables rapid management actions that are needed to prevent full-scale invasions. As biosecurity monitoring tools, camera traps can aid in the detection of nonnative species; however, the burden of image management and resources required to access cameras regularly for image collection both inflate costs and extend the latency period between invasive animal detection and manager response. Here, we describe a wireless camera network on Santa Cruz Island (SCI) that enabled instantaneous transfer of camera images from remote field sites to the cloud. Initial classification of images by machine learning allowed human reviewers to prioritize examining photos of possible concern. Comparison of AI predictions and human-validated image labels confirmed that machine-learning models had high recall (or a low false negative rate) for image sequences containing rodents. Comparisons with a prior SD-card-based camera system on SCI revealed significant improvements in data review frequency and reliability, improving the likelihood of prompt nonnative species detection. Despite higher initial equipment costs, networked cameras were cost-effective over time, outperforming traditional methods in long-term deployments. Future iterations of the network could leverage cellular or satellite networks for broader scalability, enhancing biosecurity and general conservation efforts on islands and other vulnerable protected sites.

Resumen.—La detección temprana de mamíferos no nativos permite llevar a cabo acciones de gestión rápidas que son necesarias para prevenir grandes invasiones. Como herramientas de monitoreo de bioseguridad, las cámaras trampa pueden ayudar en la detección de especies no nativas. Sin embargo, la responsabilidad de gestionar las imágenes y los recursos que se requieren para acceder a las cámaras de forma regular para recolectar las imágenes, incrementan los costos y extienden el período de latencia entre la detección de animales invasores y la respuesta del gestor. En este trabajo, describimos una red de cámaras inalámbricas en la Isla Santa Cruz ("SCI", por sus siglas en inglés) que permitió la transferencia instantánea de las imágenes de las cámaras desde los sitios remotos hasta "la nube". La clasificación inicial de imágenes mediante aprendizaje automático permitió que los revisores humanos priorizaran el análisis de fotos de posible preocupación. La comparación de las predicciones de la "IA" y las etiquetas de imágenes validadas por humanos confirmó que los modelos de aprendizaje automático tenían una alta tasa de recuperación (o una baja tasa de falsos negativos) para secuencias de imágenes que contenían roedores. Las comparaciones con un sistema previo de cámaras basado en tarjeta SD en la "SCI" revelaron mejoras significativas en la frecuencia y fiabilidad de la revisión de datos, mejorando así la probabilidad de detección rápida de especies no nativas. A pesar del mayor costo inicial de los equipos, las cámaras colocadas en red resultaron ser rentables a lo largo del tiempo, consiguiendo mejores resultados que los métodos tradicionales. Las iteraciones futuras de la red podrían hacer uso de las redes celulares o satelitales para tener una amplia escalabilidad, mejorando los esfuerzos de bioseguridad y conservación general en islas y otros sitios protegidos vulnerables.

Islands represent only around 5% of the world's total land area but account for a large proportion of the world's biodiversity (Tershy et al. 2015). Island species and ecosystems are particularly vulnerable to invasive species impacts, which have directly led to extirpations, extinctions, and loss of ecosystem function (Bellard et al. 2016, Reaser et. al 2020). Mammals, and particularly rodents in the genus *Rattus*, are among the most common and harmful vertebrates that have invaded islands, and their eradication is challenging and costly (Spatz et al. 2017, Bradshaw et al. 2021, Diagne et al. 2021). Thus, preemptive investment in biosecurity—or actions taken to prevent, detect, and rapidly respond to new incursions—is more cost-effective than attempting to eradicate an

*Corresponding author: lara.brenner@tnc.org

LJB orcid.org/0000-0002-4641-3842

established population of invasive species (Matos et al. 2018, Faulkner et al. 2020). Capitalizing on new technologies (e.g., machine learning, internet of things (IoT), and cloud-based computing) can improve the efficiency of biosecurity programs by enabling some automation of monitoring protocols like camera trapping (Jurdak et al. 2015).

Camera traps are commonly used biosecurity management tools on islands and can aid in the early detection of nonnative vertebrates (Davis et al. 2023). Cameras with passive infrared (PIR) sensors have been used in the detection of a wide variety of small- to medium-bodied, fast-moving, and cryptic invasive endotherms on islands worldwide, including rats (*Rattus* spp.), house mice (*Mus musculus*), cats (*Felis catus*), European rabbits (*Oryctolagus cuniculus*), and raccoons (*Procyon lotor*) (Anton et al. 2018, Lamelas-López and Salgado 2021, Louppe et al. 2021, Nichols et al. 2022). Timely assessment of the images is crucial when using camera traps for early detection, especially when targeting taxa with rapid generation times (e.g., rodents) or when a single individual can cause significant harm in a short period following introduction (e.g., an animal carrying a novel disease agent) (Timm et al. 2009, Matos et al. 2018).

Although cameras are a useful tool in the biosecurity toolkit, the relatively high start-up costs of professional-grade camera equipment, as well as the ongoing time and labor requirements to retrieve data and maintain systems in remote and often logistically challenging areas, can be barriers to large-scale adoption of camera monitoring networks (Wearn and Glover-Kapfer 2019). The resource-intensive nature of reviewing, managing, and storing large quantities of data generated by camera monitoring may be even more challenging than maintaining field deployments, especially when cameras are left in place for long periods (Young et al. 2018). For this reason, the use of cameras in a biosecurity context is often limited to short-term deployments for rapid assessment of species assemblages before, during, or after an eradication effort.

Although evaluating the efficacy of an eradication is crucial, it is equally important that island managers sustain long-term prevention and monitoring efforts at a sufficient scale to protect the (often substantial) investment directed at the initial eradication (Towns and Broome 2003). This is especially true for frequently visited, nearshore islands with a relatively high likelihood of reinvasion (Harris et al. 2012); for example, on Anacapa Island in the California Channel Islands National Park, a black rat (*Rattus rattus*) eradication effort cost 1.8 million USD (over 3 million USD in 2024, adjusted for inflation) to complete in 2002 (Howald et al. 2010).

Until recently, technological limitations made it difficult to continuously monitor remote islands for invasive vertebrate (re-)establishment, making rapid response in the event of an invasion unlikely or impossible. Traditional detection devices like chew cards, tracking pads, or trail cameras that store photos locally on memory cards (hereafter referred to as "SD-card cameras") must be visited on a regular basis to reduce the latency period between an animal interacting with the device and a manager becoming aware of the interaction, a level of engagement that can be difficult to maintain in remote areas over the long term. Additionally, battery failure, SD-card corruption, and other malfunctions often go unnoticed between human visits, leading to gaps in data collection that can be devastating in early stages of colonization (Russell et al. 2008a).

Here, we describe a system piloted on Santa Cruz Island for the instantaneous remote detection of nonnative mammals, and we assess efficiency gains attained by using wireless, networked cameras with the ability to upload images in real time to the cloud for immediate review and AI-assisted classification.

METHODS

Study Site

At 97 square miles in land area, Santa Cruz Island (SCI) is the largest of the 8 California Channel Islands, and it is located approximately 20 miles off the coast of Santa Barbara County, California. SCI is comanaged by The Nature Conservancy (TNC), which owns the western 76% of the island, and the National Park Service (NPS), which owns the eastern 24%. A concessionaire ferry provides public transport to areas that are open for recreation, while the coastline and beaches across SCI are accessible to private boaters with a landing permit. Bulk cargo is transported to the island by barge, and commercial fishing vessels frequently operate outside of designated marine sanctuaries around the island. The Santa Barbara Channel is a major shipping lane for international container ships bound for ports across the Pacific Ocean, including nearby Port Hueneme in Oxnard and the Port of Los Angeles in San Pedro.

SCI is home to 4 native terrestrial mammals (excluding bats); namely, the island fox (*Urocyon littoralis santacruzae*), the island spotted skunk (*Spilogale gracilis amphialus*), the island deer mouse (*Peromyscus maniculatus santacruzae*), and the western harvest mouse (*Reithrodontomys megalotis*) (Schoenherr et al. 1999). SCI and the surrounding islands in the Channel Islands archipelago are also home to a number of sensitive endemic landbirds, herpetofauna, and plants with known vulnerability to invasive species. Steep cliffs, sea caves, and offshore rocks host breeding seabirds, including Ashy Storm-Petrels (*Oceanodroma homochroa*) and Scripps's Murrelets (*Synthliboramphus scrippsi*), both of which are threatened in the state of California.

Nonnative mammals, including rats in the genus *Rattus*, cats, dogs, and raccoons, are not established on Santa Cruz Island, but they remain active biosecurity concerns due to their presence at high densities on the nearby mainland and the likelihood of accidental transmission by human activity. Within the Channel Islands archipelago, rats have successfully invaded and become established on San Miguel, Santa Catalina, San Clemente Island, and Anacapa Island (but recently eradicated from the latter). Private boats and cargo vessels have transported stowaway cats and racoons to some islands in the archipelago, and visitors have occasionally transported domestic dogs to SCI, which both pose a disease transmission threat to the endemic island fox population (Timm et al. 2009, King et al. 2014, Hoyer and Ferrara 2020).

SD-Card Cameras

In 2011, early rodent detection protocols were piloted on Santa Cruz Island, involving 15 SD-card-based passive infrared (PIR) cameras and chew cards deployed at 70 rotating sites across the island (Boser et al. 2014). In 2018, the SCI biosecurity camera fleet was downsized to 10 permanent SD-card cameras (Hyperfire HC500, Reconyx, Holmen, WI) to reduce labor costs required for regular maintenance. Long-term monitoring sites were selected based on island visitation trends and ease of overland access. Cameras were installed approximately 1 yard above the ground on a post angled at 15° toward a bait station 1–2 yards away. Bait stations consisted of a brick, with stripes at 1 inch intervals for scale, that was smeared with lure (Lenon's Muskrat Super All Call, Animal Traps and Supplies, Traverse City, MI). Upon being triggered by motion and heat, cameras were set to take a burst of 3 images with "high" sensitivity, no delay between photos ("RapidFire"), and no quiet period. Five of the 10 cameras were serviced on an approximately monthly basis, while the remaining 5 were in more remote locations and were serviced on an approximately quarterly basis when road conditions permitted. Servicing the cameras involved checking and replacing batteries, swapping data cards, replenishing lure, trimming overgrown vegetation, and making any needed repairs. At each service, staff collected data that included date of service, number of photos captured, remaining battery life (if any), whether the photos covered the entire period of deployment, and any other maintenance notes. Photos were manually reviewed for species of concern using Microsoft Photos image viewing software but were not labeled by species or otherwise cataloged due to time constraints. The 10 SD-card cameras evaluated here were in place from February 2018–March 2021.

Networked Cameras

By October 2021, all existing SD-card biosecurity cameras were replaced with a mesh network of wireless cameras (X80, BuckeyeCam Wireless) linked to a central base station, which allowed for the transmission of images from the cameras to the cloud in near-real time. Networked cameras were also deployed at several previously unmonitored coastal sites thought to represent areas of relatively high biosecurity risk, including 4 cameras placed near housing or other sites with human infrastructure that might attract commensal mammals like rats. The cameras were installed at the same angle as the SD-card cameras that they replaced and were set to take a burst of 3 images with "high" sensitivity and no delay between motion triggers. Networked cameras were lured in the same manner as SD-card cameras, but at some cameras we also piloted automated lure dispensers (https://zip.org.nz/products-list/motolure, ZIP, Wellington, New Zealand) that rebaited traps nightly for up to a year with a small amount of mayonnaise stored in a syringe within the device.

The wireless camera network comprises 3 types of components, or "nodes": (1) PIR wireless cameras; (2) radio repeaters (Echo, BuckeyeCam Wireless) that relayed the radio frequency (RF) signal to extend range and circumvent challenging topography; and (3) a base station, which received the radio transmissions, demodulated the RF signal into digital images, and uploaded them to the cloud (X80 PC Base Receiver, BuckeyeCam Wireless; Cincoze DA-1000 fanless industrial computer, Cincoze Co., Ltd). The base station was located at a high point on the island with preexisting communications structures that served as an access point to the internet. Networked cameras and repeaters used a proprietary radio (Digi XBee Pro, Digi International) operating in the ISM band to both upload images from the cameras to the cloud and download settings updates from remote users to the cameras.

Image Processing with Machine Learning

Once images reached the cloud, they were processed using Animl (https://animl.camera/, The Nature Conservancy, CA), a software platform that integrates machine learning to facilitate review and management of camera trap imagery. On Animl, images were automatically evaluated by Megadetector v5a (Beery et al. 2019), an object detection model which is trained to detect and localize (i.e., provide bounding-box coordinates for) people, animals, and vehicles within camera trap images. Objects labeled as an “animal” by Megadetector were further evaluated by a custom wildlife classifier (MIRA) trained on Santa Cruz Island camera trap data and labeled as “rodent,” “fox,” “skunk,” “bird,” or “lizard.” Any images labeled as “rodent” were reviewed within 24 h by biologists for species determination, while other images were reviewed by volunteers or staff as time allowed (See Fig. 1). For each of the native mammal classes, we calculated the number of images captured during the period of this study and the average time to first detection on camera traps.

Data Gaps and Detection Latency Analysis

We used data collected by technicians and photo timestamps to assess the number, length, and causes of gaps in data monitoring for both networks. We also evaluated the average number of days between the first day of camera (re-)deployment and the date when SD cards were retrieved (i.e., the maximum latency periods to detection in the event of a rodent incursion) for all of the SD-card camera deployments.

Calculating Start-up and Maintenance Cost Estimates

To compare start-up and maintenance costs between the SD-card camera system and the networked camera system, we calculated initial and recurring equipment costs for each system (as of 2021), as well as the average time spent commuting to, setting up, configuring, and servicing cameras at each site. Time was converted into a dollar amount by multiplying person-hours by a fixed hourly salary. Start-up costs included the cost of purchasing new equipment, time spent installing the cameras, and travel to sites (in dollars per mile). Recurring annual costs included the costs of replacement equipment, time spent servicing the cameras, and travel to sites, which was assumed to be constant in each subsequent year. To standardize calculations, this analysis was limited to the 10 camera sites that did not change across the 2 deployment eras. In reality, SD-card cameras were not visited on a monthly basis due to time and staffing constraints; however, for the purposes of the analysis, we assumed an idealized monthly maintenance schedule that would make allowances for limited resources while retaining some ability to detect nonnative mammals in a timely manner. Time spent reviewing photos was not compared between systems, as labeling of images was only introduced after the installation of the networked system and with the support of Animl.

Machine Learning Performance Evaluation

In order to understand the combined performances of the 2 machine learning algorithms employed in this system (the object detector “Megadetector v5a” and the animal classifier “MIRA v2”), we evaluated a subset of images (n = 30,655) captured over a 13-month period after the SCI-specific model had been retrained and refined on a larger dataset of biosecurity camera images. For each of the 5 animal categories (“rodent,” “skunk,” “lizard,” “fox,” and “bird”), we calculated the number of true positives (TP, where a human validated the labels applied by both Megadetector and MIRA), false negatives (FN, where a human added or changed the label after either Megadetector or MIRA failed to identify the animal), and false positives (FP, where a human removed or changed the label after either MIRA v2 incorrectly identified that the animal was present when it was actually absent). Because we were jointly evaluating an all-purpose object detector with a custom animal classifier, a TP meant that (a) Megadetector correctly identified the presence of an object in the image; (b) Megadetector correctly labeled the

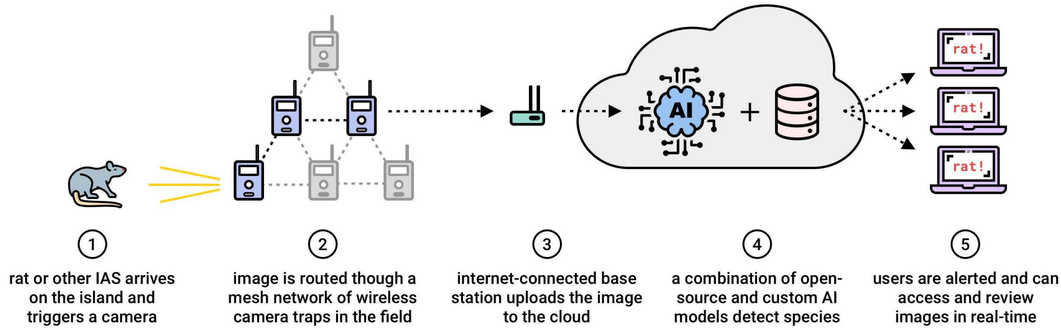

Fig. 1. Diagram illustrating the process by which images of invasive alien species (IAS) are relayed in real time to the cloud and reviewed by AI.

object as an "animal"; and (c) MIRA correctly identified the class of animal. However, an FN could mean either that Megadetector failed to identify the animal entirely or that MIRA applied an incorrect class label. Finally, an FP meant that MIRA applied an incorrect class label either to an animal or to an object that Megadetector incorrectly identified as an animal.

We aggregated the predictions at the level of the sequence (or series of photos captured following a single trigger, typically within 2–3 s), and considered predictions to be true positives if an animal was correctly predicted in any of the images in a given sequence, even if models failed to detect or misclassified the animal elsewhere in the sequence.

We then calculated model precision, or the proportion of positive ML identifications that were actually correct, as such:

$$TP / (TP + FP).$$

We also calculated model recall, or the proportion of actual positives that were correctly identified, as such:

$$TP / (TP + FN).$$

For each category, we also calculated the F1-score, which is an integrated metric of precision and recall that captures overall model performance, as such:

$$(2 * \text{Precision} * \text{Recall}) / (\text{Precision} + \text{Recall}).$$

RESULTS

SD-Card Cameras

Between February 2018 and March 2021, SD-card cameras captured 326,387 images over 9424 total possible operating days. In 20 separate instances, monitoring gaps with permanent data loss occurred when the batteries were drained after vegetation or shadows continuously triggered the camera ($n = 5$), batteries failed for unknown reasons ($n = 5$), SD cards malfunctioned ($n = 5$), cameras fell or infrastructure otherwise failed ($n = 2$), cameras were tampered with ($n = 1$), or for unspecified reasons ($n = 2$). In total, 911 out of 9424 (10%) possible operating days were not monitored due to equipment failure. On average, SD-card cameras captured 38.3 photos per camera per operating day, and camera data cards were retrieved and made available for review once every 56.5 days on average (range 12–129 days; SD = 31.4).

Networked Cameras

Between October 2021 and March 2023, the 10 replacement networked cameras captured 66,699 images. One camera went offline for almost 7 months after vegetation growth blocked the antenna's line of sight to the base station, leading to a loss of 210 out of 5460 total possible operating days (4%). Thus, on average, networked cameras captured 12.7 images per camera per operating day. Networked cameras successfully captured images of all native SCI terrestrial mammals, with average sampling days to first detection ranging from 20.7 days for island foxes (SD = 57.4) to 38.1 days for island mice (SD = 63.1) and 151.0 days for island spotted skunks (SD = 113.6). Mice and foxes were eventually detected at all 10 sites, while spotted skunks were detected at 8 of 10 sites. In addition to the taxa listed in Table 1, photos of domestic dogs ($n = 20$), insects ($n = 12$), and bats ($n = 2$) were also collected.

TABLE 1. Table of species detected per networked camera deployed between October 2021 and March 2023.

Camera number	Other/ unknown	Spotted skunk	Scrub jay	Other bird	Mouse	Herpetofauna	Fox	Empty	Person	Total photos
1	13	611	0	1824	348	2535	565	4776	54	10,726
2	3	12	3	1320	206	1472	195	6050	317	9578
3	5	90	726	2145	272	26	715	2134	197	6310
4	12	5	23	33	549	21	538	2894	21	4096
5	7	0	84	816	442	1	898	558	146	2952
6	25	7	5	262	2941	40	214	4634	798	8926
7	3	6	9	32	293	1	80	855	135	1414
8	93	17	488	1836	3096	165	1123	7002	76	13896
9	7	0	21	337	132	228	1026	1214	92	3057
10	7	5	249	1064	674	107	149	3094	395	5744
Photos per category	175	753	1608	9669	8953	4596	5503	33,211	2231	66,699
Pecent of grand total	<1%	1%	2%	15%	13%	7%	8%	50%	3%	
Percent of non-empty	1%	2%	5%	29%	28%	14%	16%	—	7%	

Camera Startup and Maintenance Cost Comparison

Start-up costs for the networked cameras were estimated to be $24,237, around 3.5× higher than the startup costs for the original SD-card-based camera network (see Table 2). During the installation, total travel required was slightly higher for the wireless camera network due to the necessity of installing a base station and 6 repeaters in addition to the cameras themselves.

Annual maintenance costs for the SD-card camera network were estimated to be $7842, nearly 9× higher than the annual costs incurred by maintaining the wireless camera network. (see Table 3) This differential was primarily due to the high labor and travel costs incurred by visiting the SD-card cameras on a monthly basis to retrieve memory cards. The break-even point occurred after 20 months of use, when the wireless camera network became more cost-effective than the SD-card cameras, even considering relatively high start-up costs (see Fig. 2).

Machine Learning Performance Evaluation

Performance of the 2 machine learning models varied widely by animal category. Model precision was lowest for skunks (18.3%, indicating a relatively high rate of false positives) and recall was lowest for lizards (60.3%, indicating a relatively high rate of false negatives). Model precision and recall were both highest for rodents (99.8% and 93.4%, respectively), indicating relatively low rates of both false positives and false negatives for this category, with high overall model performance (See Table 4).

DISCUSSION

Camera System Comparison

Networked cameras captured images of all terrestrial mammals native to SCI, as well as images of domestic dogs brought to the island by visitors. On average, networked cameras captured fewer images per day than SD-card cameras (12.2 vs. 34.6 photos per camera per day). This may be due to differences in baiting regimes attracting fewer animals, different trigger sensitivities across camera models, or a lower rate of false triggers in networked cameras. Real-time data allowed managers to immediately notice excessive photos triggered by overgrown vegetation, wind, or shadows and either remotely adjust settings or visit the camera to remove the source of the trigger. In contrast, high rates of

Table 2. Start-up cost comparison between networked and SD-card cameras. Equipment costs were as of 2021, while labor costs were estimated at $45/h. Travel costs were estimated to be roughly double the standard U.S. government mileage reimbursement in 2021 ($0.65) to account for additional costs of shipping fuel to the island and wear and tear to vehicles operating on 4-wheel-drive roads.

Startup costs	Cost (per unit/h)	Number (units/h)	Total
Networked cameras			
Cincoze DA-1000 field computer	$993	1	$993
Buckeye ×80 base station receiver	$675	1	$675
Antenna and cable for base station	$360	1	$360
Buckeye ×80 cameras	$1110	10	$11,100
Buckeye ×80 repeaters	$460	6	$2760
Buckeye ×80 batteries and solar panel	$330	16	$5280
Mounting hardware	$30	16	$480
Labor	$45	55	$2,475
Travel	$1.30	88	$114
Networked camera startup total			$24,237
SD-card cameras			
Reconyx Hyperfire HC500	$450	10	$4500
32 GB SD card (2-pack)	$20	10	$200
Rechargeable AA batteries (24 pack)	$65	10	$650
Mounting hardware	$30	10	$300
Labor	$45	27	$1197
Travel	$1.30	70	$91
SD-card camera startup total			$6938

Table 3. Annual maintenance cost comparison between networked cameras and SD-card cameras.

Annual maintenance costs	Cost (per unit/h)	Number (units/h)	Total
Networked cameras (1.15 visits per camera per year)			
Labor	$45	17	$765
Travel	$1.30	101	$131
Networked camera annual maintenance total			$896
SD-card camera (12 visits per camera per year)			
Labor	$45	150	$6750
Travel	$1.30	840	$1092
SD-card camera annual maintenance total			$7842

false triggers in SD-card cameras went unnoticed until the data card was reviewed, meaning that in the most extreme cases, a single card was filled with tens of thousands of empty images after a single month of deployment.

Because photos collected by SD-card cameras were not labeled, we were unable to compare the contents of images captured between systems. However, compared to results of biosecurity camera trapping on SCI conducted using the same methods (Boser et al. 2014), networked cameras captured relatively fewer empty photos (50% of the total photos versus 68%), more photos of deer mice (28% versus 4%) and herpetofauna (14% versus <1%), and relatively fewer photos of island foxes (16% versus 60%). This may be due to differences in camera placement, baiting regimes, interannual environmental variability, long-term environmental change, or all of the above.

With annual maintenance, networked cameras were generally reliable, and during the period evaluated here only 4% of total monitoring days were effectively unmonitored due to equipment failure, compared to around 10% of monitoring days in SD-card cameras (even with much more frequent maintenance). Thus, for long-term (>20-month) deployments, we found that networked, wireless cameras were more cost-effective than SD-card cameras, despite higher initial costs. Cost savings over time increased with the duration of deployment. We did not consider the cost of replacement networked camera equipment in the annual maintenance costs, as the short duration of this initial study (<2 years) was not enough time to evaluate equipment lifespans and failure rates. These should be considered when refining cost estimates over time, as the manufacturers of both camera models used in this study offer only short-term

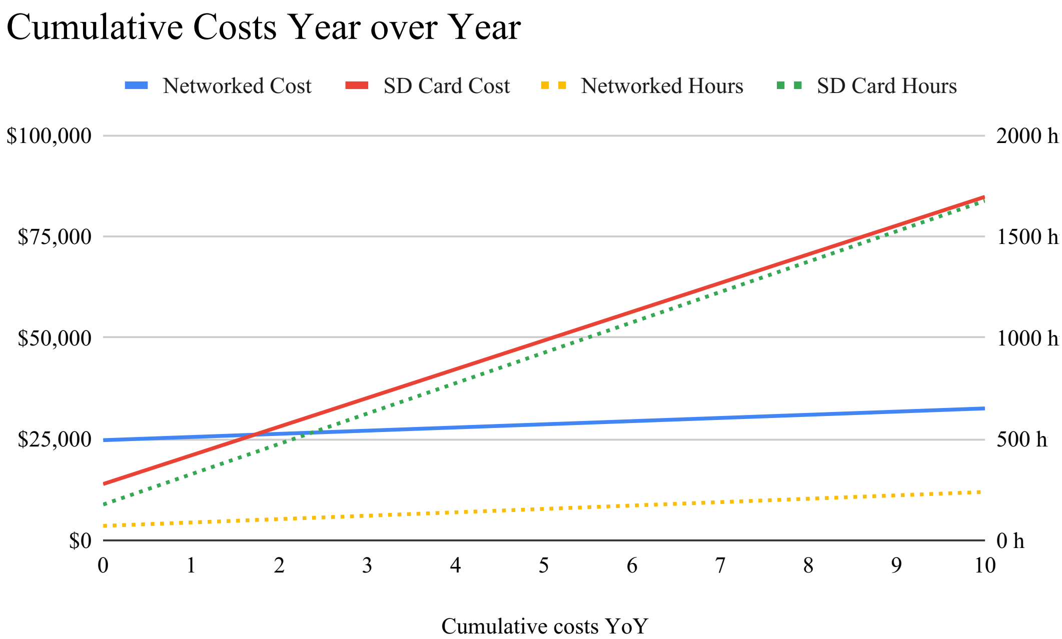

Fig. 2. Cumulative costs of networked cameras versus SD-card cameras year-over-year in dollar amounts (left axis) and labor in hours (right axis).

TABLE 4. Model precision, recall, and F1 score for each animal category in MIRA v2, aggregated at the sequence level.

Label	True positives	False positives	False negatives	All (TP + FN)	Precision	Recall	F1
Rodent	18,880	37	1339	20,219	0.998	0.934	0.965
Skunk	109	487	13	122	0.183	0.893	0.304
Lizard	597	1073	393	990	0.357	0.603	0.449
Fox	740	892	15	755	0.453	0.980	0.620
Bird	3977	977	1136	5113	0.803	0.778	0.790

(<1-year) warranties for failing equipment. Because most of the cost savings returned by the networked cameras derived from the reduction in labor cost, organizations relying primarily on volunteers for camera servicing and maintenance may not realize the same level of efficiency gains as reported here. However, regardless of absolute labor costs, automation of routine fieldwork on remote islands is likely to result in cost savings over time.

Image Processing with Machine Learning

Technological advances and efficiency gains realized by the networked cameras allowed us to incorporate image labeling into our workflow. Automatic image upload to and storage on the cloud-based Animl platform allowed us to recruit off-site volunteers to review and label images, reducing staff labor requirements. The filter, sort, and query functionality of the Animl platform facilitated maintenance of a structured, downloadable dataset, which introduced the possibility of developing a long-term database of native mammal detection and distribution on SCI, creating and training data for improving a species classification model over time, and enabling new scientific insights into native wildlife behavior, activity, and distribution.

Although we did not attempt a cost-benefit analysis of integrating AI classification into our image review workflow, the addition of an island-specific classifier allowed us to prioritize review of images of rodents, likely reducing time to detection in the event of a rat incursion. Our evaluation of classifier recall indicated that

Megadetector and MIRA correctly identified rodents in 93% of sequences that contained at least 1 image of a rodent. This low rate of false positives was likely facilitated by training datasets intentionally biased toward images of rodents, the taxa of concern from a biosecurity perspective. A high recall rate increased our confidence that the vast majority of rodent sequences were correctly labeled by AI, facilitating a workflow in which rodent-labeled images could be safely prioritized for immediate review. MIRA was trained on images of native SCI deer mice, and barring an incursion, precision and recall for images of nonnative rats on SCI cannot be formally evaluated. However, based on experience deploying these models on mainland camera trap imagery containing rats, we anticipate that MIRA would perform well in the event of a *Rattus* sp. detection on SCI. Megadetector v5a is a free, open-source model provided by Google, and the custom SCI classifier MIRA was developed for $13,430 in 2019.

Considerations and Future Directions

Although long-term costs for maintaining networked cameras approached $33,000 over 10 years, early detection efforts such as these are more cost-effective than an island-wide eradication or ongoing local rat control following an invasion, both of which can easily run into the millions or tens of millions of dollars depending on the size of the island (Duron et al. 2017). Early detection devices such as camera traps are typically deployed with the understanding that an invasive species detection will result in a rapid management response to curb an invasion. If logistical, legal, or policy considerations are likely to limit a managing agency's ability to act quickly in the event of a rat or other native mammal incursion, the value of early detection devices is diminished (Russell et al. 2008b).

While the wireless camera network described here relied on a radio protocol to transmit images to the cloud, similar models can be developed and scaled up using cellular networks or high-bandwidth satellite internet (e.g., Starlink). The specific hardware solution required may differ depending on the characteristics of the environment where the cameras are deployed, including terrain, cell connectivity, internet availability, and satellite coverage, as well as budget and project timeline (see Table 5). Biosecurity camera networks that we have piloted outside of SCI have required varying solutions to deal with challenges unique to each project and study area. On Nonsuch Island, which regularly experiences rat incursions from nearby islands of Bermuda (Madeiros 2005), an existing internet connection facilitated the installation of a small-scale Buckeye camera network that was installed with reinforcements to protect the devices from seasonal hurricane winds. On preserves in Hawai'i, we worked with managers to deploy a patchwork of different camera types, including radio-linked and cellular cameras, that took advantage of existing deployments, varying terrain, and internet and cellular availability. At one such preserve, this network allowed managers to respond to a feral cat detection near a predator-proof fence within 24 h, a process that would normally take weeks (Pacific Rim Conservation, personal communication).

Real-time camera networks that incorporate AI image labeling can also be readily adapted to address other conservation needs that necessitate continuous monitoring and rapid response—for example, poaching, oil spill response, trespassing, incursions to predator exclosures, preventing human-wildlife conflict, and monitoring live traps. Even if real-time responses are not strictly required, these camera systems can increase efficiency of traditional species monitoring efforts—such as understanding endangered species distributions, habitat associations, and abundance over time.

Early detection of nonnative mammal incursions is a concern and priority shared by wider Channel Islands and California Islands land managers. Remote cameras deployed at docks for the National Park Service and concessionaire vessels demonstrated that rats, opossums, cats, and raccoons are present at key departure points to SCI. Thus, islands and portions of islands that experience high visitation could benefit from the implementation of networked camera traps like those described above to assist in the rapid detection of invasive mammals after unintentional introductions. In combination with a suite of other detection methods and a strong focus on mainland-based preventative measures (including education), networked biosecurity cameras that incorporate machine learning can improve the efficacy of early detection measures and should be considered part of any island biosecurity toolkit.

TABLE 5. A comparison of the advantages and disadvantages of various types of networked and non-networked camera traps.

Camera type	Equipment costs	Remote area suitability	Remote settings adjustment	Real-time data	Rugged terrain suitability	Autonomous nodes	Requires internet connection	Easily portable
SD card[a]	Low	Moderate	No	No	Moderate	Yes	No	Yes
Cellular[b]	Moderate	Low	Yes	Yes	High[e]	Yes	No	Yes
Radio-linked[c]	High	High	Yes	Yes	Moderate	No	Yes	No
Satellite[d]	Very high	High	Yes	Currently text only[f]	High	Yes	No	No

[a]Must be visited regularly to offload images.
[b]Recurring costs for cell plan; requires strong cell signal.
[c]Requires line-of-sight between nodes and internet connectivity at base station.
[d]Recurring costs for satellite link-up; often cannot send large files.
[e]Assuming strong cell signal.
[f]No images.

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