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FOREST PRODUCTS INNOVATION

Eagle Eye - Applying the Internet of Things to landscape scale Wedge-tailed eagle management

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Eagle Eye - Applying the Internet of Things to landscape scale Wedge-tailed eagle management

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by

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Executive Summary

This project examined the application of the Internet of Things (IoT) to the management of the endangered Tasmanian wedge tailed eagle (WTE) in a landscape shared with industrial forestry operations and electricity transmission infrastructure. Broadly, the IoT utilises sensors, communications networks and human interface systems to support efficient decision making.

An IoT approach to monitoring WTE nest activity has the potential to increase economic activity and animal welfare outcomes whilst reducing the worker safety concerns and costs that are associated with the current helicopter-based nest activity checking practices. To facilitate this, two different types of sensors, Passive Infrared (PIR) and Ultrasonic (US), were tested to identify which was the most effective, efficient, reliable and robust to detect nesting activity by WTEs. Data from these sensors was collected via a network of wireless Gateways (or Portals) using industry standard LoRa protocols, processed and stored in a cloud-based repository then reported through a web-browser based dashboard and corporate information systems (Microsoft's Power BI).

Success in this project would lead to information collected by an IoT solution that would enable forest and electricity network managers to make more timely and objectively informed management decisions around operations that may interact with WTEs, with improved productivity, reduced costs, increased safety and positive animal welfare outcomes, compared to the current regime.

The project identified that the PIR sensor provided the most informative data for WTE management and was successfully supported by the LoRa network deployed throughout the study landscape, and the web-browser based data dashboard, that could be accessed from anywhere with an internet connection to provide the information to support decision making. However, before operational deployment of this technology is considered, three issues need to be addressed. Firstly, the PIR sensor used was not completely reliable in its operation. However, it is expected that this can be addressed through refinement of the hardware and firmware. Secondly, the current satellite communications technology used to support LoRa networks lacks the required reliability and serviceability, so this limits the deployment of LoRa to those areas with mobile phone network coverage, where the technology was more reliable and effective. It is expected that in the near future, the satellite technology will improve in reliability, serviceability and costs, taking away the geographic constraint to deploying LoRa. Finally, the relevant regulators need to be satisfied that the installation and presence of the equipment has negligible impact on WTE breeding success. Whilst the initial findings in this project indicate negligible impact, further data collection on nest activity from nest trees with and without sensors will be needed to confidently determine if this is indeed the case. An economic analysis comparing the costs of the current airborne nest activity checking to an Eagle Eye IoT approach to nest activity monitoring indicated a strong financial case in favour of the Eagle Eye IoT approach.

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Introduction

Current management of Tasmanian wedge tailed eagles

The Tasmanian wedge-tailed eagle *Aquila audax fleayi* (WTE) is listed as endangered under state and federal legislation due to a low number of successful breeding pairs, loss and disturbance of breeding habitat, and high mortality due to persecution and human-related accidents (Gaffney & Mooney 1992; Mooney 1997; Mooney & Holdsworth 1991). WTEs are the second most disturbance sensitive (when breeding) raptor in Australia (Marchant & Higgins 1993).

Management prescriptions implemented via the Tasmanian forest practices system aim to reduce disturbance to nesting birds. Most known nests occur on Permanent Timber Production Zone Land and private property (Threatened Species Section 2006) and are thus in areas potentially subject to forestry activities (harvesting, transport, re-establishment, crop protection). Early research on the effects of forestry disturbance on eagle breeding success by Mooney & Holdsworth (1991) resulted in the adoption of a mandatory 10 ha minimum reserve around all known nests (Forest Practices Authority 2013). Subsequent monitoring found this was effective if additional operation exclusion zones (500 m and 1 km line-of-sight) were also applied during the breeding season (Mooney & Taylor 1996). Under the Tasmanian forest practices system, there are operational constraints applied to these exclusions zones from the 1st of July to the 31st of January inclusive, and extended to the end of February if breeding is running late. The sensitivity of breeding pairs to disturbance varies during the nesting season and peaks at the beginning of each critical phase of breeding (i.e. courting/nest lining, egg laying/ incubation, hatching and fledging) (Wiersma et al. 2015). This makes managing and maintaining WTE population challenging for land and infrastructure managers. An example of the potential impact exclusions zones can have on forestry operations and electricity transmission infrastructure management is shown in Figure 1.

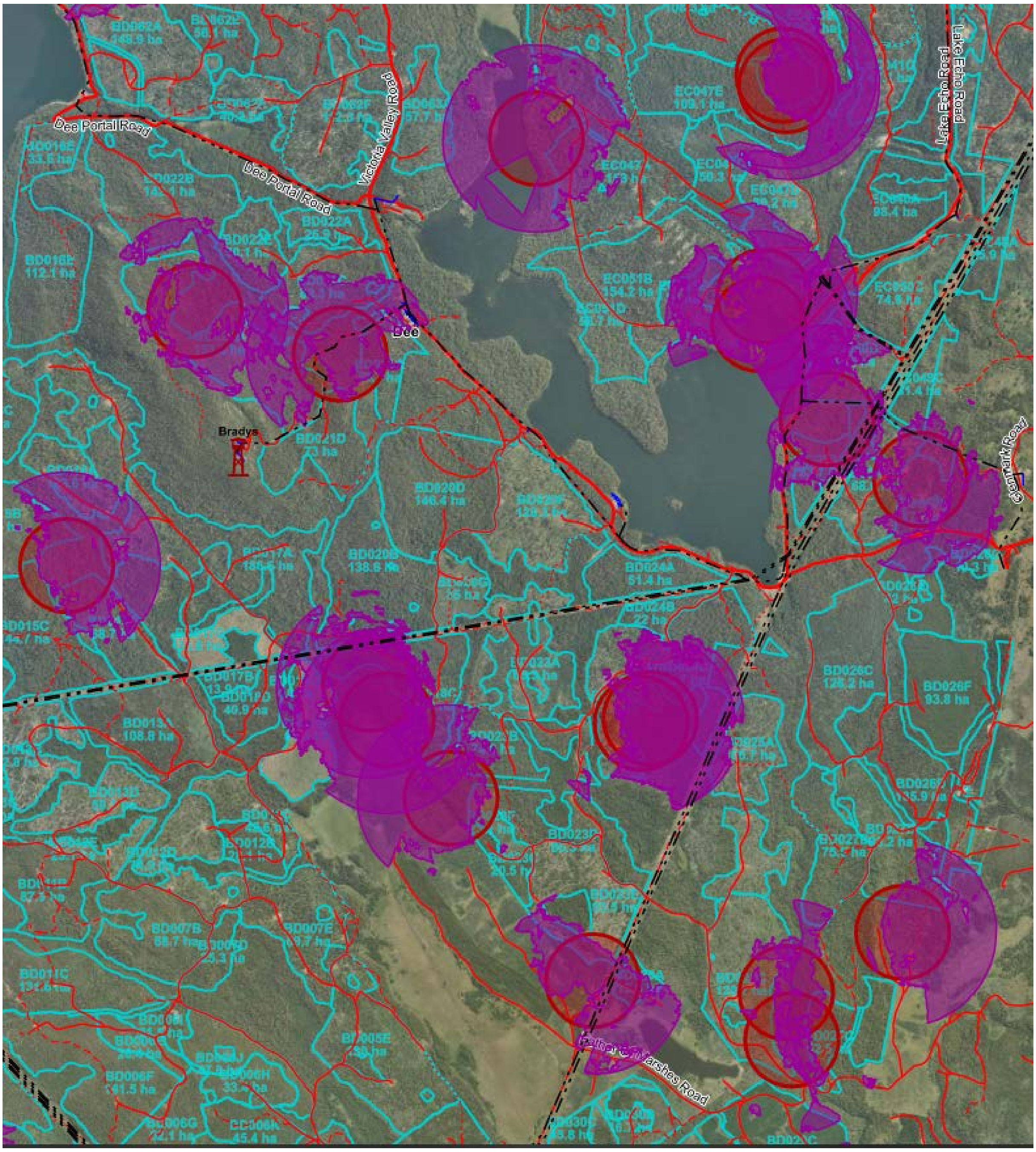

Figure 1: An aerial photo of a section of the study area used in this project showing the overlap between WTE breeding constraint period exclusion zones, commercial forestry areas, road and electricity infrastructure. The WTE nesting season exclusion zones are shown by red circles (500 m radius) and magenta patches (1 km line-of-sight). Operational forestry areas (provisional coupes) are shown with light-blue outlines, electricity transmission corridors are shown with dashed lines and roads are shown as red lines. The Bradys fire tower is shown as a point of reference.

The ‘activity’ of a nest refers to whether a breeding attempt is underway (e.g. presence of an incubating bird or a chick), and nest activity checks should only be carried out by those who have gained competency in eagle nest searching/activity checking. (Wiersma et al. 2015). The method selected to detect activity will depend on the forest type, the experience of searchers and resources available. The timing of checks should also consider the variability in timing of breeding that can occur between years and regions (Mooney and Taylor 1996). There are two main methods for checking the activity of a known nest, from the ground and from the air, (Wiersma et al. 2015) and these have different profiles of disturbance risk to nesting WTEs. Since nest activity checks are done during the breeding season it has been preferable that fixed-wing aircraft should be used in aerial checking as the noise associated with rotor-wing aircraft can impact on breeding eagles (Wiersma et al. 2015). Eagles can become aggressive during the breeding season and this has resulted in mid-air collisions with helicopters that were hovering near to a nest site (Wiersma et al. 2015). However, in late 2018 the Forest Practices Authority (FPA), on the advice of a workplace safety consultant, modified the approach to aerial checking from utilizing a single-engine fixed wing aircraft to trialing a helicopter operated a higher altitude. Whilst this has addressed immediate workplace concerns, and appears to have reduce direct interactions with WTEs, the safety of aerial checking remains a significant focus, and there are still potential animal welfare issues to be considered.

Direct measurable signs of nest activity commonly consider the presence of incubating adults or the production of a chick. There are two periods in the breeding season when such nest occupancy assessments can be conducted with minimal disturbance by trained individuals (Mooney and Holdsworth 1991). The first of these is the incubation period during September. However, determining whether an adult is incubating is difficult unless an egg is clearly visible, or adults are noted in an incubation pose over two weeks. The second period is during late October or early November, when chicks are about 4–6 weeks of age and are large enough that with their white down they can be clearly seen from an aircraft or from the ground with a telescope (Wiersma, et al. 2009). Experts consider this second period to be the preferred time for activity checking as results can be considered more confidently.

The forest practices operational exclusion zones (500 m or 1 km line-of-sight) for active nests are in place for 7 to 8 months (July – January/February) each year (the constraint period) to minimise the operational interactions with birds when they are most sensitive to disturbance. Based on the nest activity checks, if a nest is found to be inactive (no breeding activity), the operational constraints can be lifted 2 – 4 months early.

There are over 1900 WTE nests listed on Tasmania’s Natural Values Atlas, which is about six times more nests than there are breeding pairs. Across the state, it is estimated that there are approximately 800 nest sites that can affect forestry and power transmission management activities, or about 300 to 400 in any one year of operations (some nests affect operations almost annually, others less frequently), and all will have exclusion zones placed around them for a minimum of four months during the constraint period. However, as only around 15% of these nests are used for breeding each season, the prescriptions feature a substantial precautionary component, representing a substantial financial and logistical impost on forestry and power network management companies.

Internet of Things (IoT) technology

Rapid advances and improvements in telecommunications and satellite technologies, along with higher quality sensor devices combined with increased battery endurances, have broken down many of the cost and technology barriers that have previously made remote monitoring unreliable or cost prohibitive. The technology is rapidly becoming ‘main-stream’ when combined with cloud-based computing.

Growth in the deployment of IoT devices worldwide continues to grow rapidly. It is estimated that the number of devices deployed is expected to exceed 75 billion by 2025, compared to approximately 15 billion devices in 2015 (Statista 2019).

Being able to reliably collect data remotely requires a dependable power source. One of the biggest users of energy in a remote telemetry system is the communications equipment. A typical 4G modem can consume around 430mA while active and approximately 250mA in standby, with typical active periods for IP data transmission usually in excess of 15 seconds per data sending event (Maxon Australia 2019).

Technology such as LoRa have tackled the energy and cost aspects of remote sensing using a number of techniques. LoRa is a very low consumer of energy (Sanchez-Iborra & Cano 2017) minimising its draw on the battery through a variety of techniques without compromising on transmission range. A comparison of relative range and power consumption of different communication technologies is shown in Figure 2.

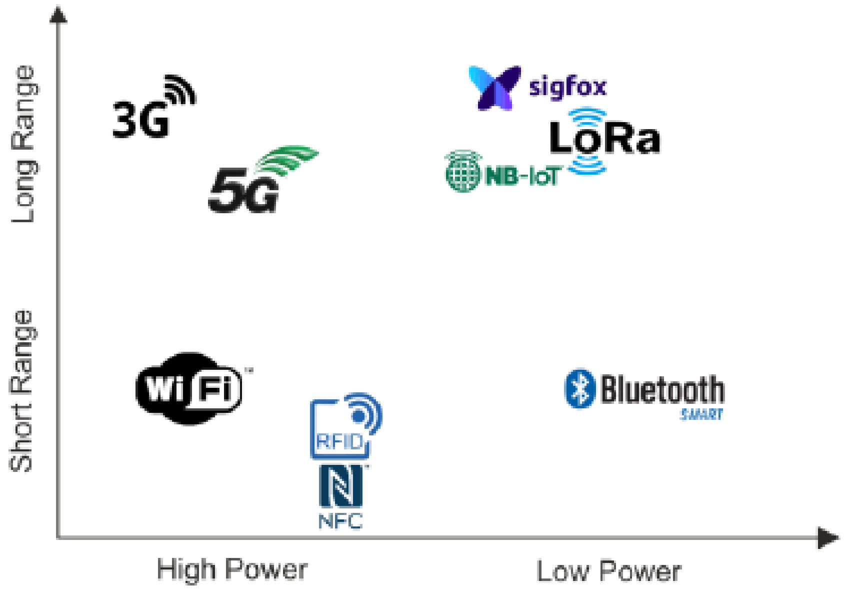

Figure 2: A comparison of relative range and power consumption by communication networks (from Meyer et al. 2019)

LoRa also side steps the usual licensing costs associated with purchasing a 3G/4G chip, which typically results in an artificially inflated hardware cost. A 4G modem module for direct embedding on hardware solutions costs around US$51.84 (DigiKey - UBlox Module 2019a) whilst a LoRa radio module costs around US$7.66. (DigiKey – LoRa Module 2019b) A typical unit cost for a LoRa based IoT sensing device is approximately $100 – the addition of 4G capability would increase the cost by nearly 50% alone.

As a result of these technological and communication advices, sensor devices are now far more compact, reliable and robust, with a communications range of around 6 to 18 km depending on environment and data-rate (Sanchez-Iborra et al. 2018). This makes them ideal for deployment into remote and difficult locations as they require minimal ongoing maintenance and human interaction post deployment. Further, there is a deep market for the development of customised and bespoke sensors, further reducing costs for the establishment of a remote sensor network.

The use of IoT for wildlife monitoring

Modern communications and sensor technologies are giving wildlife biologists unprecedented capability to monitor animal behaviour. Wilmers et al. (2015) describes how "bio-logging" can increase our understanding of wild animal physiology, behaviour and their habitat environmental conditions. Ayele et al. (2016) propose IoT communication system modifications to improve the effectiveness of IoT for monitoring of wildlife. Boulmaiz et al. (2016) looked at the deployment of bioacoustics IoT sensors to monitor bird populations in remote locations, whilst Sheng et al. (2019) also studied the application of IoT bioacoustics sensors for monitoring bird populations, with a particular focus on improving signal processing efficiencies to reduce device power consumption. Debauche et al. (2020) described the application of IoT in monitoring the success of using artificial nesting boxes for population recovery of birds. Gamboa-Soto (2021) proposes a model of making IoT biodiversity data globally available through cloud computing platforms making raw data easily accessible for wildlife researchers worldwide. Zualkernan et al. (2021) bring the focus of using IoT and Convolutional Neural Networks to monitor bats for conservation purposes and tracking bat-borne viruses such as Covid-19. Ojo et al. (2021) describe the application of IoT to manage the interaction of wild animals with viticulture, Figure 3. Michener & Jones (2012) proposed a model of ecoinformatics, where the vast amounts of IoT monitoring data can be processed and used meaningfully to support management decisions.

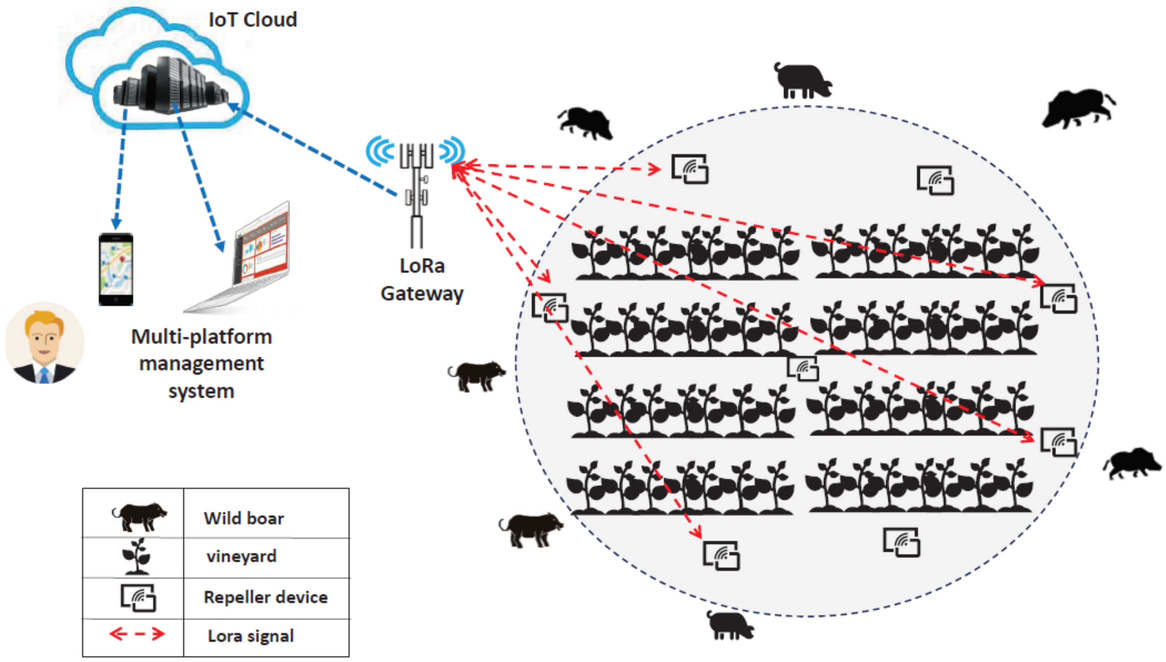

Figure 3: A schematic of an IoT system to monitor and manage wild animals (in this case wild boars in vineyards) from Ojo et al. 2021.

Objective of this project

This project set out to develop a real-world model of IoT use to monitor WTE nest activity and deliver information that would support multiple objective management decisions. To achieve this, required the development and field testing of candidate IoT capable sensors, the deployment of a LoRa network across a remote sample region of Tasmania and the development of data collection, storage, analysis and access tools within internet cloud-based infrastructure.

Methodology

Sensor and LoRaWAN development

To detect WTE nest activity, two candidate sensor types were identified. These were a Passive Infrared sensor (PIR) and an Ultrasonic rangefinder sensor (US). These sensors can in isolation detect environmental changes (activity) and have been used in concert to detect and classify moving objects with a high degree of accuracy (Odat et. al 2018). The PIR sensor is triggered by changes in thermal energy (infrared radiation) in its field of view (FoV). The PIR typically detects infrared radiation in the 8-14 um wavelengths which spans wavelengths emitted by animals and plants in sunlight (Welbourne et al. 2016). For this trial the OSD2-L Elenex PIR sensor was used. The specifications for this sensor are:

Sensing Range	0.3 – 7 m
Delay Time	0.3 – 18 sec
Sensing Element	Passive Infrared

The US sensor measures the time of the return flight of an ultrasonic pulse, typically above 18 KHz in frequency, between a transceiver in the sensor and the target, and uses the data to calculate distance (Klemen et al. 2015). In this case the target would be the surface of the nests or an eagle (or another animal) on the nest. They are effective over a range of several meters and can have an accuracy of less than 1 mm (Klemen et al. 2015) and can be programmed to take measurements at user selectable intervals. Birds typically have an upper threshold of sound detection of about 10 KHz and do not hear ultrasound (Beason 2004), so the frequency emitted by the US sensor was unlikely to be heard by the eagles. For this trial the US sensor chosen was the DUS2-L Ellenex, with the following specifications:

Range	5 m
Accuracy	+/- 1% span
Resolution	1 mm
Minimum Distance	20 cm
Stability	1 mm in 1 m (typical)

A LoRa node collects the sensor data and forwards it wirelessly to a Portal or Gateway. The node used in this project operated under the LoRa protocol (https://lora-alliance.org/about-lorawan/) and transmitted in the frequency range of 915 to 928 MHz. The node was programmed to transmit the sensor data at two-hourly intervals.

Sensors and node "packages" (See Figure 4) were designed and produced by Ellenex Pty Ltd (https://www.ellenex.com/), who assembled them using off-the-shelf components, housed in a single high-impact ABS, IP67 rated case, but with separate power supplies for sensors and the node. In each package the sensors were powered by a pair of 3.6V (for 7.2 volts in total) "AA" sized non-rechargeable high-capacity 2.6 AH Li-$SOCl_2$ batteries, whilst the node was powered by a single non-rechargeable 3.6 volt high-capacity 5.5AH lithium Li-$SOCl_2$ "C" cell battery. The 3dB antenna was mounted on the outside of the housing, along with a power button and mounting bracket to attach the housing to the tree. The housings were painted to minimise their visual impact which might have otherwise deterred nesting by WTEs (see Figure 5).

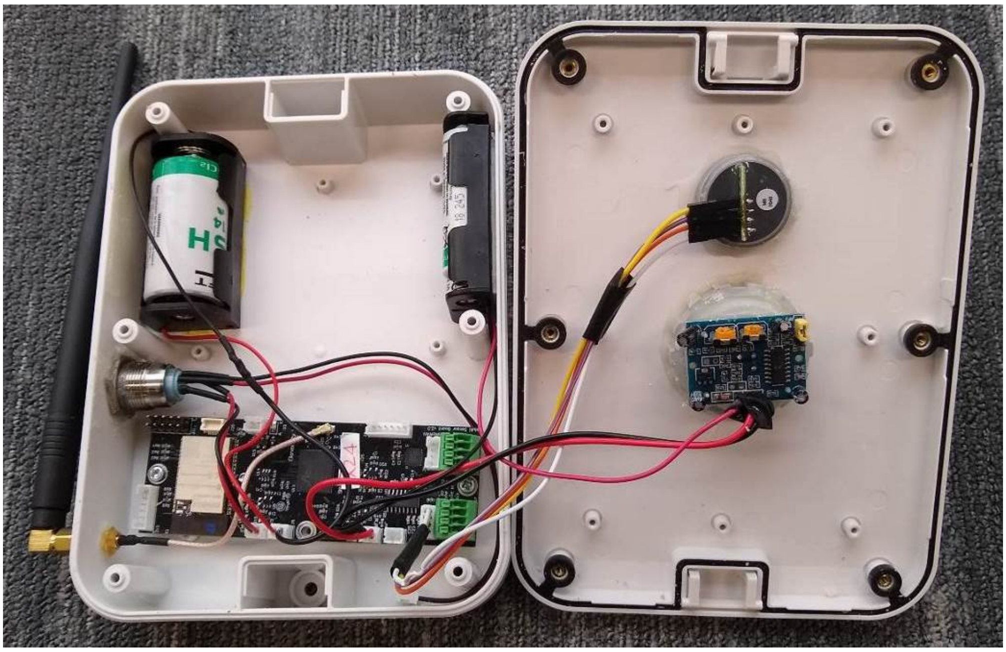

Figure 4: The arrangement of the sensor and node components and batteries inside the housing.

Figure 5: An example of the sensor and node package used in the project. The upper cone on the front of the housing leads to the PIR sensor lens, the lower cone surrounds the transceiver of the US sensor. The units were mounted to the tree so that the sensors aimed at the upper surface of the nest.

In the first nesting season (2019), to receive the signals from the nodes, Portals from Fleet Space Technologies (www.fleetspace.com) were initially selected (Figure 6). These Portals were enabled with satellite communications through the Iridium satellite network. The Portals act as an Edge Server and contain both a LoRa gateway and satellite modem (Fleet Space 2021). The Portals had the capacity to connect with up to 1000 sensors withing a notional 15 km range (equivalent to a coverage of just over 70,000 Ha) and were housed in an IP65 rated enclosure (Fleet Space 2021). The Portals were powered using 12-volt DC either by a transformer from a 240-volt power supply (where available) or a 12-volt lead acid battery supported with an 80-watt solar panel and charge regulator enclosed in a IP65 rated case. A few weeks after deployment, the 80-watt solar panels were replaced with 120-watt solar panels to provide additional charging capacity necessary to maintain battery charge. The Portals were fitted with -5dB antennas to receive signals from the nodes.

Figure 6: The Fleet Space Portal housed in a IP 65 rated enclosure. The satellite communicaiotns antenna is within the enclosure.

For the second nesting season (2020) the Fleet Space Portals were replaced with Definium Nexus 8 LTE Gateways (Figure 7) due to poor service and reliability of the Portals. The Gateways used the same power sources, housings and operated on the same LoRa communications protocols, but were fitted with SIM cards to operate on the Telstra mobile phone network. The original 5db antennas were used for LoRa coverage, except at Bradys which was fitted with a 3dB as this performed better than the 5dB antenna at this site.

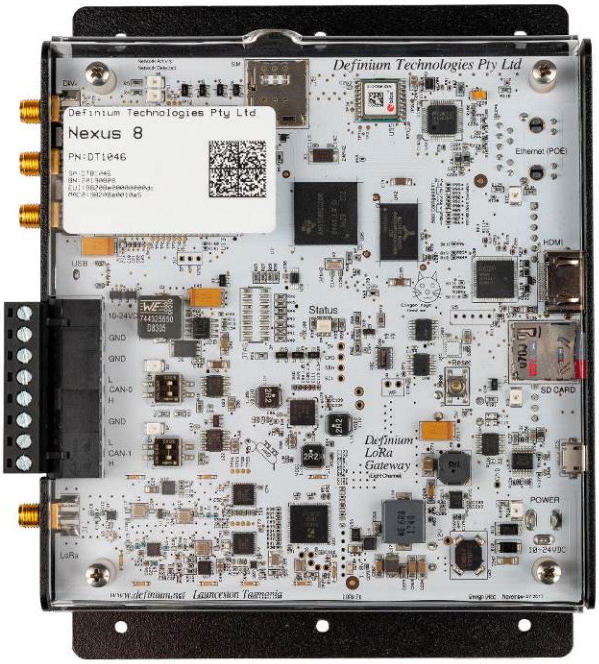

Figure 7: A Definium Nexus 8 LTE enabled LoRa gateway.

Identification of suitable study nests

For this study, 16 WTE nests trees were to be fitted with the sensor and node packages (Table 1). A candidate list of approximately 40 nest trees located in the southern central highlands of Tasmania (see Figure 8) was provided by STT staff with experience in managing WTEs in the region. This region of Tasmania was selected as it covered areas where there were forest operations and electricity infrastructure, as well as being within reasonable daily travel distance to Hobart for field work. It was also expected that the hilly topography and extreme weather conditions, with mean minimum temperature of July (the coldest month) of just, 0.4 deg C, and a mean annual rainfall of 1167 mm at nearby Tarraleah (BoM), would also provide an environmental challenge to the functioning of the technology. The candidate nests trees were selected based on having good nesting activity histories indicating a high likelihood of them being used for nesting in the study period. From this list of candidate nest trees, the 16 trees to be fitted with sensors were selected (see Table 1) based on ease of accessibility on foot, suitability for climbing to install the sensor packages, and condition of the nest (see Figure 9 for their locations). These nests were spread over an area of approximately 110,000 hectares. To provide a control sample to examine if there was an impact on nest selection by the WTEs due to the installation and presence of the sensors, a random sample of 16 nest trees were selected (see Table 1) from the remaining candidate tree set (see Figure 10 for their locations).

Table 1: Nests used in the project with sensor and camera IDs where used.

Nest fitted with sensors and cameras			Control nests (no sensors or cameras)
Nest ID*	Sensor Pack ID	Camera ID	Nest ID*
1374	20051	6	504
1406	2010F	21	739
1499	2004E	5	897
1608	20055	2	1013
1700	2011D	NA	1504
1897	200F7	NA	1564
1904	20054	1	1804
1958	2010C	3	1877
2242	20053	NA	1899
2340	2001D	4	1943
2443	2010E	20	2103
2444	200F6	NA	2119
2496	200F8	NA	2230
2550	2004D	NA	2235
2686	2010D	NA	2243
2696	2011C	NA	2244

*Nest ID is the nest identifier from the Natural Values Atlas (DPIPWE)

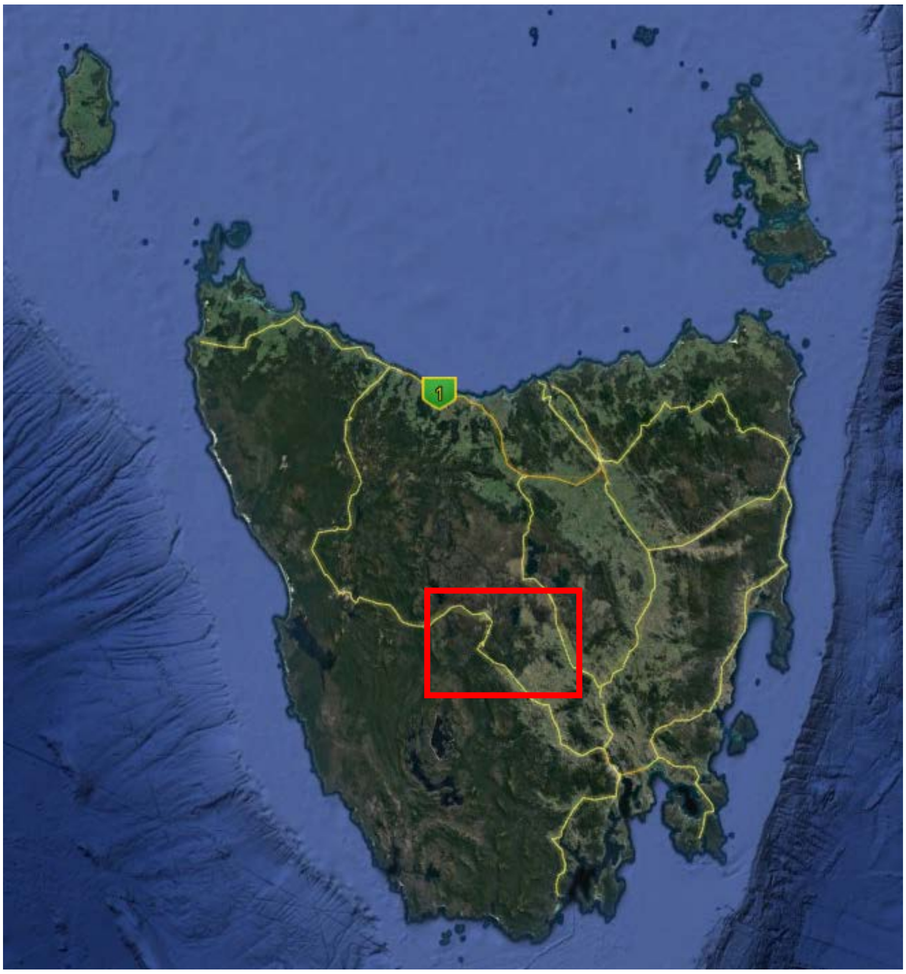

Figure 8: The study area was located within the red rectangle indicated in the figure (image from Google Earth)

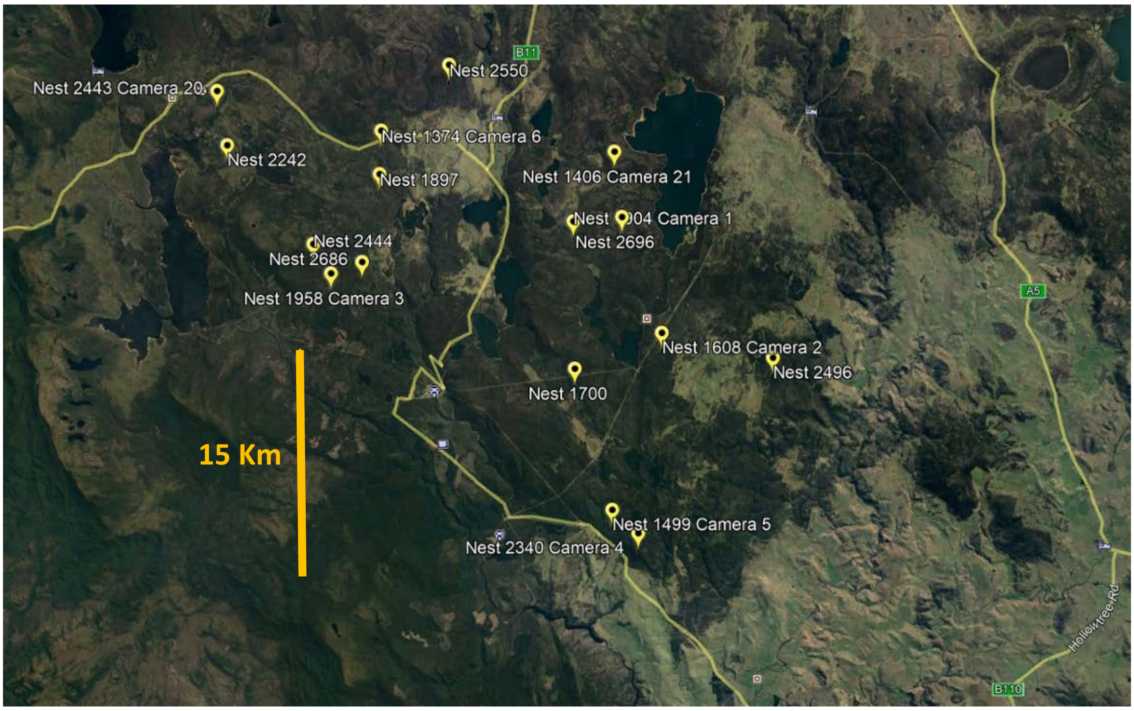

Figure 9: Location of nests trees in the study area (yellow markers) that were fitted with sensors and cameras in 2020. The orange bar represents a distance of 15 Km for scale. (image from Google Earth)

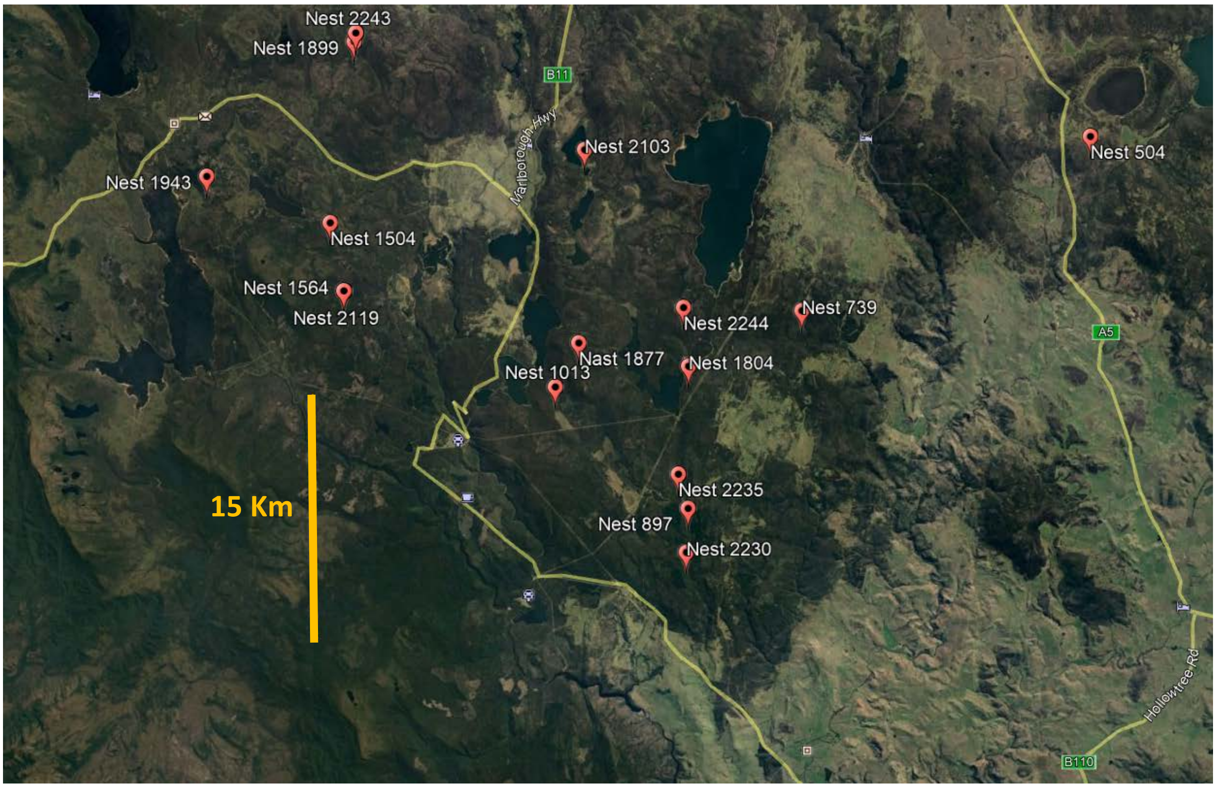

Figure 10: Location of the study control nest trees (red markers). The orange bar represens a distance of 15 Km for scale (image from Google Earth).

Installation of sensors, cameras, Portals and Gateways

Before any fieldwork was conducted, approval to carry out the work was sought from the Tasmanian Department of Primary Industries, Parks, Water and Environment Animal Ethics Committee. The Committee reviewed the project's objectives and methods and issued the Approval Certificate 19/2018-19.

To install the sensors on the nest trees, an experience tree climber was contracted. All visits to the nest trees were done in April to June, outside the constraint period. The tree climber used ropes to climb up to the nests and attached a mounting bracket to the tree trunk or a branch approximately 2.3 m above the nest bowl, using 100 mm screws (Figure 11). The location on the stem or branch that the bracket was attached to was determined by the direction of the nearest Portal/Gateway so there was a clear as possible signal path from the node antenna, ie the path was not immediately blocked by the stem(s) of the tree. The sensor housing was then attached to the bracket with a ball mount. The ball mount allowed enough articulation so that the sensors could be aimed directly at the nest bowl. The sensors were powered up and the connection to the nearest Portal/Gateway was confirmed before leaving the site.

Figure 11: The sensors and cameras were installed by climbing the nest tree and securing them to the tree trunk above then nest with brackets featuring ball joints so the devices could be aimed directly down at the nest bowl.

Wireless video cameras were also installed on a sub-set of trees with the sensors (Table 1). These video cameras were used as a source of data to help confirm the type of activity detected by the sensors (eg, WTEs, other animals, moving foliage or shadows) and to monitor the physical condition of the sensors. The video cameras used were Arlo Go Wireless Security Cameras https://www.arlo.com/en-us/cameras/go/VML4030-200NAS.html, which are weatherproof (IP65), movement activated (by their own PIR), battery powered with solar recharging and transmitted video (with sound) over the Telstra mobile phone network. Coverage by the Telstra mobile phone network determined which nest trees were selected to be fitted with the cameras. The cameras were set-up to record a 10 second video clip when triggered within the times of 9 am and 4 pm daily (to preserve battery capacity). The cameras were attached to the trees approximately 1 m above the sensors (see Figure 12) so the sensor and the nest were fully within the camera's FoV (see Figure 13).

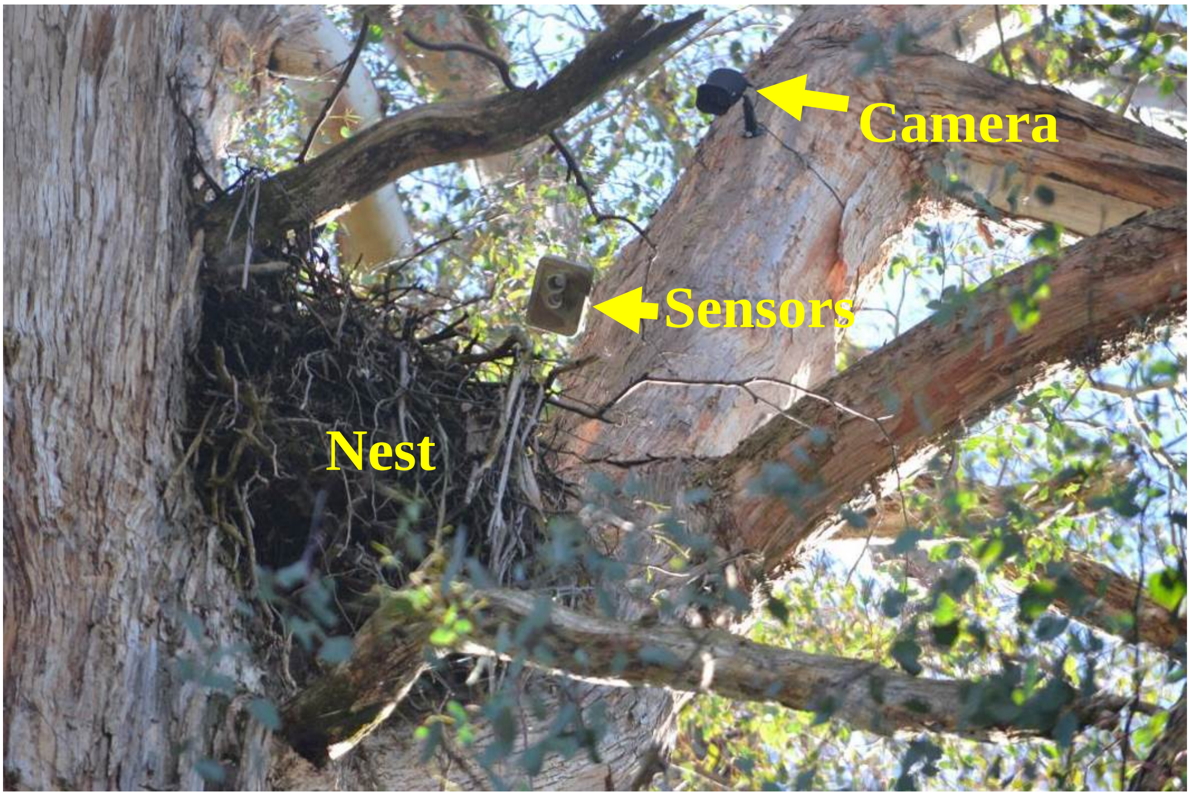

Figure 12: An example of the relative mounting positions of the cameras (where fitted) and sensors above the nest bowl.

Figure 13: An example of the field of view of the video cameras which includes the sensor and nest

The types of Portals and Gateways, and the dates they were installed at each location is shown in Figure 14 is listed in Table 2. When the Derwent Bridge Portal was replaced with a Gateway the installation was moved a few hundred meters to the top of a hill to access the Telstra mobile phone network. At Bradys, the Portal and the Gateway that replaced it, was mounted on the STT fire tower and powered from the tower's 240-volt mains supply (see Figure 15). At all other sites, the Portals/Gateways were suppled power from a 12-volt battery, which was recharged from a 120-watt solar panel (Figure 16).

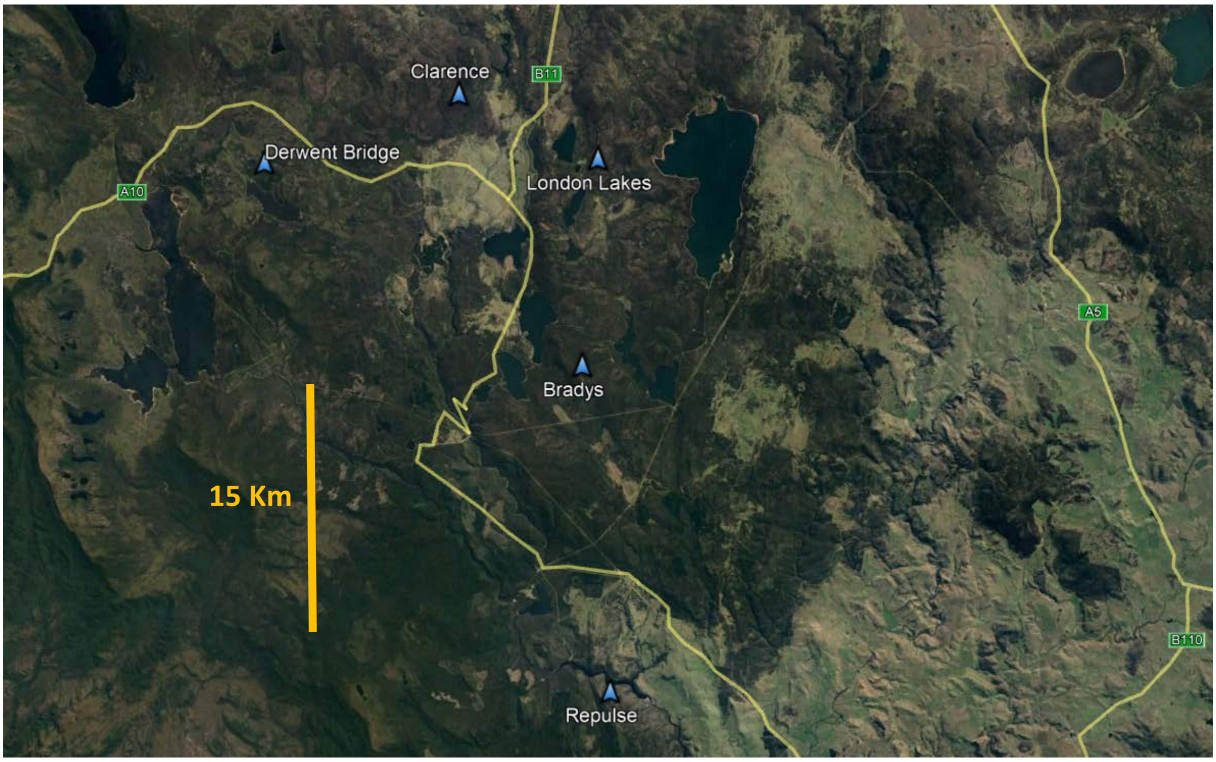

Figure 14: The locaiton of the Portals/Gateways in the study area (Blue markers). The orange bar represents a distance of 15 Km for scale.

Table 2: Dates the Portals/Gateways were installed at each site

Site	Date Fleet Space Portal installed	Date Definium Gateway installed
Bradys	May 2019	March 2020
Repulse	May 2019	March 2020
Derwent Bridge	May 2020	October 2020
Clarence	NA	April 2020
London Lakes	NA	September 2020

For the first nesting season of this project (2019), only seven nest trees were fitted with sensors, with six of these also fitted with the video cameras, before the nesting season constraint period came into place on July 1st. In the second season (2020), sensors were fitted to all 16 candidate trees (including replacing the seven sensors deployed in 2019) and two additional cameras (for a total of eight) were installed over the period April to June 2020. All 16 sensor packages installed in 2020 had been upgraded to correct a firmware bug which had caused a loss of contact between the seven sensors (nodes) deployed in 2019 and the Fleet Space Portals.

Figure 15: A Gateway installed on a fire tower and powered from 240 volts via a transformer.


Figure 16: A field deployed stand-alone Gateway (London Lakes) with solar and battery power supply.

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Data management

Data transfer and storage

The cloud-based infrastructure was based on IoT reference architecture from Microsoft. This ensured a scalable and reliable platform could be setup for storing and analysing the data to identify the data signatures of nesting WTEs. The communications network for the trial initially used satellite communication linkages from Fleet Space (www.fleet.space) to retrieve data from the remote locations while LoRa was used to traverse the "last mile" to the node device itself

The two-hourly sensor data packages transmitted by the nodes and collected by the Fleet Space Portals were stored on the Portal then transferred to an overhead satellite as a package every few hours and collated in the Fleet Space Nebula database. From the Fleet Space Nebula database, the data were transferred to the INDICIUM DataBus and then transferred to Microsoft Azure data storage tables. Following the replacement of the Fleet Space Portals with Definium Gateways, the sensor data collected by the Gateways were transferred to the INDICIUM DataBus (and then the Azure data storage tables) via a LOIROT network server (see Figure 17). The data collected for the PIR and US sensors were the hit counts and distance respectively.

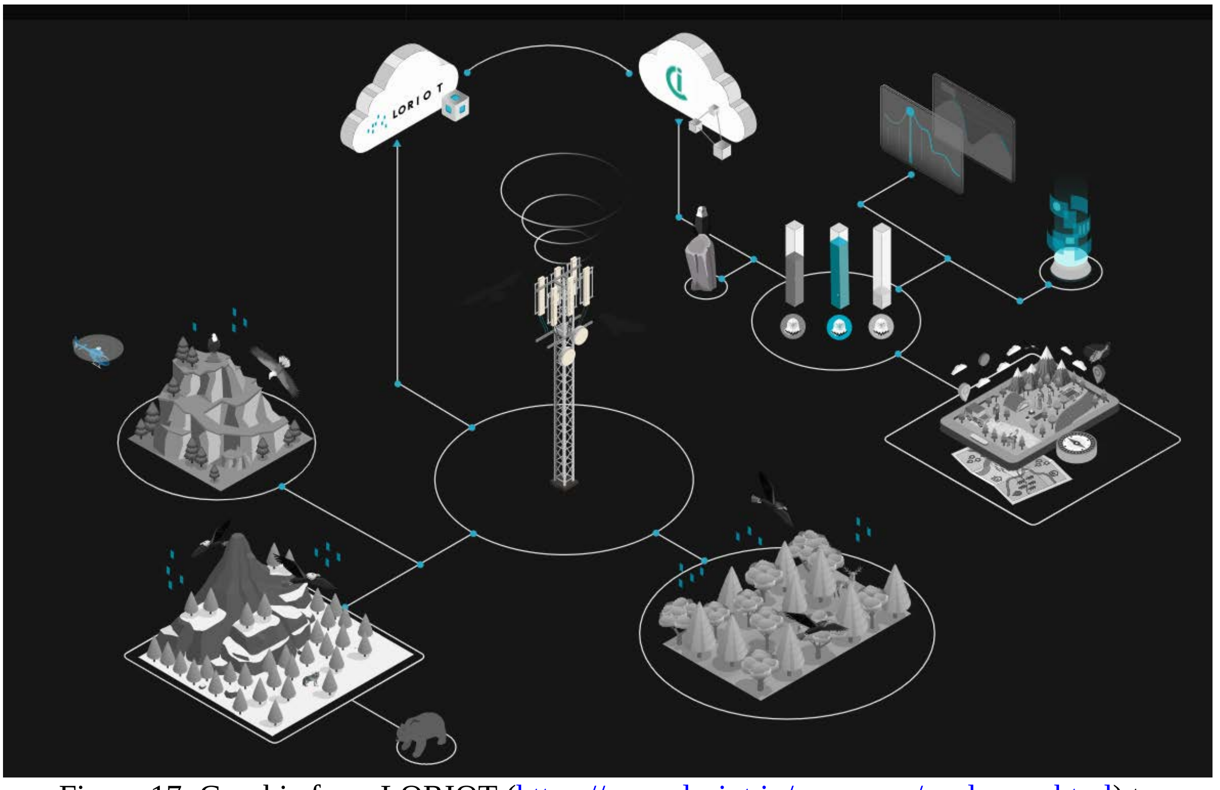

Figure 17: Graphic from LORIOT (https://www.loriot.io/use-cases/eagle-eye.html) to illustrate the LoRa IoT network.

The data collected for each sensor/node package were time stamped for UTC and the node's unique hexadecimal ID code. The PIR sensor data were representative of the number of registered movements detected (hits) within its FoV with totals accumulated over time. This accumulation was done to reduce the chance of data loss if a data package was not received by the Portal/Gateway. The hit count was decumulated in the Azure environment to provide the actual count figure for the number of hits between each received transmission of data. The US data were representative of the distance (in cm) measured once in the preceding two-hour period.

Video clips from the cameras were stored on the Arlo server web portal and could be downloaded on an *ad hoc* basis for a period of 30 days then deleted by Arlo. A custom API was written to retrieve the video files from the Arlo web portal and store them in Azure Storage Blobs. This both archived the files for longer periods, but also allowed for direct integration into dashboard reporting.

Live data display

The decumulated PIR hit data and US distance data was made available on a web browser dashboard (INDICIUM Cloud) covering a period of the preceding 14 days. The data was presented in graphical format representing the number of hits from the PIR and distance readings for the US sensor (Figure 18).

A Microsoft Power BI based GUI was also developed to provide a “heat map” of nest activity (from the PIR sensors) across the study region accessible from within the STT business system (Figure 19).

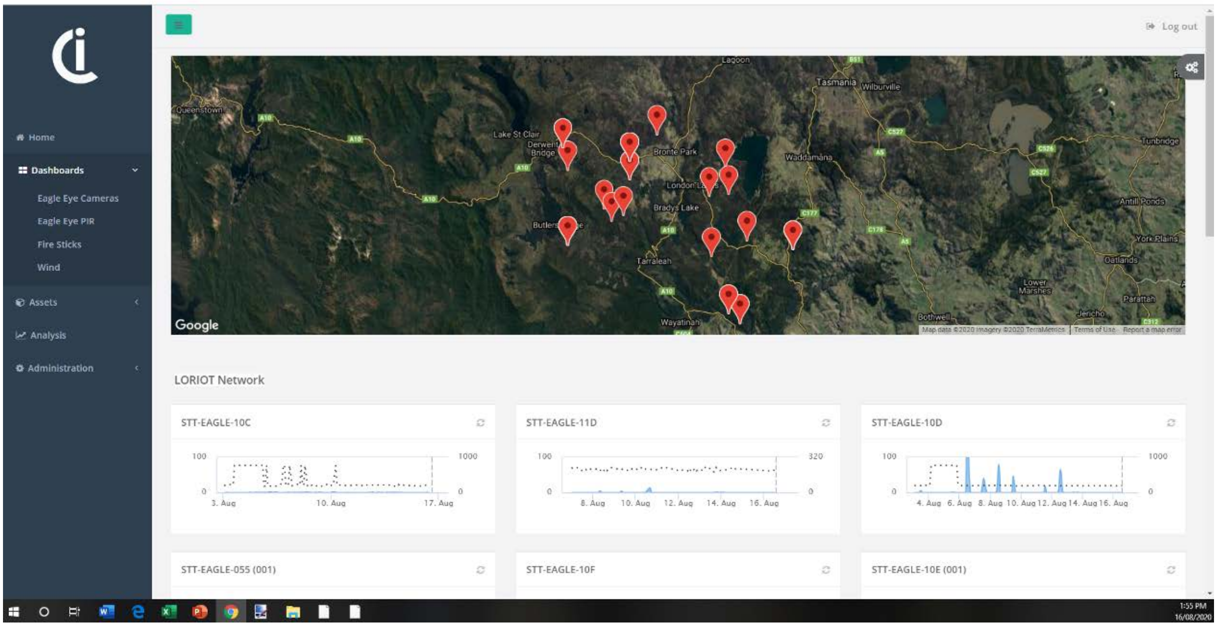

Figure 18: A screen shot of the INDICIUM Cloud Eagle Eye web-browser based dashboard. At the top is a map showing the location of the nest with sensors. Below this is a graphical representation of the sensor data coming from each nest (only 3 nests are shown). In the graphs, the dotted lines are US distance measurements, the blue spikes are PIR hit records.

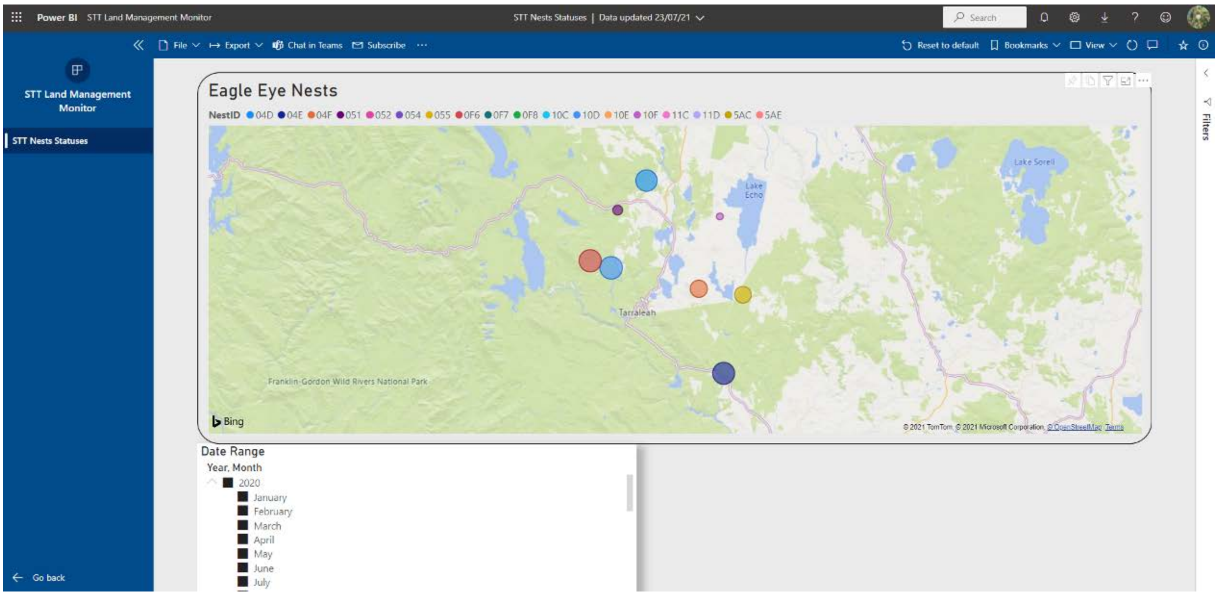

Figure 19: A MS Power BI report of the PIR readings for each nest are shown on a map as colored circles. The bigger the circle, the greater the level of activity detected.

Nest activity verification

The 32 project nests (the nests with sensors and controls nests) were included in the annual forest industry nest activity checking program for 2020. The project nests were inspected for breeding activity by a skilled observer in a helicopter, between the 19th and 22nd of October 2020. Nests were classified as either Active, Not Active or Manage as Active. The classification of Manage as Active indicates that the nest could not be found or clearly observed so as a precaution its status (and management constraints) were set the same as an Active nest.

Data analysis and presentation

Only a few weeks of data were available for the 2019 nesting season from the seven sensors deployed, so these data were not used for analysis or reporting. This was due to issues with hardware and firmware which prevented the data being collected.

For the 2020 nesting season, the data for each PIR and US sensor was downloaded from the Indicium MS Azure storage table as an MS Excel comma delimited file (.csv). The date range used for analysis and reporting was from the 16th of June 2020 to the 28th of February 2021 (39 weeks) to cover the full (extended) official WTE management constraint period of 37 weeks, and the preceding two weeks for range calibration purposes of the US sensor.

The data was checked for missingness and obvious outliers. Where the data from the sensors had large gaps (equivalent to months of data) or was missing entirely, these sensors were excluded from the analysis. The obvious outliers in the data were also excluded. This data cleaning meant that data for 11 PIR sensors and 13 US sensors was carried forward into the analysis.

For the data from each US sensor, weekly means and standard errors for the change in distance between the sensor and the nest surface were calculated. This was done by firstly determining the baseline distance from each sensor to the surface of their respective nests as being the mean of the US sensor measurements taken in the last 14 days of June 2020. For each nest, all US distance readings for the 37-week constraint period (July 1st to February 28th) were then subtracted from their respective baselines to indicate the absolute change in distance (in cm) from the sensor to the target (nest or bird). This meant that a positive change in distance represented a decrease in the distance from the US sensor to the target, whilst a negative value for the change in distance represented an increase in the distance from the US sensor to the target.

A Mann-Kendall Test (Mann 1945, Kendall 1955) conducted in MS Excel for each valid US sensor dataset (n=13) was used to determine the direction and significance of the trend in the weekly mean data to a significance level of 5% ($p<0.05$). A significant positive trend would indicate the target surface had gotten closer to the sensor, potentially indicating nest occupancy as the US pulses would be bouncing off the bird sitting or standing on the nest and the longer the bird was on the nest, the more often the pulses would be from the bird rather than the nest surface. A significant negative trend would indicate the target surface had gotten further away, potentially due to a lack of nest maintenance and collapse of a vacant nest.

For the PIR data, weekly means and standard errors for each sensor were calculated for the 37-week extended constraint period (July 1st 2020 to February 28th 2021). The PIR readings on nest 2686 (sensor 2010D) were consistently higher than the other sensors, likely due to the sensitivity being set to a higher level on that sensor. The raw sensor readings for all the other sensors were transformed prior to analysis by multiplying them by three to put them on a comparable scale to 2010D.

For the purposes of the analysis, Nest Activity was based on a combination of airborne checks and camera data. However, in the case of nest 2550, which was Manage as Active due to an obscured view in the airborne check, the PIR sensor data profile was characteristic of the other active nests, so it was classed as Active.

For each weekly dataset of Nest Activity x Sensor type, a W-test for normality of the residuals was performed in Genstat (20th Ed.) with a p-level greater than 0.05 indicating the residuals were normally distributed. If the normality test p-level was between 0.05 and 0.1, the data could be accepted with some caution. The normality tests of the PIR data was initially done on the data from the 11 nests with acceptable PIR data. The normality of the residuals of the data for the Not Active nests was particularly poor from week 13 onwards. The data for the two nests that appeared to give false-positive PIR signals (Nests 1499 and 2444) were excluded, and a second test for normality of residuals on the reduced dataset (n=5) was performed. This greatly improved the normality of the residuals so the PIR dataset used in the ANOVA excluded these two nests.

Two of the Active nests either failed (Nest 1608 as seen on camera) or appeared to fail (Nest 2696 displayed same PIR sensor output pattern as Nest 1608) about Week 17. Despite this, their full PIR data sets were included in the analysis, as dropping it out would leave data for only two Active nests in the analysis and this was considered to be too small a sample size.

To find if there was a significant difference between the sensor data received from the Active nests compared to the Not Active nests, as determined by the airborne nest activity check and camera data, a 1-way ANOVA was undertaken. The Analysis of Variance function in Genstat (20th Ed.) was used for the PIR data whilst the Unbalanced ANOVA function in Genstst (20th Ed) was used for the US data as there was a large imbalance in the US data for Active (n=4) and Not Active (n=9) nests. These functions were fitted to the weekly sensor means using the model:

$y_{(w1\text{-}w37)} = mean + act + e$

Where:

$y_{(w1\text{-}w37)}$ = the weekly sensor data means for the 37 weeks of the extended nesting season

mean = the mean of the sensor readings for each nest activity status (Active, Not Active)

act = the nest status from the aerial checks (either Active or Not Active)* and was set a fixed treatment term

e = the error term

*note, Nest ID 2550 was recorded as Manage as Active from the aerial observations due to poor view of the nest. The pattern of the PIR signal recorded for this nest was consistent with other active nests so its data was included in the Active category for nest activity data analysis. Nest ID 1374 was recorded as Active from the aerial observations, however no nesting activity was seen on the installed camera, so this nest was classed as Not Active for the data analysis.

Economic analysis comparing nest activity checks by aircraft to using sensors for monitoring nest activity.

To further inform considerations on the viability of a proposed IoT approach to WTE management, an economic analysis of the current approach of airborne nest activity checks vs remote sensing through IoT was undertaken. This analysis used assumptions based on parameters from the current study as well as information from the Tasmanian forest industry and WTE management experts.

The current airborne WTE nest activity checking method being trialled uses a highly experienced observer to fly low over the forest in a helicopter to position themselves close enough to view nest activity. The nest is typically checked only once in a nesting season rather than being continuously monitored as can be done with IoT sensors. Once the nest has been recorded as Active, it continues to be managed as such, even if it subsequently fails. In addition, there is a chance of the nest not being able to be located or clearly viewed from the helicopter, in which case it will continue to be managed as Active regardless of its actual status.

The results of the trial indicate that detecting WTE activity in ‘real time’ using sensors, helps reduce instances of nests either not being able to be clearly observed for activity (5 out of the 32 project nests), or not being recorded as failed after the airborne checks has been carried (2 recorded as failed out of 5 Active nests with sensors).

The key implication of managing an inactive nest (ie. an inactive nest classed as Manage as Active or classed as Active but failed post inspection) as Active is the constraint on harvesting and transport over a period from October to January (inclusive) or February in late seasons is unnecessarily applied. In some instances, in addition to a delayed harvest, it would also imply re-routing forestry transport and potentially constructing a new road.

Cost-effectiveness approach has been adopted for the purposes of this assessment. The analysis was carried out in nominal prices using a CPI of 2% (RBA long-term average). Cost profiles of both current and proposed IoT methods were modelled over a ten-year period, which was determined by the life expectancy of the sensor and Gateway hardware. Present value (PV)[1] of each method was determined using a discount rate of 8.5%.

For the airborne activity checking, all costs were annualised based on the given 2021 cost figures. For the Eagle Eye IoT method, the costs of the hardware, it's set-up and installation were applied in the first year, with costs associated with network subscriptions, data cloud hosting and web interface maintenance annualised.

For each year, the costs of the un-necessary operational constraints applied to nests that had failed post airborne inspection or were 'Not Active', but classed as 'Manage as Active' were included in the airborne check scenario model only.

Specifically, the key modelled economic impacts of unnecessary constraints were:

- The delay of harvesting quantified by accounting for the Time Value of Money (TVM)[2]. For instance, 4-month delay in harvesting activity (see Appendix A for detailed assumptions) amounts to approximately $90k in lost revenue in present value terms.
- Re-routing forest product transport to less direct (longer and more time consuming) routes. Cost of rerouting was calculated using the average extra distance obtained from the Wedge-Tailed Eagle Costing tool and the costs of travelling this distance estimated in terms of fuel and labour.
- Construction of new roads to accommodate re-routing.

Whilst it is impossible to accurately predict how often re-routing (the cost of extra travel distance) or new road construction would occur, based on expert advice, it was conservatively assumed that a new road would be required in 1% and re-routing would occur in 10% of all cases where the nesting season constraints impact harvesting.

For the state-wide (all of affected industry) WTE monitoring program, it has been assumed that a total of 1000 PIR only sensors (fully refined and calibrated to improve reliability and eliminate false-positives) would be required for a total of 800 nests (allowing for a 25% replacement rate of faulty sensors/nodes). It also assumes Gateway deployment is not constrained by mobile phone network coverage. See Appendix A for a detailed breakdown of cost assumptions used in the model.

[1] Present Value (PV) is the current value of future cash flows given a specified rate of return.
[2] The time value of money (TVM) is the concept that a sum of money is worth more now than the same sum will be at a future date due to its earnings potential in the interim. The time value of money is also referred to as present discounted value.

Results

The results presented in this section are only for the 2020 nesting season (July 1st 2020 to February 28th 2021).

Aerial nest activity checks

The results of the airborne nest activity checks are shown in Table 3 and a summary in Table 4.

Table 3: The results from the standard forest industry airborne checks for nest activity status carried out between October 19th and 22nd (week 17 of the constraint period) on the set of study nests.

Nests with sensors		**Control nests**	
Nest ID	**Activity status**	**Nest ID**	**Activity status**
1374	Active*	504	Not Found - Manage as Active
1406	Active	739	Active
1499	Not Active	897	Not found - Manage as Active
1608	Active	1013	Not Active
1700	Not Active	1504	Not Found - Manage as Active
1897	Not Active	1564	Not Active
1904	Not Active	1804	Not Found - Manage as Active
1958	Not Active	1877	Active
2242	Active	1899	Not Active
2340	Not Active	1943	Not Active
2443	Not Active	2103	Not Active
2444	Not Active	2119	Not Active
2496	Not Active	2230	Not Active
2550	Poor view - Manage as Active	2235	Not Active
2686	Active	2243	Active
2696	Active	2244	Not Active

*Whilst nest 1374 was recorded in the aerial check as being Active, no activity was seen on the installed video camera, indicating a false positive from the airborne check. A similar false positive was also recorded from the airborne check in the 2019 season, as there was no activity seen on the camera on the nest (data not shown).

Table 4: A summary of the aerial nest check results for the project nests cross checked with video camera data

	Confirmed		**Unknown or conflicts**
	Active	**Not Active**	
Sensor nests	5	9	2 (1 poor view – Manage as Active & 1 false positive – Manage as Active)
Control nests	4	8	4 (all not found – Manage as Active)

Sensor data collection

A summary of the sensor data collection is presented in Table 5 for the US sensors and Table 6 for the PIR sensors

Table 5: A summary of the data quality collected by the US sensors

Nest ID	Sensor Pack ID	US data used in analysis	Comment on data quality
1374	20051	Y	Good data
1406	2010F	N	Only late season data available* – not used
1499	2004E	Y	Good data
1608	20055	Y	Good data
1700	2011D	Y	Good data
1897	200F7	Y	Good data
1904	20054	Y	Good data
1958	2010C	Y	Good data
2242	20053	N	No sensor data collected, possible sensor fault
2340	2001D	N	No data collected from node
2443	2010E	Y	Good data
2444	200F6	Y	Good data
2496	200F8	Y	Good data
2550	2004D	Y	Good data
2686	2010D	Y	Good data
2696	2011C	Y	Good data

*The signal reception from this nest was poor in the early part of the season and was rectified mid-season by the installation of a Gateway nearby.

Table 6: A summary of the data quality collected by the PIR sensors

Nest ID	Sensor Pack ID	PIR data used in analysis	Comment on data quality
1374	20051	N	Very high readings in early months, possible sensor fault
1406	2010F	N	No data collected by sensor, possible sensor fault
1499	2004E	Y	Good data (but false positive by sensor)
1608	20055	Y	Good data
1700	2011D	Y	Good data
1897	200F7	Y	Good data
1904	20054	N	No data collected by sensor, possible sensor fault
1958	2010C	Y	Good data
2242	20053	N	Only late season data available*
2340	2001D	N	No data collected from node
2443	2010E	Y	Good data
2444	200F6	Y	Good data (but false positive by sensor)
2496	200F8	Y	Good data
2550	2004D	Y	Good data
2686	2010D	Y	Good data
2696	2011C	Y	Good data

*The late season data only became available when the Fleet Space Portal was replaced with a Definium Gateway.

From Tables 5 and 6 it can be seen that there was data available for analysis from 13 US sensors and 11 PIR sensors.

Sensor data analysis

As stated previously, for the purposes of the data analysis, Nest Activity was based on a combination of airborne checks, camera data and in one case, sensor signal profile in the absence of any other information. Nest 1374 was classed as Not Active for the analysis based on camera data and the case of nest 2550, which was Manage as Active due to an obscured view in the airborne check (and no camera data), the PIR sensor data profile was characteristic of the other active nests so it was classed as Active.

A summary of the Mann-Kendall analysis for trends in the US data is presented in Table 7, whilst the results of the 1-way ANOVA on the US weekly grand mean data is shown in Figure 20, and the summary of the W-test for normality of the residuals of the US grand mean data is shown in Appendix B.

Table 7: Results from the Mann-Kendall test for data trends in the US data

Nest ID	Sensor Pack ID	Nest Active	MK-stat	p-value for trend	Trend significant (p<0.05)	Direction of trend*
1374	20051	No	129	p=0.081	No	Nil
1499	2004E	No	-150	p=0.034	Yes	Negative
1608	20055	Yes	-10	p=0.906	No	Nil
1700	2011D	No	-138	p=0.073	No	Nil
1897	200F7	No	-110	p=0.153	No	Nil
1904	20054	No	-384	p<0.001	Yes	Negative
1958	2010C	No	-268	p<0.001	Yes	Negative
2443	2010E	No	90	p=0.244	No	Nil
2444	200F6	No	230	p=0.002	Yes	Positive
2496	200F8	No	-134	p=0.082	No	Nil
2550	2004D	Yes	-148	p=0.055	No	Nil
2686	2010D	Yes	-40	p=0.610	No	Nil
2696	2011C	Yes	-224	p=0.004	Yes	Negative

*A positive trend indicates the target is getting closer to the sensor, a negative trend indicates the target is getting further from the sensor.

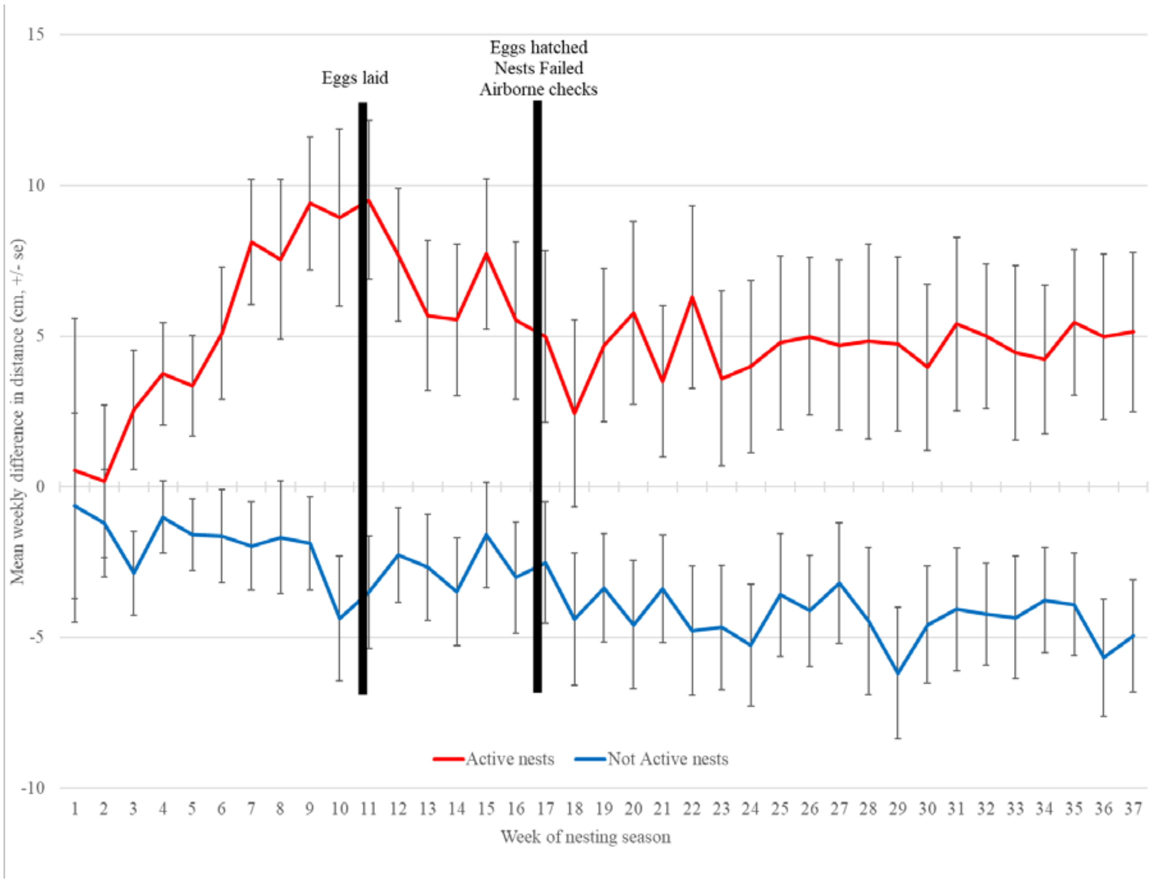

Figure 20: Weekly grand means with standard errors of the weekly difference in distance for the US data for the 37 weeks of the 2020 nesting season operational constraint period (Starting 1st June 2020) for Active and Not Active nests. A positive difference indicates the target is closer than the pre-season distance whilst a negative difference indicates the target is further away than the pre-season distance. The thick vertical black lines indicate significant events in the constraint period in that week.

The results of the 1-way ANOVA on the PIR weekly grand mean data is shown in Figure 21, and the summary of the W-test for normality of the residuals of the PIR grand mean data is shown in Appendix C.

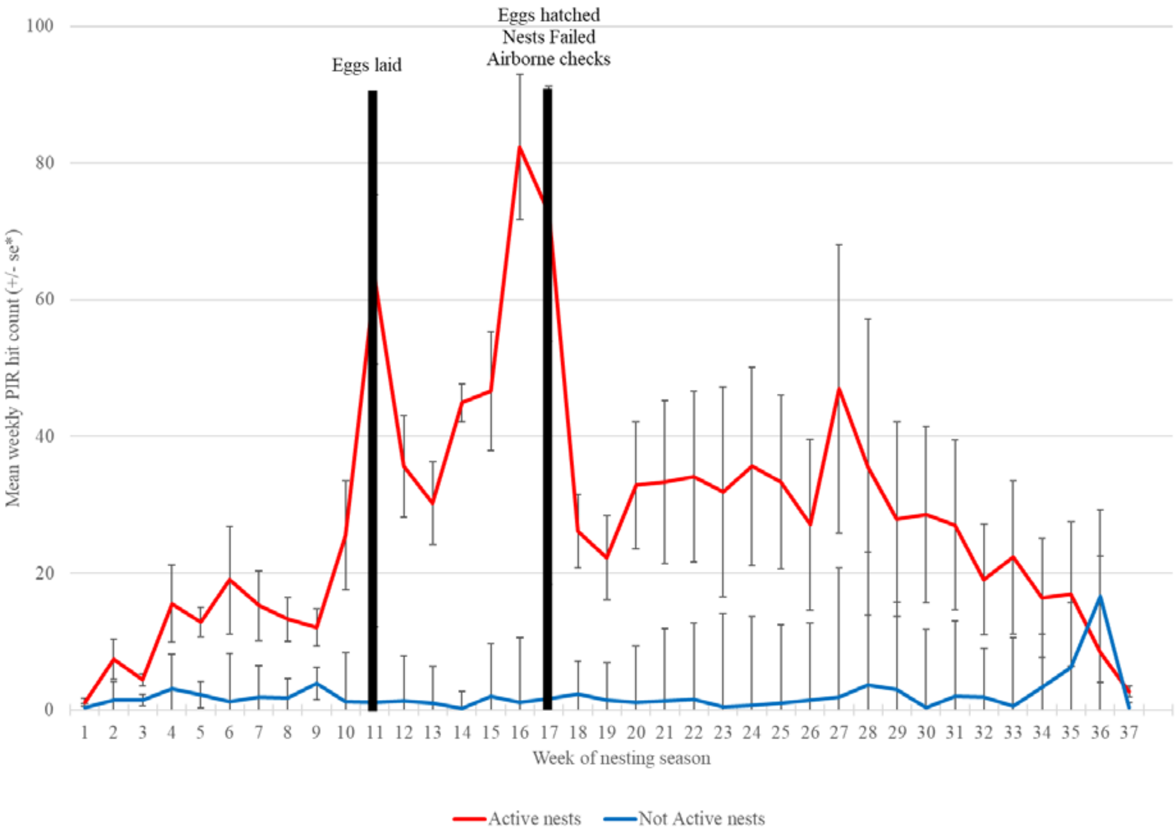

Figure 21: Weekly grand means of the sensor hit count with standard errors for the PIR data after transformation, for the nesting season operational constraint period (Starting 1st June 2020) for the Active and Not Active nests (including failed nests). The data from the two false positive nests was excluded from this analysis. The thick vertical black lines indicate the significant events in the constraint period in that week.

The weekly mean and standard error data for the individual US sensors are presented in Figure 22, whilst the weekly mean and standard error data for the individual PIR sensors (including failed nests and false positives) are presented in Figure 23.

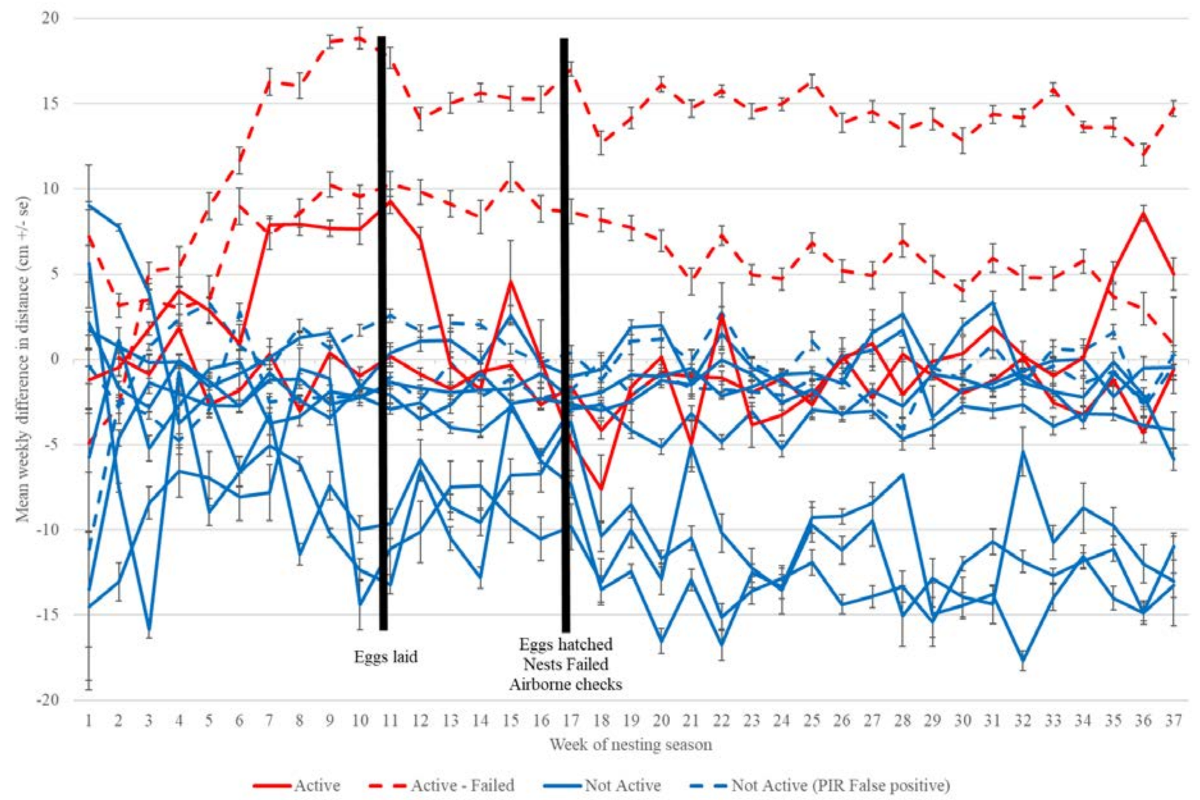

Figure 22: The mean weekly difference in distance (with standard errors) measured by each of the US sensors (n=13) over the nesting season constraint period. The thick vertical black lines indicate the significant events in the season in that week.

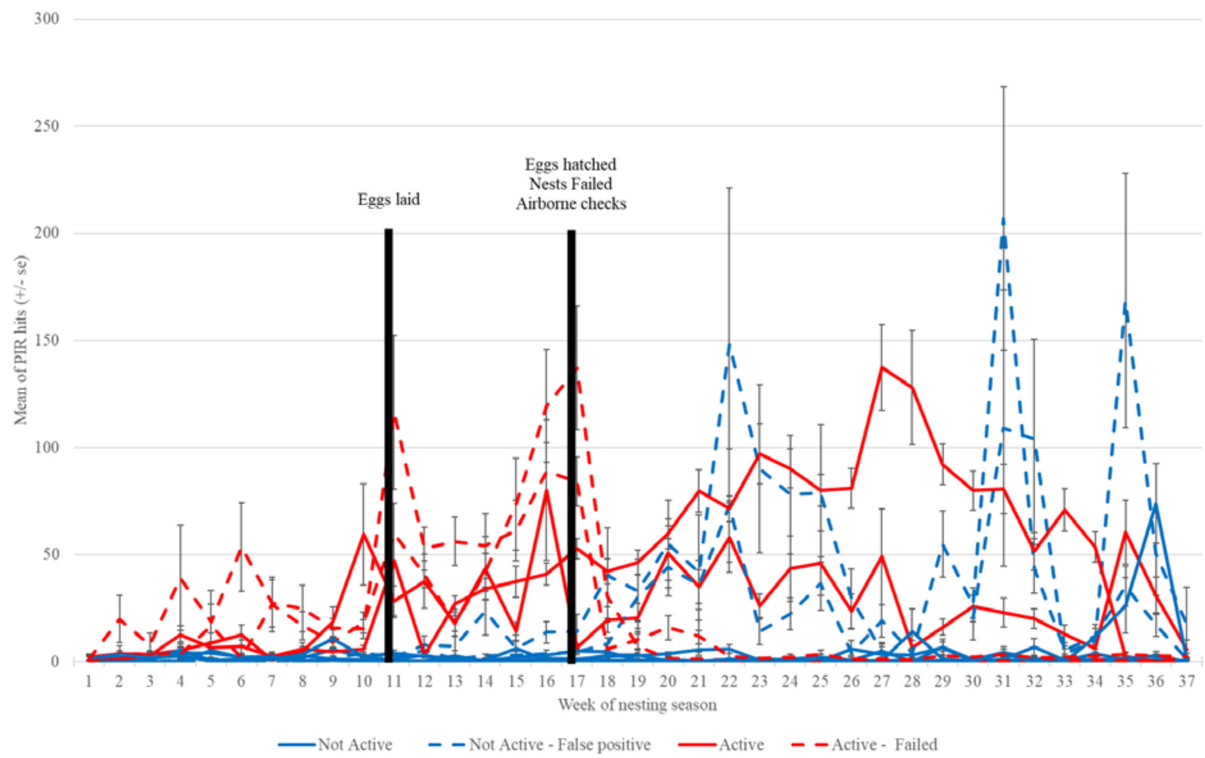

Figure 23: The mean weekly number of PIR hits with standard errors after transformation, from each of the PIR sensors (n = 11) over the nesting constraint period. The thick vertical black lines indicate the significant events in the season in that week.

False positives in PIR data

In Figure 23, the readings for two of the PIR sensors are indicated as being false positives (dashed blue lines), as there were relative high hit counts recorded by the sensor, similar to Active nests, particularly from week 17 through to week 37. However, these nests were confirmed as Not Active from the airborne checks and for one of the nests, additionally by the installed camera (Nest 1499). Photos of Nest 1499 taken in Week 9 (Figure 24) and Week 22 (Figure 25) of the constraint period show that in Week 9, the sun was low and there was little shading on the nest surface (static contrast), whilst in Week 22 the sun was higher and foliage higher in the canopy cast shadows that moved quickly on the nest surface (dynamic contrast).

Figure 24: An image of Nest 1499 at 12:45 pm on the 28th of August 2020 (Week 9 of the nesting season), showing that the nest is not shaded by foliage.

Figure 25: An image of Nest 1499 at 2:58 pm on the 27th of November 2020 (Week 22 of the nesting season) showing the nest partially shaded by foliage.

Nest Failure

The camera on Nest 1608 was able to captre the loss of both eggs that resulted in the failure of the nest. The first egg lost was on October the 5th whilst the second egg was lost on the 24th of October, or week 17 of the constraint period. In both cases it appeared that the eggs were damaged by a juvenile WTE co-habitating on the nest with the nesting parents (see Figure 26), possibly their off-spring from a previous season. Following the loss of the second egg, the WTEs were observed to spend a decreasing amount of time at the nest over the following few weeks. This behavior was reflected in the PIR signals for the failed nest dropping to a level that was similar to Not Active nests (Figure 23). A concequece of this in the data analysis appears to have been an adverse impact the normality of the residuals from about week 20 onwards (Appendix C). As mentioned earlier in the results section, dropping these failed nests out of the analysis would make the sample size (n=2) too small.

Figure 26: A screenshot of the video showing the resident juvenile WTE handling the broken shell of the second egg to be lost on Nest 1608.

Outputs of the economic analysis comparing the current airborne nest activity checks to using sensor for activity checks.

A summary of the economic analysis comparing the costs (program costs and the costs of constraints) of the current state-wide airborne activity checks program to an Eagle Eye IoT approach, over a 10-year period is shown in Figure 27.

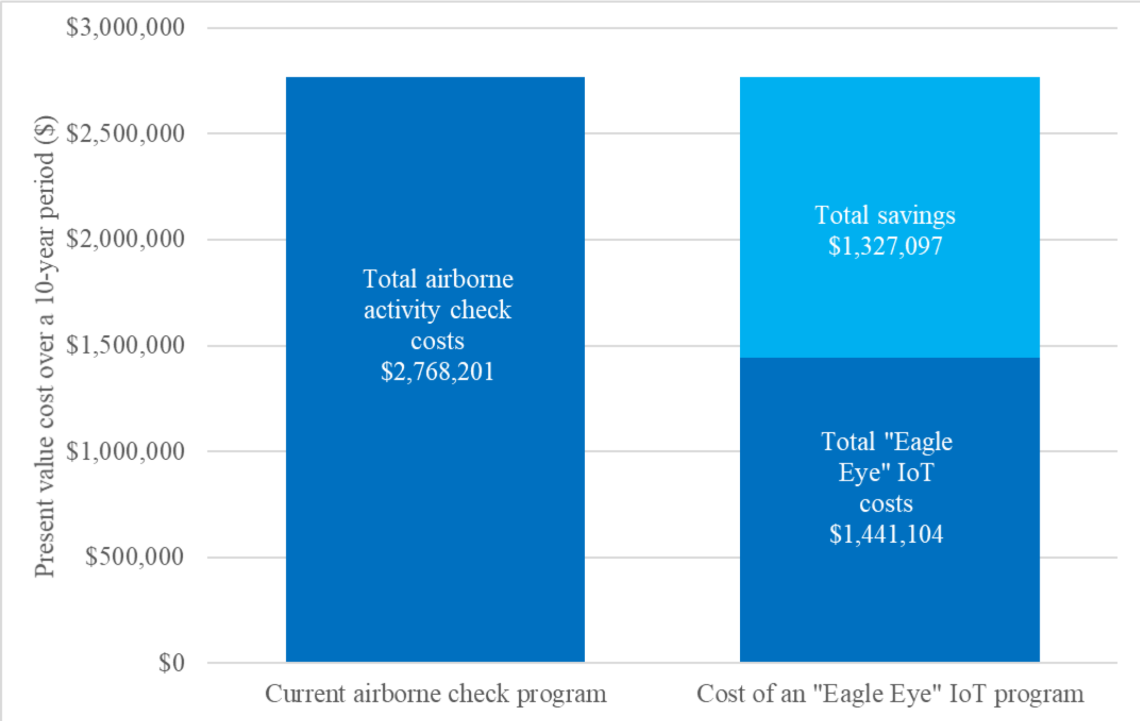

Figure 27: The ‘most likely’ costs and savings of an “Eagle Eye” IoT program compared to the current practice of airborne nest activity checks over a 10-year period.

To test the robustness of the business case, the results for the economic analysis are also reported for +/-10% change (by an increase in one scenario against a decrease in the other) in assumptions over a 10-year period, as well as a scenario with an overall increase of Eagle Eye program costs of 40% (see Table 8 for outputs).

Table 8: A comparison of changes in scenario NPVs and IRRs when different input costs (+/-10% or +40%) are processed through the economic model compared to the baseline scenario

Category	**Most likely (Baseline)**	Impact (and Direction) of 10% change	Impact (and Direction) of 10% change	Impact of a 40% increase in Eagle Eye Program costs
Present value of costs of Current Aerial Check program over 10-years	**$2,768,201**	$3,541,896 (Increase)	$2,119,735 (Decrease)	$2,768,201
Present value of costs of the Eagle Eye Program over 10-years	**$1,441,104**	$1,276,974 (Decrease)	$1,555,777 (Increase)	$2,031,754
Present value of the annual savings of Eagle Eye Program ($ per year)	**$60,323**	$107,853	$28,198	$36,822
Present value of the total savings of Eagle Eye Program (over 10 years)	**$1,327,097**	$2,264,921	$563,958	$736,447
Internal rate of return of Eagle Eye Program (IRR)	**37%**	71%	19%	20%

Discussion

This project has demonstrated the potential of using IoT to help manage a protected species in a working forest landscape. Additionally, it has established a knowledge base and infrastructure resource to expand the application of IoT into other aspects of land management for commercial and conservation objectives.

The result of the airborne nest activity checks on the nests with sensors and control nests (Table 4) appears to show that the installation and presence of the sensors and cameras did not discourage WTEs from using the nests with the rate of nest use appearing to be the about the same for both nest classes (sensor trees v's controls). However, monitoring these nests over several years will be required to confirm if this is the actual case.

In general, both the US and PIR sensors were able to differentiate between the group of Active and Not Active nests as shown in Figures 20 and 21, and this was achieved to a significant degree in most cases through the 37-week constraint period as shown in Appendix B & C.

These results also demonstrate the effectiveness of the LoRa network established to support the sensor deployment, by successfully transferring the sensor data from deep in the forest to the cloud, where it could be easily accessed from the desktop in real time as a graph or geographic heat map (see Figures 18 and 19 respectively), or accessed later for in-depth analysis, to guide management decisions as needed.

It was found in the first season of this project (2019) that the current satellite-based technology for linking LoRa networks to the cloud still requires some refinement in reliability and serviceability. The first season also demonstrated the importance of good firmware set-ups to accommodate the vagaries of the natural environment and constraints imposed by challenging installations. In the second season (2020), the LTE connections (mobile phone network) did prove to be effective, robust and reliable in relaying data from the LoRa network to the cloud. However, the major constraint on this approach is the need to operate within an established mobile phone network, which currently excludes the application of LoRa from extremely remote areas.

The actual range of the LoRa network was found to be quite variable in practice, not unexpected given the topography of the study area. WTE nests are generally built in trees on the southeast facing upper mid-slope of hills (Wiersma et al. 2015), and this would heavily attenuate signal propagation to the northwest of the nest. In one case, poor signal strength was exhibited over just 12 km of range (between Nest 1406 and Bradys) and was mitigated by installing a Gateway closer to the nest (London Lakes), whilst in another case, good signal was received from across 28 km of range (Nest 2443 to Bradys). This demonstrated that there needs to be some careful thought given to the physical location of LoRa infrastructure in complex environments, as noted by Sanchez-Iborra et al. (2018).

In service, the US sensors appeared to be the more reliable of the two sensor types. Only one out of the 16 US sensors appeared to fail whilst out of the 16 PIR sensors, three were either faulty or failed (Tables 5 & 6).

Whilst the US sensors appeared more reliable, the PIR sensors appeared to be more informative.

When comparing the US results in Figure 20 to the PIR results in Figure 21 it could be suggested that the US sensor was the more effective of the two types in detecting nest activity. The US sensor was more reliable (less prone to false positives or failure) and more effective in differentiating between Active and Not Active nests (the difference is statistically significant in 29 weeks of US data compare to statistically significant in 9 weeks of the PIR data – see Appendix B & C).

When looking more closely at the performance of the individual sensors shown in Figures 22 and 23, a story emerges that the PIR sensors may be more useful than the US sensors in monitoring nest activity. In Figure 22, the data from two of the US sensors on Active nests appeared to be poorly differentiated from the data from Not Active nests for most of the constraint period, potentially providing a false-negative result. From the Mann-Kendall tests, most of the significant data trends for Active and Not Active nests were generally negative, suggesting using data trends is not a reliable method of detecting WTE nesting activity. It may be that the environment in which the US sensors were operating in, or the nature of the target, or a combination of both was causing erroneous distance readings. US sensor performance can be detrimentally affected by changes in temperature and humidity, and air currents can reflect US waves (Kelemen et al. 2015) providing substantially different path lengths across samples. The returning US beam pattern can be attenuated by the nature of the target surface, complex surfaces (such as a nest with a bird) will reflect a US beam with slightly different intensities, amplitudes and times, inducing variation in time-of-flight calculations (Massa 1999). Because of the inherent exposure of these sensors to a broad range of environmental variation, the causes of these errors would not easily be mitigated in this application.

The US data for the two Active nests that failed was well differentiated from the data for the Not Active nests (Figure 22). However, the data gives no clear indication of when or if the nests failed. In contrast, the PIR sensor data on the nest confirmed by video to have failed (both eggs lost before hatching) shows a strong decrease in the number of hits soon after the last egg was damaged (Figure 23) and this is consistent with observations from the video recordings. This strong decrease in PIR hits from week 17 was closely mirrored by the PIR data from a second nest, indicating it too had failed. It should be noted that the video evidence suggests the nest failure was not due to the airborne check and these events both occurring together in the same week was coincidental.

The confirmed nest failure occurred just a few days after the aerial nest activity checks so was not picked up in the aerial check, so the nest was classified as Active for the full nesting season. This highlights a limitation of the current approach to the one-off aerial checks compared to the continuous sensor monitoring of the nests, in that any post aerial check change in activity is not registered. Had the failure of the nests(s) been recognised in the aerial check, as the sensors appear to show, then the nesting season operational constrains for these nests could have been lifted by up to 20 weeks earlier. If 40% of nests fail and none are picked up in the airborne checks, this means a lot of operational constraints are applied that need not be, representing a large opportunity cost to industry. Knowing the rate of nest failure would also be valuable information in the ongoing management of the species, especially given its conservation status.

The PIR sensors did exhibit a false positive signal profile on two nests. It is not clear what contributed to the false positive signals, however, PIR sensors are known to be susceptible to environmental noise that can trigger false positives (Zhang et al. 2007). There were no animals captured on video that could have triggered the PIR on Nest 1499 in such a way as to deliver the signal profile recorded. PIR sensors work by responding to changes in thermal energy patterns in their FoV (Welbourne et al. 2016). It is possible that shadows of foliage waving in the wind, that were cast onto the nest surface, provide enough thermal heterogeneity to trigger the PIR. The PIR false positive readings generally started about week 13 (late September) of the constraint period season (Figure 23), much later than the true positives readings commenced (a potential point of differentiation between true and false positives) and this coincided with the Spring equinox. The strongest false positive signals were given over late Spring and Summer and then declined into Autumn. The stills captured from video taken of Nest 1499 showed that in August there was no shading on the nest in the middle of the day (See Figure 24), whilst in late November there were shadows cast on the nest surface by foliage higher in the canopy in the middle of the day (see Figure 25), and this foliage was moving in the wind. For future application, it may be possible to refine the PIR sensor design to make it less sensitive to this type of environmental noise (Zhang et al. 2007). Alternatively, a different sensor type could be employed which would have greater target selectivity and noise rejection compared to the PIR. One such sensor type could be a bioacoustic sensor featuring a birdsong recogniser. This technology has been shown to be very effective in detecting and classifying birdsong in noisy environments and can be integrated into IoT solutions (Boulmaiz et al. 2016). A bioacoustic sensor would have an advantage over a PIR sensor in that it would be less sensitive to placement in the tree, in that a PIR sensor needs to be aimed directly at the nest surface, whilst a bioacoustics sensor would only need to be placed within reasonable proximity of the nest to pickup the vocalisations of the WTEs. As such, a bioacoustics sensor is likely to be amenable to deployment by drone, rather than tree climbing, potentially speeding up installation and reducing costs.

This study also found that false positives could also be recorded in the airborne checks. There was a singe false positive found in the 2020 aerial checks (confirmed by the absence of activity on that nest by video). It should also be noted that there was a false positive found in the 2019 aerial checks, also confirmed by video. These false positives represent an opportunity cost to industry as operational exclusions are needlessly continued for these nests. In the Control set of nests, four nests were not found, so were managed as Active (Table 3). Of the Control nests that were found, two-thirds were Not Active, so based on that sample, 2-3 of the unfound nests, may also have been Not Active, representing a type of false positive from the airborne checks, and an opportunity cost to industry. These false positives could be reduced by follow-up checks if the financial and nest disturbance costs are justified.

The longevity of the sensors is yet to be determined. Ongoing monitoring will be required to assess the lifespan of the sensor and node batteries and the durability of the hardware itself. LoRa based sensors are reasonably expected to last up to ten years or more in remote and difficult to access installations (Okafor and Delaney 2019, Perles et al. 2018). The hardware has proven reasonably robust enduring a year of harsh conditions in the forest. STT will continue to monitor these sensors for as long as they remain operational.

The results of the economic analysis indicate that the current state-wide aerial activity checks program is delivered at an average cost of $277k per year or a total of $2.77 million over 10 years in present value (PV) terms. The PV of the total costs of the 'Eagle Eye' monitoring program is around $1.44 million over 10 years. Based on the 'most likely' assumptions, an introduction of the sensor monitoring 'Eagle Eye' style IoT program for nest activity checking has the potential to deliver over $1.33 million in savings over a ten-year period or over $60k per year. This would generate an internal rate of return (IRR) of 37%, suggesting a strongly positive business case (Table 8).

These savings are largely achieved due to avoiding four months of harvesting and transport constraints by correctly identifying the 40% of Active nests that fail post-airborne check, and

10% of nests that are Not Active but could not be seen in the airborne check and are thus managed as Active. The calculations of this are conservative, assuming that a harvesting delay would occur on just 10% of the total area within the line of sight of these nests, 10% of coupes would require rerouting of transport and 1% of coupes would require new roading.

As reported in Table 8, a 10% reduction in costs of the aerial check program and a simultaneous 10% increase in the 'Eagle Eye' costs would still result in $28k of annual savings and an IRR of 19%. On the other hand, any reduction in capital or operating costs of the 'Eagle Eye' program (such as achieved through sharing some of the capital and operating costs with other forest management tasks) would only enhance the business case further. Finally, an overall increase of 40% in Eagle Eye program costs still produced a positive economic return and an IRR of 20% (Table 8).

It should be noted that the current analysis did not attempt to quantify any additional benefits of the 'Eagle Eye' program that may result from improved workplace safety, positive animal welfare outcomes and enhanced knowledge leading to better management of the WTE population. Such benefits are likely to be significant.

Conclusions

The project demonstrated the potential of an IoT approach as an alternative to airborne checks for WTE nest activity. Data on nest activity was collected continuously by sensors monitoring WTE nets across the landscape, relayed by a LoRa network to the cloud, where it was accessible from a desktop computer in the office (or home) in a format that could be used to inform commercial and conservation management decisions.

The PIR sensor produced the most informative data compared to the US sensor. However, the PIR sensor had a lower level of reliability compared to the US sensor and in a couple of cases, delivered false-positive readings. It is conceivable that both these issues with the PIR technology could be ameliorated with refinement of the sensor hardware and calibrating its set-up.

The LoRa network set up for this project was successful in transferring the sensor data to the cloud in the second season. However, its current dependence on the established mobile phone network does limit its deployment across the landscape. This should be resolved when reliable, affordable and effective satellite communications systems come into service in the near future.

Once the sensor data was in the cloud it could be easily accessed with very little lag-time though a web-based portal or corporate IT systems, such as MS Power BI.

The economic analysis provided an insight to the potential to achieve positive financial benefit of using an IoT approach to monitoring WTE nesting activity compared to the current practice.

More broadly, this project has also provided a springboard into the application of IoT across other landscape management functions.

Recommendations

To make an operational IoT solution effective for WTE nest activity monitoring, the following is recommended:

1. Work on refining the PIR sensor to make it more reliable and selective for its given task.
2. Examine the development of a more target selective sensor, such as an acoustic sensor and birdsong recogniser. An acoustic sensor may also be more conducive to faster and cheaper drone-based installation, compared to a PIR sensor.
3. Examine more closely and extensively the impact on WTE breeding of installing sensors on nest trees.
4. A more comprehensive economic analysis be carried out to compare the costs of the current airborne nest activity checks and an IoT approach to nest activity checks, to include a sensitivity analysis.
5. IoT be tested for other uses in land and biodiversity management. This would spread the costs of capital, network operations and data repositories maintenance, and thus increasing the commercial feasibility of IoT solutions.
6. Keep a watching brief on developments in satellite communications technology to support LoRa which would allow a push of the technology into all geographic areas.

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Researcher’s Disclaimer

Appendix A

Assumptions used in the economic analysis (worst and best values are +/- 10% of most likely cost) and based on the Tasmania-wide industrial forest estate.

Category	Units	Worst	Most likely	Best	Source
Number of Nests	#	800	800	800	Specialist advice
Program lifespan	years	10	10	10	Specialist advice
CPI	%	1.8%	2.0%	2.2%	RBA target inflation rate
Discount rate	%	7.7%	8.5%	9.4%	STT 2019-20 Annual report
Monthly discount rate	%	0.6%	0.7%	0.8%	
WTE Sensor Monitoring Program					
Category	**Units**	**Worst**	**Most likely**	**Best**	**Source**
Sensor Cost (each)	$ ea	275	250	225	Manufacturer’s quote
Number required	#	1,100	1,000	900	Specialist advice
Replacement rate	every 10 years	28%	25%	22.5%	Specialist advice
Replacement rate	every year	3%	3%	2%	Specialist advice
Cost of standalone gateway (inc. install)	$ ea	5,500	5,000	4,500	Manufacturer’s quote
Number required	#	39	35	32	Specialist advice
Cost of gateway on powered site (inc. install)	$ ea	2,750	2,500	2,250	Manufacturer’s quote
Number required	#	20	18	16	Specialist advice
Tree climbing capacity per day	#	2	2	2	Specialist advice
Number of days		550	500	450	Specialist advice
Cost of tree climbing	$ per tree	660	600	540	Specialist advice
Cost of tree climbing per day	$ per day	1,320	1,200	1,080	Specialist advice

Category	Units	Worst	Most likely	Best	Source
Total cost of tree climbing	$	726,000	600,000	486,000	Specialist advice
Travel cost - average	$ per day	110	100	90	Specialist advice
Number of days	#	550	500	450	Specialist advice
Cloud hosting and IT support for data	$ per year	4,356	3,960	3,564	Specialist advice
LTE Network access per gateway	$ per year	132	120	108	Specialist advice
Total LTE network cost	$ per year	7,696	6,360	5,152	Specialist advice
Dashboard set up	$	1,100	1,000	900	Specialist advice
Program coordination	Staff days per year	11	10	9	Specialist advice
Cost of program coordination	$ per day	660	600	540	Specialist advice
Current costs of Airborne nest activity checks					
Category	**Units**	**Worst**	**Most likely**	**Best**	**Source**
Aerial Search costs	$ per nest	484	440	396	STT’s historical data
Average number of nests searched per year	#	414	376	338	STT’s historical data
Number of staff days p.a. involved in the current program	#	33	30	27	Estimate based on the STT’s historical data
Staff cost	$ per day	715	650	585	Estimate based on the STT’s historical data
% nests that are not picked up in aerial search (hence Managed as Active) that are Not Active	%	11%	10%	9%	Results of the ‘Eagle Eye’ trial

Category	Units	Worst	Most likely	Best	Source
% of Active nests that fail after aerial check (from end October)	%	44%	40%	36%	Results of the 'Eagle Eye' trial
Cost of managing an active nest:					
Category	**Units**	**Worst**	**Most likely**	**Best**	**Source**
Size of nest reserve	ha per nest	10	10	10	FPA WTE management prescriptions
Area within 1000 m of the nest minus the 10 ha reserve not harvested for 4 months (past October)	ha per nest	27	30	33	Calculation, assuming that on average 10% of the total area within the line of sight will be impacted.
Area within 1000 m line of sight minus the 10 ha reserve	ha per nest	304	304	304	Calculation
% area unable to be harvested permanently	%	0%	0%	0%	-
Average profit per ha - selective logging	$/ha	1,395	1,550	1,705	Industry expert estimate
Average cost of building a road - gravel	$	36,000	40,000	44,000	Industry expert estimate
% of coupes when new road is needed	%	1%	1%	1%	Specialist advice based on the historical data
Cost of re-routing	$ per 10 km	2,700	3,000	3,300	Industry expert estimate
% coupes required rerouting	%	9%	10%	11%	Specialist advice based on the historical data

Appendix B

Test of residual normality of US data and significance of difference between weekly grand means for US sensor data from Active and Not Active nests. The highlighted P-values should be considered with caution as the residuals were not normally distributed.

	Week									
	1	2	3	4	5	6	7	8	9	10
W-test Active nests	0.816	0.759	0.486	0.221	0.779	0.627	0.928	0.589	0.869	0.776
W-test Not active nests	0.769	0.252	0.864	0.57	0.518	0.801	0.653	0.045	0.376	0.269
P-value 1-way ANOVA	0.846ns	0.663ns	0.048*	0.045*	0.036*	0.031*	0.003**	0.017*	0.002**	0.004**
	Week									
	11	12	13	14	15	16	17	18	19	20
W-test Active nests	0.628	0.603	0.594	0.298	0.957	0.784	0.557	0.392	0.487	0.505
W-test Not active nests	0.682	0.294	0.731	0.960	0.991	0.405	0.019	0.179	0.648	0.179
P-value 1-way ANOVA	0.002**	0.004**	0.021*	0.015*	0.012*	0.024*	0.057ns	0.103ns	0.027*	0.019*
	Week									
	21	22	23	24	25	26	27	28	29	30
W-test Active nests	0.632	0.878	0.376	0.354	0.473	0.25	0.697	0.535	0.463	0.608
W-test Not active nests	0.42	0.76	0.03	0.07	0.133	0.003	0.115	0.234	0.511	0.347
P-value 1-way ANOVA	0.05*	0.014*	0.043*	0.025*	0.039*	0.017*	0.045*	0.048*	0.014*	0.03*
	Week									
	31	32	33	34	35	36				
W-test Active nests	0.801	0.248	0.462	0.898	0.918	0.607				
W-test Not active nests	0.785	0.011	0.316	0.319	0.486	0.058				
P-value 1-way ANOVA	0.023*	0.01**	0.032*	0.025*	0.01*	0.01*				

Appendix C

Test of residual normality and significance of difference between weekly grand means for PIR sensor data from Active and Not Active nests. The two false positive sensor data was excluded from the analysis. The highlighted P-values should be considered with caution as the residuals are not normally distributed.

	Week									
	1	2	3	4	5	6	7	8	9	10
W-test Active nests	0.272	0.056	0.034	0.118	0.385	0.093	0.047	0.422	0.749	0.143
W-test Not Active nests	<0.001	0.751	0.757	0.976	0.049	0.664	0.32	0.396	0.063	0.2
P-value 1-way ANOVA	0.382ns	0.178ns	0.047*	0.144ns	0.007**	0.135ns	0.093ns	0.032*	0.058ns	0.058ns
	Week									
	11	12	13	14	15	16	17	18	19	20
W-test Active nests	0.472	0.311	0.077	0.825	0.814	0.892	0.995	0.979	0.21	0.487
W-test Not Active nests	0.011	0.057	0.088	0.199	0.059	0.298	0.072	0.604	0.235	0.019
P-value 1-way ANOVA	0.008**	0.011*	0.009*	<.001***	0.006**	<.001***	0.026*	0.013*	0.039*	0.038*
	Week									
	21	22	23	24	25	26	27	28	29	30
W-test Active nests	0.546	0.123	0.103	0.286	0.355	0.113	0.193	0.004	0.039	0.177
W-test Not Active nests	<0.001	0.008	0.243	0.512	0.548	0.003	0.162	0.013	0.013	0.03
P-value 1-way ANOVA	0.085ns	0.092ns	0.17ns	0.116ns	0.1ns	0.171ns	0.156ns	0.309ns	0.234ns	0.146ns
	Week									
	31	32	33	34	35	36				
W-test Active nests	0.147	0.249	0.048	0.015	0.004	0.01				
W-test Not Active nests	0.167	0.01	0.06	0.041	<0.001	<0.001				
P-value 1-way ANOVA	0.175ns	0.156ns	0.19ns	0.303ns	0.472ns	0.676ns				