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INVESTIGATING THE SPATIAL BEHAVIOR AND HABITAT USE OF THE MATSCHIE'S TREE-KANGAROO (DENDROLAGUS MATSCHIEI) USING GPS COLLARS AND UNMANNED AIRCRAFT SYSTEMS (UAS)

Jonathan B. Byers

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Investigating the Spatial Behavior and Habitat of the Matschie's Tree-kangaroo (*Dendrolagus matschiei*) using GPS Collars and Unmanned Aircraft Systems (UAS)

Dr. Anna E. Klene

Abstract

Understanding the movement patterns and habitat needs of the endangered Matschie's tree-kangaroo (*Dendrolagus matschiei)* is important for their conservation and management. Endemic to the montane cloud forests of the Huon Peninsula in northeastern Papua New Guinea, these elusive arboreal marsupials are tremendously challenging to study using traditional observational methods.

This study is an assessment of novel techniques to overcome the significant challenges to in-situ data collection in remote and rugged tropical cloud forests. Animal locations are remotely tracked using purpose built altitude and motion logging GPS collars and habitat structure data is measured using photogrammetry from small Unmanned Aircraft Systems (UAS) aerial imagery. Leveraging the autocorrelation of regular GPS location sampling, this study applied a Time-Local Convex Hull (T-LoCoH) analysis to investigate particular locations that may be important to *D. matschiei* as well as potential barriers to movement that would be inside of the home range as identified in previous studies. A novel technique of ground surface interpolation from canopy gaps is presented to overcome the challenges of photogrammetric reconstruction of terrain surfaces under closed canopy forests. From this a variety of forest structure variables were calculated to understand the 3D complexity of these heterogeneous cloud forests.

This investigation found that custom GPS collars can provide high fix success rates in dense multilayer forests found at the research site. The regular sampling intervals resulted in areas of utilization that were notably smaller than with traditional home range analyses, and provided insight into landscape features that the animals do not use. *D. matschiei* were found to preferentially use trees that were taller than average and were found in closer than average proximity to canopy emergent trees. The reconstruction of 3D habitat data from UAS aerial photogrammetry resulted in forest structure maps that have significant potential to overcome the necessity of manual habitat data collection that hinders large scale habitat research, for this and many other species.

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For me this experience and direction would not have happened without the trust and encouragement of filmmaker Joe Pontecorvo, who sent me to PNG as a camera operator at exactly the time when my thesis was needing a research question.

The local landowners, leaders, and advocates for the YUS Conservation Area are truly global leaders in community conservation efforts, and it is with their permission and support that this research is possible. TKCP Field Technicians Nicholas Wari and Stanley Gesang spent months living in the field diligently tracking these animals and downloading the data. Without their commitment and efforts, this project would have been impossible. The local guides including Eki, Optus, Jux, Gems, and others shared their deep knowledge of the forest and of wild tree-kangaroos, and were instrumental in the capture and recapture of the animals. This work was build on the foundation of excellent research by Dr. Jared Stabach and Dr. Gabriel Porolak, whose earlier collaring efforts and habitat data collection provided an essential baseline comparison.

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1 INTRODUCTION

As one of the largest and highest montane regions in Papua New Guinea (PNG), the Huon Peninsula's unique geology has left it geographically isolated and many of its species exist nowhere else on earth (Flannery, 1995). The Matschie's tree-kangaroo (*Dendrolagus matschiei)* is the largest mammal endemic to the peninsula and is significant for the local Indigenous people, providing an important protein source as well as cultural and ceremonial products (Mack, 2005). Due to hunting pressure and habitat loss from agricultural expansion and logging it is listed as endangered by the International Union for Conservation of Nature (IUCN) with an estimated population of fewer than 2,500 mature individuals (Ziembicki & Porolak, 2016). However, accurate estimates of *D. matschiei* population size and habitat requirements are difficult to make because of their naturally low population densities, solitary behavior, and the challenge of effectively surveying these elusive animals in their remote and mountainous range (Porolak et al., 2014).

Advances in remote sensing techniques, including animal telemetry and bio-logging, have facilitated improved understanding of behavior and habitat for many wildlife species, while simultaneously creating new challenges (e.g. Ropert-Coudert & Wilson, 2005; Cagnacci et al., 2010; Kays et al., 2015). The Matschie's tree-kangaroo provides an excellent subject to apply remote sensing techniques to overcome the tremendous challenges of *in situ* research (Stabach, 2005). Previous studies that used remote sensing techniques include scat sampling (Pugh, 2003), vegetation transects (Jensen, 2005), very high-frequency (VHF) and global positioning system (GPS) collars (Flannery, 1995; Porolak et al., 2014; Stabach, 2005), and satellite land-cover classifications (Pugh, 2003; Stabach, 2005; Stabach et al., 2009) to investigate the home range and habitat use of *D. matschiei*. These studies have provided important knowledge about the behavior and ecology of the Matschie's tree-kangaroo in the wild and provide an ideal foundation for the continued refinement and validation of new techniques. While these studies found evidence that "*D. matschiei* may not be a habitat generalist" (Stabach, 2005), understanding what specific habitat they depend on was limited by the inexistence of sufficiently high-resolution remote sensing data, or dependence on manually locating the animals to collect habitat information (Stabach et al., 2009; Porolak et al., 2014).

Since these studies were conducted some significant advancements have occurred that potentially give us the tools to understand the habitat requirements of *D. matschiei*, including: substantial improvements in the accuracy, longevity, and reliability of GPS antennas and the addition of biologging sensors on GPS collars (e.g. Cooke et al., 2004; Ropert-Coudert & Wilson, 2005); development of more robust spatiotemporal behavior investigation tools (e.g. Calenge et al., 2009; Lyons et al., 2013); and the rapid development of portable unmanned aircraft systems (UAS) and digital photogrammetry tools (e.g. Anderson & Gaston, 2013; Christie et al., 2016).

1.1 Objectives

This research has two objectives. The first is to assess the fine-scale use of space by individual *D. matschiei* to identify barriers to movement and areas of important habitat using custom designed GPS collars and spatiotemporal investigation tools. As part of this, an evaluation of the effectiveness of the GPS collars developed for this project will be made, geometric home ranges of individual Matschie's tree-kangaroos created using each animal's GPS location data during 2017/2018 will be compared to previous studies, and design feedback on the collars provided for future deployments.

The second objective is to identify habitat structure characteristics of potential ecological importance to *D. matschiei*, such as clearings, forest canopy gaps, and canopy emergent (i.e. forest overstory layer) trees. This study presents a novel technique of developing a canopy height model (CHM) and other forest structure metrics from very high resolution (~5 cm/pixel) UAS imagery. Because of the substantial challenges of, and limited publications about, the application of UAS to remote montane tropical cloud forest research, an assessment of techniques will be presented.

This synthesis of spatial behavior from GPS collars and forest structure data to investigate habitat structure preferences could provide novel insight for other difficult to study animals in similarly challenging habitats. Improved understanding of critical habitat will be used to inform and prioritize ongoing land management and conservation efforts to protect *D. matschiei* populations in the wild.

1.2 Study Area

This research was conducted at the Wasaunon Field Research Area (Wasaunon), Morobe Province, PNG located between latitude 6°3' and 6°1'S and longitude 146°51' and 146°58'W on the northeastern side of the Huon Peninsula in the Sarawaged mountain range with an elevation range from 2122 to 3067 m and slopes in excess of 60° (Figure 1). The Wasaunon area is designated as a no-hunting zone by clan landowners in the local villages of Yawan, Towet, and Worin as part of the larger YUS Conservation Area (National Gazette No. G5., 2009). It is located approximately 9 km from the nearest village and is accessed by footpath or helicopter. The area is covered extensively (98%) by upper montane tropical rainforest, interspersed with small clearings of alpine grassland (Pugh, 2003; Gillieson et al., 2011). Mean annual precipitation is estimated to be 2717 mm and the mean annual air temperature is 13.4°C (Fick & Hijmans, 2017).

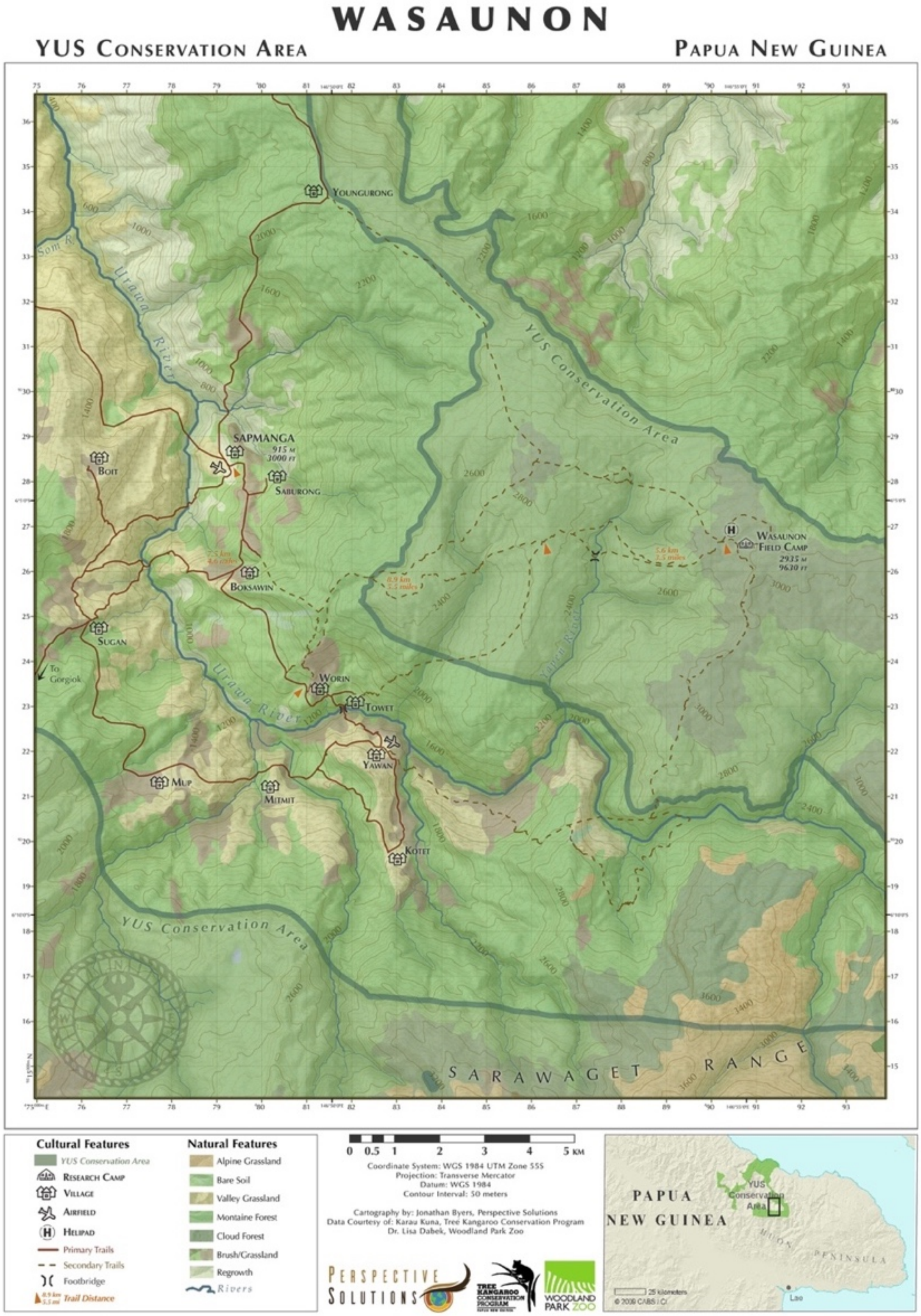


Figure 1. Map of the Wasaunon Research Camp and Surrounding Areas, Morobe Province, Papua New Guinea. Vegetation from Gillieson et al. (2011).

2 ECOLOGICAL AND CONSERVATION CONTEXT

The Matschie’s tree-kangaroo, also known as the Huon tree-kangaroo, belongs to the family Macropodae which includes 55 species of kangaroos, wallabies, and their relatives (Flannery, 1995). The non-profit Tree-kangaroo Conservation Program (TKCP) has been working in Papua New Guinea since 1996 to study and protect the Matschie's tree-kangaroo, the program’s flagship species, as well as the critically endangered Eastern long-beaked echidna (*Zaglossus bartoni*), the vulnerable New Guinea pademelon (*Thylogale browni*), and the endemic bird of paradise species, the Huon astrapia (*Astrapia rothschildi*; Dabek & O’Neil, 2007). In the Huon Peninsula’s Yopno-Uruwa-Som (YUS) watershed area where the TKCP focuses its work, primary drivers of biodiversity loss are over-hunting and habitat destruction through subsistence-use forest clearing (Ancrenaz et al., 2007; Ningal, 2007). The damaging effects of climate change were emphasized by severe droughts and frost in 1997 associated with El Niño–Southern Oscillation (ENSO) and were linked with food shortages and increased hunting pressures on wild animals, and with significant loss of high altitude forests from fire and frost (Cobon et al., 2016). The conservation of intact forest habitat along elevational gradients such as the YUS landscape is of particular importance in potentially mitigating the biological consequences of climate change (Brodie et al., 2012).

Because Indigenous landowners own over 90% of the land in PNG, local communities are true stewards of the forest. In 2009, TKCP collaborated with local landowners, PNG’s Department of Environment and Conservation, and Conservation International to establish PNG’s first and only nationally-recognized Conservation Area (CA). This unique project recognizes and empowers local landowners in the process of protecting and managing their own resources. YUS CA protects over 60,000 ha of the Huon Peninsula’s uniquely diverse habitat and wildlife and serves as a “wildlife bank”, providing safe refuge for wildlife within a no-take zone (Ancrenaz et al., 2007). As wildlife populations grow within YUS CA, offspring disperse to buffer zones where they can be sustainably hunted by local communities for protein and cultural uses. Anecdotal evidence suggests these measures have resulted in greater abundance within no-take zones and dispersion into buffer and agricultural zones (Sowang, T., personal communication) but further research is essential to make effective conservation and management decisions (Ziembicki & Porolak, 2016).

3 SPATIAL BEHAVIOR AND HOME RANGES

3.1 Background

3.1.1 Prior Investigations of Spatial Behavior

To overcome the challenges of observational location data collection, fieldwork was conducted between 2004 and 2007 to deploy VHF and GPS telemetry collars, establish vegetation transects, and study food plants (Porolak et al., 2014). Between March 2004 to November 2007, 15 Matschie's tree-kangaroos were captured at the Wasaunon Field Research Site and fitted with a VHF collars (MOD-205 VHF Transmitter; Telonics Inc., USA). They were manually tracked daily for six months and locations were recorded with handheld GPS units. Vegetation data for each location was also collected. Home ranges of 81.3 ± 16.5 ha were found using 90% Harmonic Mean (HM), 72.4 ± 24.7 ha using 90% Kernel (KM), and 139.6 ± 26.5 ha using 100% Minimum Convex Polygon (MCP) techniques (*Table 1;* Porolak, 2008). While these home range and utilization distribution calculation techniques are historically the most commonly used in wildlife biology, they are known to be significantly affected by outliers and are unable to differentiate use patterns in internal space (Burgman et al., 2003; Nilson et al., 2008). Additionally, because Matschie's tree-kangaroos are known to be extremely sensitive to human disturbance it is unknown what effect the process of manually locating them using VHF has on their movement and space use patterns (Stabach, 2005).

In 2004, three adult female Matschie's tree-kangaroos were captured and fitted with Televilt Posrec^{TM} GPS collars (model C200). These collars were programmed to collect 2 locations per day (6:00 am and 6:00 pm local time) for a five-month study period and had an additional VHF transmitter that was used to locate the animal daily. Data on the slope, aspect, temperature, tree species, canopy closure, tree height, and other habitat characteristics were collected at each location. Stabach (2005) presented a preliminary assessment of home range sizes from the 3 GPS collars deployed and found a mean fixed kernel home range of 28.3 ± 2.3 ha at 90% UD. These collars had very low GPS fix success rates (~20%) resulting in less than 1 location per day, which was less than half the number of locations that the manual VHF tracking of the GPS-collared animals produced and illustrate the challenges many researchers have had using GPS collars to study animals in dense forests (Frair et al., 2010). Stabach et al. (2012) noted a significant clustering of the animal locations, "indicating a high level of site fidelity", and that the animals revisited specific areas, "due either to a food resource..., protection, or some other factor." The geometric MCP and Kernel techniques used by previous studies are known to overestimate home ranges (Stark et al., 2017) were insufficient in understanding the specific resources and habitats used by *D. matschiei*.

3.1.2 Techniques for Investigating Spatial Behavior

Recognizing that GPS locations are spatially autocorrelated and incorporating the time stamps from GPS locations allows researchers better to understand the movement patters of animals through time on finer spatial scales (Fieberg & Börger, 2012). The primary approaches taken to leverage the temporal data from GPS collars have been movement based (e.g. Calenge et al., 2009) or kernel (area) based (e.g. Getz & Wilmers, 2004). Time - Local Convex Hull (T-LoCoH) is a nonparametric kernel home-range technique that was developed to make use of the temporal correlation of animal movement from GPS locations (Lyons et al., 2013). It is more sensitive to edge effects and boundaries than other methods and while it is known to underestimate home range size, its sensitivity to barriers to animal movement make it ideal for mapping the fine-scale forest composition and structure patterns that the Matschie's tree-kangaroo depends upon (Lichti, 2011; Reinecke et al., 2013; Stark et al., 2017).

T-LoCoH operates in R (R Core Team, 2018), and while it is considered to be a nonparametric technique, there are still a number of values that must be selected that influence the outcomes (Dougherty et al., 2017). T-LoCoH uses a hybrid space-time metric called "Time Scaled Distance" (TSD) to calculate the distance between points in non-Euclidian space, which it does by determining the theoretical maximum velocity at which an animal travels (Lyons et al., 2013). The value for *s,* the time scaling parameter, is very important and depends significantly on the time between location data, the number of points, and the rate at which the animal moves. Where $s=0$ time would not be accounted for in selecting nearest neighbors, and where s is large, time would be the only factor determining the selection of nearest neighbors (T-LoCoH Tutorial, 2014). Three techniques can be used for nearest-neighbor selection including automated, fixed kernel, and distance. This project used the fixed kernel, or *k-method,* to develop utilization hulls for comparison with previous studies and to determine areas of use/nonuse.

Time-use metrics output by T-LoCoH include the number of separate visits (*nsv;* a measure of revisitation), and the mean number of locations per visit (*mnlv;* a measure of the duration of visits). These metrics can reveal temporal patterns in location data which could correspond to important resources that *D. matschiei* depend on, such as food plants or shelter. These values depend on the inter-visit gap (*ivg*) value that defines separate visits, as well as the geometry of the hulls. T-LoCoH depends on fairly regular location sampling (i.e., from GPS collars), so opportunistic (e.g., manually collected radio telemetry data from previous studies), cannot be reanalyzed using this technique.

3.2 Methods

3.2.1 GPS Collar Animal Location

During a two-week site visit in October 2017, three female and three male Matschie's tree-kangaroos were captured. Animals were located by groups of skilled local hunters and trackers and captured using the techniques described by Stabach (2005) and Porolak (2008). Animals were given a light sedative upon being brought back to the field camp and kept for measurements and fitting GPS and VHF collars before being released to the same tree where they were captured after ~2 hours. One of the females (MTK 1) had a joey, or young tree-kangaroo, at foot. Both were captured, but the juvenile male was not collared because the collars were not designed to accommodate the change in neck size of a growing animal. In total, 5 animals were collared: three with custom GPS collars (Hawk-Owl Systems, Essex, MT), and two with VHF radio telemetry collars (Telonics, Inc., Mesa, AZ).

The GPS collars were developed specifically for this research project and incorporate a 25 mm ceramic patch antenna, barometric pressure sensor, binary motion sensor in a housing, and lithium ion batteries underneath the animals' chin. The GPS collars were programmed to record locations with 4 hour intervals, and no limit was set on how long the collar would attempt to get a location fix. The motion data was summed as number of movements per hour, and barometric pressure data was used to calculate maximum and minimum elevations during that hour, as well as number of vertical movement changes. This data was stored separately from the GPS location data. Four collars were built for this project and brought into the field, however one had a problem with the VHF telemetry radio used to manually locate the animal and retrieve the collar, so it was not deployed.

The GPS collared animals were located weekly to biweekly depending on conditions and field technician availability using VHF radio. Data recorded by the sensors was stored on board and also downloaded remotely by field technicians from a distance of 50-200 m to limit animal disturbance using 915 MHz telemetry radio in case the collar could not be retrieved. Only the data retrieved remotely was presented here. While previous studies also tracked the locations of the GPS collared animals daily, this project specifically did not track the VHF locations of the GPS collared animals daily to minimize the impacts of human disturbance on their behavior. The VHF-only collared animals were located as frequently as weather conditions and field staff capacity would allow.

3.2.2 Data Processing

The GPS collar data required significant processing including removing unused or incorrect data, formatting inconsistencies, and preparing files for input into R with a Python script. Because the process of remotely downloading the data over telemetry radio often failed during the field download process, there were substantial blocks of incorrect data that required removal. Failure of the GPS to acquire a fix resulted in false latitude, longitude, or time values, and any rows with faulty values were removed.

3.2.3 Temporal and Spatial Behavior Analysis

GPS and VHF points were imported into an ArcGIS File Geodatabase and a minimum bounding geometry tool was used to create the 100% MCP area. To develop a basic understanding of movement rate and interval patterns the Tracking Analyst function in ArcMap 10.6 (ESRI Inc., Redlands, CA) was used to visualize movement patterns that include their temporal component. These can be displayed statically but also as animations which can be useful in understanding movement. This visualization was used in selecting the time parameters for further investigation using T-LoCoH.

This study focused on multi-day temporal patterns (such as foraging away from a central location) and investigation of what locations individual *D. matschiei* returned to on a regular basis. Based on the tutorial by Lyons (2014) and Lyons et al. (2013) the time scaling value of s=0.15 was selected based on plotting the s term, and an inter-visit gap value of 24 hr was used.

3.3 Results

3.3.1 Collar Performance and Data Collection

The collars deployed in October 2017 and collected in April 2018 resulted in 77% GPS location fix success rate (Table 1 and Figure 2) - an improvement from the ~20% fix rate found by Stabach (2005). The batteries on all GPS collars had failed before their retrieval date, however the VHF transmitters on the GPS collars were powered separately and did not fail, thus allowing the animal to be located for collar retrieval. Downloading collar data remotely was generally successful and prevented the complete loss of data if a collar could not be retrieved. All animals that had GPS collars were collared with a VHF telemetry collar for radio tracking before a follow-up deployment of update collars between October 2018 and April 2019.

ID	Collar Type	Start Date	# days	# locations	# of GPS Fixes Attempted	% Fix Success	Average Sampling Interval
MTK 1	GPS	9/27/2017	72.3	329	433	76.0%	4.9 hours
MTK 2	GPS	9/30/2017	82.7	376	502	74.9%	4.8 hours
MTK 3	GPS	10/2/2017	139.5	655	836	78.4%	4.2 hours
MTK 4	VHF	12/9/2017	124	79	-	-	1.57 days
MTK 5	VHF	12/9/2017	124	80	-	-	1.55 days
TOTAL	**GPS only**			1360	1771	76.8%	

Table 1. Summary of Tree-kangaroo VHF and GPS collar deployment and performance.

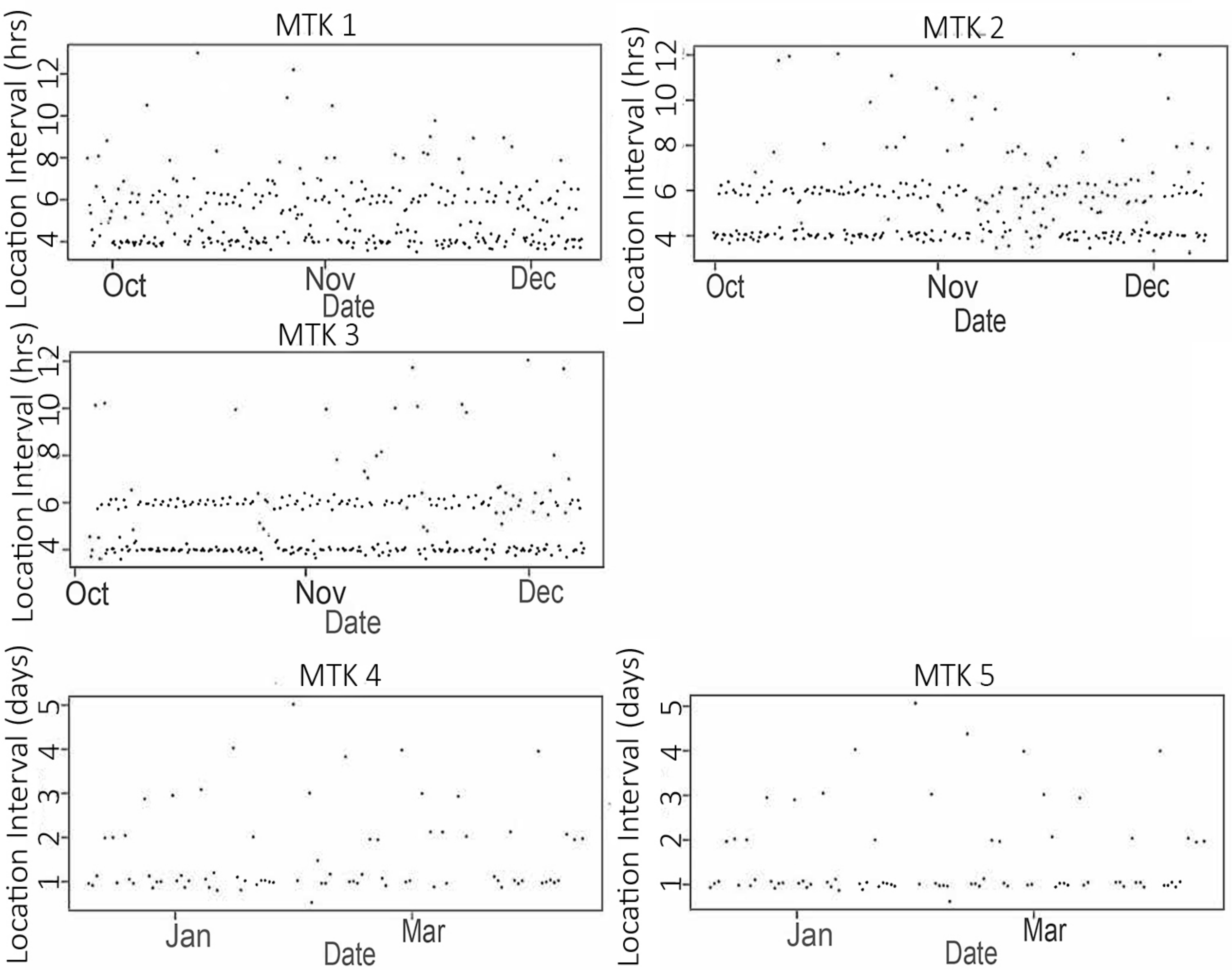


Figure 2. Sampling frequency of GPS and VHF collars. The y axis for MTK 1, 2, and 3 (tracked using GPS collars) is in hours, while the y axis for MTK 4 and 5 (tracked using VHF collars) is in days.

3.3.2 Home Ranges

The Minimum Convex Polygon bounding geometry around 100% of GPS collar locations shows an average area of 23.6 ha (N=3), with a smaller home range for females of 14.4 ha (n=2) and 41.8 ha for the male (Table 2). This same data processed using T-LoCoH shows a 95% iso-hull area average of 15.36 ha (N=3), with an area for females of 12.02 ha (n=2) and 22.6 ha for the male. The 100% MCP of the VHF tracked animals results in far larger (2-3 times) home ranges with an average of 76.6 ha (n=2; Table 3, Figures 3 and 4).

ID	*Method*	*Sex*	*100% MCP (ha)*	*95% ISO Area (ha)*	*10% ISO Area (ha)*
MTK 1	GPS	F	15.4	9.6	0.6
MTK 2	GPS	F	13.4	10.4	0.7
MTK 3	GPS	M	41.8	22.6	2.0
MTK 4	VHF	F	57.3		
MTK 5	VHF	M	95.9		

Table 2. Home range area estimates for each individual animal collared comparing Minimum Convex Polygon and T-LoCoh results.

Author	*Method*	*Sample size (# of animals)*	*MCP (100%)*	*Kernel (50%)*	*Kernel (90%)*	*T-LoCoH (95%)*
Porolak (2008)	VHF	15	139.6 ± 26.5	13.8 ± 2.9	68.7 ± 14.2	-
Stabach et al. (2012)	GPS	3	-	7.3 ± 1.9	28.3 ± 2.3	-
Byers (2019)	GPS	3	21.7 ± 18.2	NA	NA	15.4 ± 6.7
	VHF	2	76.6 ± 19.3	-	-	-

Table 3. Mean home range area estimates from previous studies and this research. Location collection method and sample size are shown along with results from 100% Minimum Convex Polygon (MCP), and Harmonic Mean means calculated using 50% and 90% Kernels, and 95% Time Local Convex Hull (T-LoCoH) techniques.

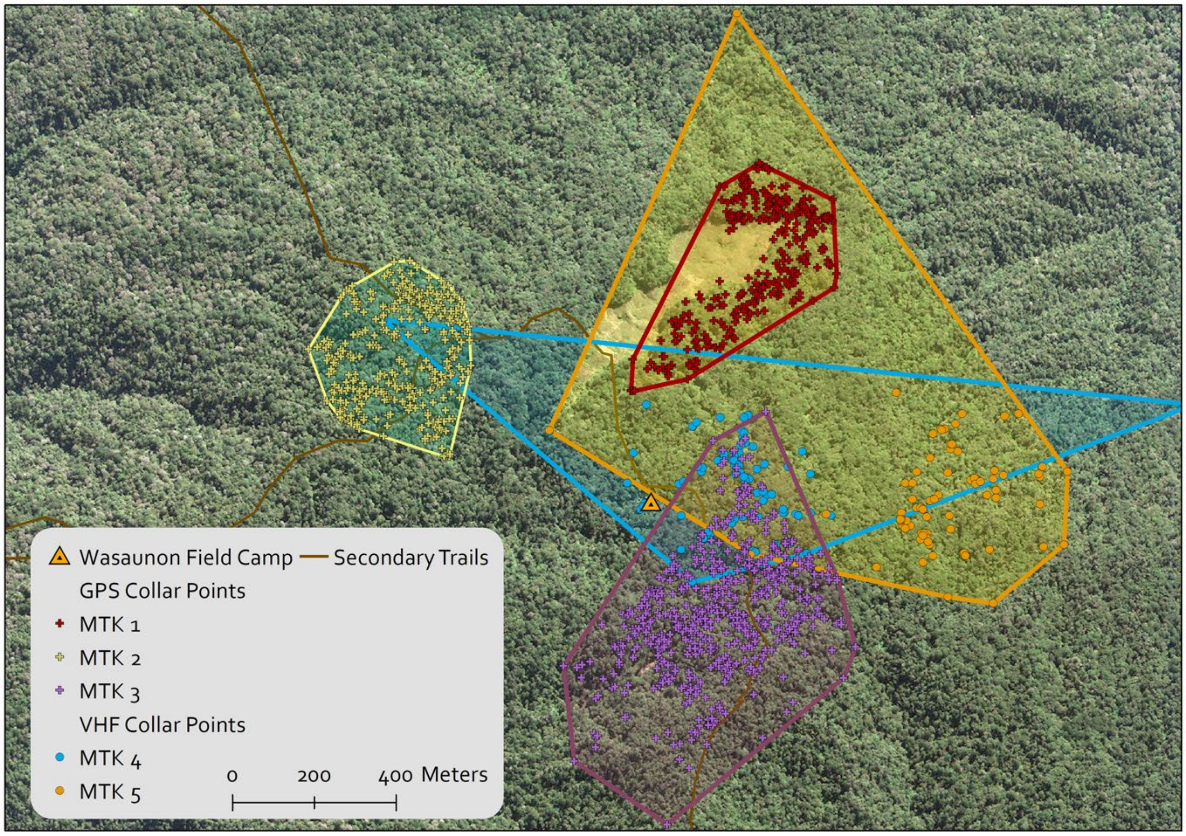


Figure 3. Map showing animal locations from GPS collars and from VHF collars. The bounding geometries show 100% MCP. The Wasaunon camp and local trails are also shown. Base map is WorldView-2 (imagery ©2018 DigitalGlobe, Inc).

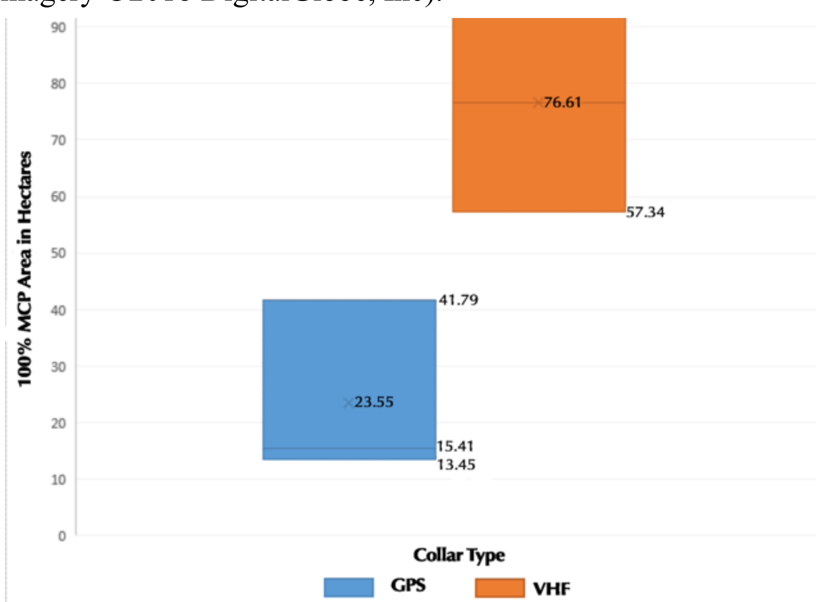


Figure 4. Plot of area within 100% MCP for each of the GPS and VHF collars.

3.3.3 Spatial Behavior and Movement

Tree-kangaroos observed in this study generally move very short distances between recorded locations, with a mean distance between GPS locations of ~30 m (Figure 5). A temporal analysis of GPS locations shows an average time to independence of 72.6 hours, indicating very slow movement and significant site fidelity. The ISO value hulls show clear areas of non-utilization within the MCP area of MTK 1, indicating that they do not use the open grassland (Figure 6).

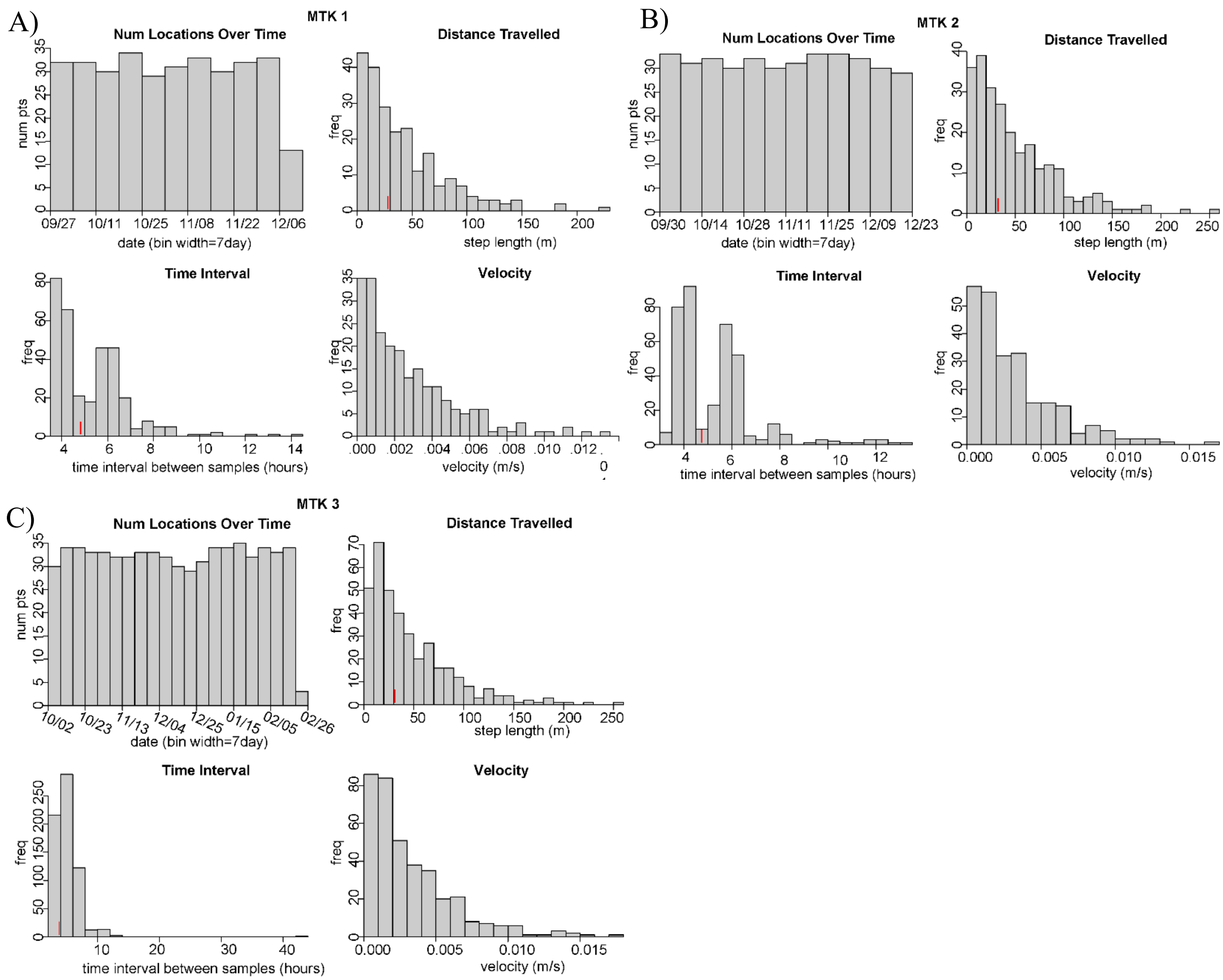


Figure 5. T-LoCoH Descriptive Plots. Clockwise from upper left for each animal show number of GPS locations per 7 days, distance traveled between locations (red bar is the mean), velocity between locations, and time interval between successful GPS location fixes.

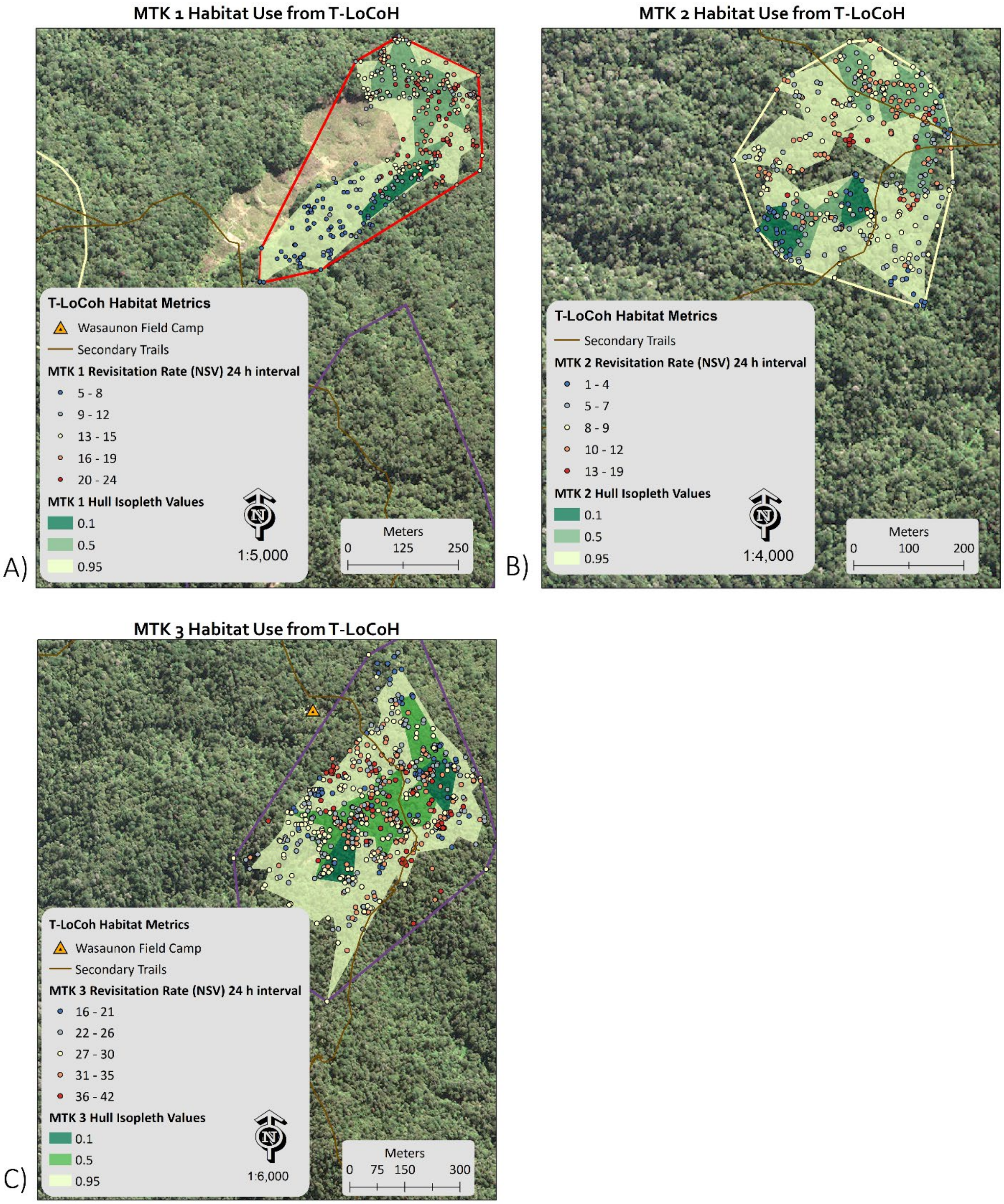


Figure 6. Maps of T-LoCoH Revisitation Rates and Utilization Hulls. Location revisitation rates from visits separated by 24 hr windows using T-LoCoH show blue points represent areas visited infrequently and red the most frequent. Revisitation rates are dependent upon number of locations recorded by each collar, and are not standardized. Isopleth values represent minimum areas containing 10%, 50%, and 95% of points.

3.4 Discussion

3.4.1 GPS Collar Design and Performance

The far higher fix success rate of the GPS collars built by Hawk-Owl Systems compared to the rates obtained by Stabach (2005) highlight the substantial recent improvements in small GNSS antennas. While these collars were not programmed to record which GNSS constellation they were using for their locations, or the accuracy of the position, it is likely that the substantially greater number of satellites available for location acquisition over only using the GPS constellation account for some of this improvement. Additionally, the large ceramic patch antennas and unlimited fix acquisition times contribute to the higher success rates, which are notably higher than those found in recent literature from other tropical arboreal animals (e.g. 36.6% fix success rate, white-footed tamarins (*Saguinus leucopus*; Sanchez-Giraldo & Daza, 2019).

Despite this substantial improvement, the collars overall did not fully realize their designed performance. Most notably, the projected lifespan for the collars was at least 4 months, however all collars failed before this point. This was likely caused in part by the long times required to get a successful GPS fix. While the dense forest canopy could explain the long fix times, the collars also had the tendency to rotate around the animals neck (Figure 7) potentially because they were

Figure 7. GPS Collared Tree-kangaroo in the forest canopy Image showing the rotation of the GPS antenna under the neck of MTK 1. Box facing down contains GPS, VHF, and Telemetry antennas. Screen capture from "A Life in the Clouds: A NATURE Short Film"

designed to not change the animals balance and have less battery weight in the front than the heavier collars used on ungulates. The higher fix success rate of these collars reveals the potential importance of this parameter in designing GPS collars for deployment in dense tropical forests. This fix attempt timeout setting was limited in the redesign of the collars deployed in 2018-2019 to preserve battery life. Particularly with novel techniques such as this, the specific design of the GPS collar can make substantial differences in data collections, but few studies report on the design parameters of the equipment used which makes it difficult to compare the performance of this collar with the results of other studies (e.g. Frair et al., 2010).

Another design challenge identified was that by the end of the deployment, all of the 915 MHz telemetry antennas had been broken or chewed off by the animals close to where they emerge from the case. This severely limited the range from which they could be downloaded, and while all the collars were retrieved during this study, this problem could be catastrophic if the collar was not retrieved. The recommendation that this antenna be partially enclosed within the housing surrounding the GPS antenna was taken into account during the redesign for collar redeployment in late 2018.

The barometric pressure altitude data recorded by the collars was not used for this study because the elevation values recorded by the collars reflect both the movement of the animal throughout the forest canopy, but also variations in barometric pressure from weather, and no barometric pressure sensors in fixed locations were deployed at the study site. Another challenge presented by the design of the collars was the technique of data recording and storage. By recording the GPS locations separate from the elevation data, interpolation would be required to match the altitude values (recorded hourly) to the GPS locations (recorded hourly + the amount of time required to acquire a GPS fix). These problems were addressed in the redesign and redeployment of the collars and a test box containing the exact same components as the animal collars was deployed in a fixed known location to provide barometric pressure reference for the deployed animal collars. Instead of altitude ranges, actual elevation values will be recorded in sync with GPS locations.

The failure of GPS location fixes can introduce significant habitat bias (Frair et al., 2004). Rapid location fixes are more likely to be recorded where there is less obstruction from leaves and branches – namely, higher in the forest canopy, near canopy gaps, or in forest types with more open structures, but slower with more failures in the densest portions of the forest. Further assessment of the errors or biases from these collars is necessary if this location data is to be used to make correlations with specific trees from high resolution remote sensing data. Additionally, the intermittent nature of GPS sampling means that the actual movement patterns of collared animals remain unknown. A potential solution to this is the introduction of GPS-corrected dead-reckoning sensors that are becoming available. One challenge with this on small animals such as tree-kangaroos is the increased power use of this type of sensor, which thus requires larger batteries and heavier collars.

3.4.2 Home Range Sizes

It is interesting that the 100% MCP home range sizes from 2017-2018 GPS tracking are smaller than the 90% Kernel ranges found by Stabach et al. (2012), particularly when the 100% MCP is known to overestimate the area used. While the three animals in each study do not present a statistically significant sample size, it is plausible that the removal of hunting pressure with the establishment of the YUS conservation area in 2009 would result in an increase in the number of animals. Anecdotally, the local trackers reported having much easier times finding animals to collar in 2017 than in previous research efforts (L. Dabek, personal communication). If *D. matschiei* are solitary and territorial, that could explain a reduced home range area.

Also, the 100% MCP values from VHF tracking in 2017/2018 are strikingly larger than the 100% MCP values from GPS tracking. Because Stabach et al. (2012) do not present a 100% MCP value it is difficult to make a direct comparison, but the difference in area between VHF and GPS methods found in 2017-2018 does seem roughly proportional to the values presented by Porolak (2008) and Stabach et al. (2012). While the cause is unknown of the extreme outliers during the VHF tracking in 2017-2018, or the large size difference between the GPS and VHF values in previous studies, it is possible that these are the result of *D. matschiei* to human disturbance, with the animal moving outside of their core areas when rangers try to locate them using VHF tracking. This behavior was noted twice during the process to recapture animals in October 2018, where animals would appear to move rapidly outside their known range, mostly on the ground, when trackers would go to locate them, and was reported other times by rangers (N. Wari, personal communication). It also is possible that the outliers were the result of errors in VHF location data recording and processing, as these locations are manually recorded using a handheld GPS, entered into a notebook, and later digitized, rather than an automatically generated record directly from the collar.

3.4.3 Spatiotemporal Ranges

The 10% iso hulls presented in Figures 6 show the areas of the highest density of use through time, presumably places with habitat types or structures that are among the most important to *D. matschiei.* From field experience, these areas coincide with high structural heterogeneity and older large trees. This study did not investigate potential movement corridors, which can be examined with hull elongation in T-LoCoH or using movement-based models such as CTMM (Calabrese et al., 2016).

Finding appropriate parameter values in T-LoCoH was challenging as there are few publications to provide guidance. Those that do often use significantly higher numbers of locations, usually because they are studying a larger animal which can carry a heavier GPS collar with larger batteries (e.g. Lyons et al., 2013; Stark et al., 2017) and are not appropriate for this species. Because of the subjectivity of parameter selection, Dougherty et al. (2017) propose an algorithm for choosing s and k values for T-LoCoH, however their technique does not incorporate the time used of locations, and so was not included here.

3.4.4 Habitat Use and Movement

This investigation of spatial behavior of *D. matschiei* using T-LoCoH revealed clear boundaries around forest clearings and canopy gaps that the animal did not use. Each animal seems to have several locations it returns to on multiple visits. These locations could be ideal sites to deploy remote cameras for future non-invasive behavior research. While Stabach et al. (2012) suggest that the importance of different forest compositions should be investigated, these results indicate that the importance of different forest structures should also be examined. While T-LoCoH can be used with elevation data, it is ultimately an areal technique. For 3D home range questions, other studies suggest using movement and travel-path probability techniques which incorporate elevations, such as a movement-based kernel density estimator (Tracey et al., 2014; Fleming et al., 2016) or continuous time movement model (CTMM; Calabrese et al. 2016).

Because of the untested biases of GPS collars in different habitat types it is difficult to make broad conclusions about whether *D. matschiei* prefers areas of forest heterogeneity, or whether these are associated with better GPS satellite signal. Additionally, the elevation and motion logging data collected by these collars were not utilized in this analysis, but there is a burgeoning field of animal movement behavior research that leverages machine learning to make inferences and predictions from very large high frequency sampling datasets that could be a promising future direction (e.g. Nathan et al., 2012; Wilson et al., 2008).

3.5 Conclusions

This investigation into space use using GPS collars and T-LoCoH supports the hypothesis that Matschie's tree-kangaroos are not habitat generalists. They clearly prefer using small portions of their home range, and totally avoid some areas that would otherwise be included in their home range by MCP or Kernel techniques. The home range areas assessed by Porolak et al. (2014) from VHF collar locations and MCP or Kernal methods are nearly an order of magnitude larger than the utilization distributions of other tree-kangaroo species (Coombes, 2005). The MCP home ranges from the 2004-2007 and 2017-2018 VHF collars are 2-3× larger than the MCP home ranges from the GPS collars during the same studies. While not conclusive, this supports the hypothesis of local trackers that this could be due to the sensitivity of *D. matschiei* to human disturbance, although the reduction of hunting pressure from local villagers accompanying the establishment of the conservation area may also have contributed. A larger sample size, comparing the data between the GPS and VHF collars, and studying home range size at different proximities to villages, as well as inside and outside the no-take zone could help resolve some of these questions.

The variations in area between the Minimum Convex Polygon and T-LoCoH hulls illustrate the importance of methodology in defining habitat utilization. T-LoCoH is better at excluding areas that are inside the kernel home range, but which the animal does not use. It was previously unknown whether grasslands were barriers for tree-kangaroo movement and a visual assessment of habitat from UAS orthoimagery shows that grasslands are clear boundaries to *D. matschiei* movement (Figures 3 and 6). This is valuable insight because these alpine grasslands cover extensive areas of the high elevation mountains above 3,000 m and effectively provide an upper boundary for tree-kangaroo distribution. Furthermore, the large expansions of alpine grassland during drought years may aid in predicting the effects of climate change on tree-kangaroo habitat.

As an arboreal animal, the Matschie's tree-kangaroo is dependent on a complex 3-dimensional forest structure. To understand the resource needs and behaviors of the Matschie's tree-kangaroo, home range and resource selection studies should include vertical movements and temporal patterns to identify their needs, threats, and potential barriers to movement (McLean et al., 2016; Powell & Mitchell, 2012).

4 INVESTIGATING FOREST STRUCTURE FROM AERIAL PHOTOGRAMMETRY

4.1 Background

4.1.1 Remote Sensing of Habitat Variables

Cagnacci et al. (2010) state, "Animal positions... show where individuals interact with the ecosystems around them." From a conservation perspective, understanding the habitat composition and structure associated with an animal's location allows land managers to evaluate what features are important and effectively implement actions that protect vital habitat (e.g. Craighead, 1979). Understanding the habitat preferences of wild animals is also important in the management of captive populations which are increasingly important as wild populations are pushed to the brink of extinction (Conway, 1995). Traditionally, understanding the habitat variables associated with an animal's location required manual measurements. The far higher number of locations and collected data from GPS collars necessitates a shift towards remote sensing techniques to measure habitat variables associated with those numerous locations (e.g. Cagnacci et al., 2010; Hebblewhite & Haydon, 2010; Kays et al. 2015).

Previous research using remote sensing to investigate tree kangaroo habitat has focused on categorizing forest composition from 2D satellite imagery (Pugh, 2003; Stabach, 2005; Stabach et al., 2009). Based on manually collected habitat data, Porolak (2008) reports that *D. matschiei* were found in *Dacridyum nidulum* (a large canopy emergent tree) at 51.71% of VHF tracked locations. In attempting to categorize *D. nidulum* forests using satellite imagery, however, Stabach et al. (2009; 2012) found that Landsat 7 ETM+ (6-band multispectral, pansharpened to 14.25 m/pixel) and SPOT-4 (4-band multispectral, 20 m/pixel) imagery were of insufficient resolution to classify heterogeneous forest types, with a mean classification accuracy of 70.6%. The increasing availability of very high-resolution (sub-meter) satellite data provides novel ways to investigate habitat use on fine scales, however the near continuous presence of clouds in tropical regions (particularly at higher elevations like those found on the Huon Peninsula) hinder the regular acquisition of satellite imagery (Chambers et al., 2007).

For many organisms, the 3D structure of their habitat is as important as, or even more important than, the species composition of the habitat (e.g. Goetz et al., 2010; Williams et al., 2002; Davies et al., 2017). Particularly for arboreal animals, forest canopy structure dictates movement pathways, food resources, and shelter from predators, which in turn are reflected in the locomotor adaptations and movement patterns of the organism (McLean et al., 2016). For better-studied prehensile-tailed vertebrates, forest gaps are known barriers (Emmons & Gentry, 1983), and forest height (as a proxy for forest maturity) is an important predictor of abundance (Palmentiri et al., 2012). Clearly this is also the case for *D. matschiei,* which were only observed on the ground in 2 of 141 sightings by Stabach (2005), and were not recorded crossing the open grassland by the GPS collars used here. Because of their distinct evolutionary heritage and physiology from arboreal primates, *D. matschiei* and related arboreal macropods would be expected to have unique movement patterns, yet we know almost nothing about the movement patterns of these animals in the wild (Procter-Grey & Ganslosser, 1986).

Nearly all similar investigations of forest habitat structure characteristics use aerial light detection and ranging (LiDAR; a.k.a. Airborne Laser Scanning (ALS); e.g. Davies et al., 2017; McLean et al., 2016; Zhao et al., 2012). However, the applications of these techniques are limited in Papua New Guinea, and many other parts of the world, by the lack of publicly available data and the extremely high cost of custom aerial LiDAR data collection. Advances in aerial photogrammetry from small, lightweight unmanned aircraft systems (UAS) have opened many possibilities applicable to wildlife biology including: direct observation of animals with visible light or thermal infrared cameras (Kays et al., 2019), detection of arboreal animal nests (Van Engel et al., 2015), and on demand acquisition of extremely high resolution visible and multi-spectral imagery for habitat analysis (Anderson & Gaston, 2013; Chabot & Bird, 2015). Additionally, the relative low cost of these systems make these tools attainable by many research projects, but implementation of these tools from both a technical and regulatory standpoint remains challenging particularly in remote, rugged, high elevation areas (Koh & Wich, 2012).

Visible spectrum (*i.e.* Red, Green, Blue or RGB) cameras are the most commonly deployed on UAS and can be used to identify vegetation using object- and pixel-based classification approaches, particularly when combined with machine-learning approaches (e.g. Sandino et al., 2018). However, multispectral cameras are better suited for vegetation classification than RGB cameras, and are being used for a follow-up study at Wasaunon that will not be addressed by this report. Thermal infrared imaging from UAS could be a powerful tool for identifying arboreal animals (e.g. Kays et al. (2019) with tropical primates), however the small body size, insulating fur, and solitary behavior of tree-kangaroos would likely challenge the currently available thermal IR sensors.

Significant advancements in the process of digital photogrammetry allow the production an extremely high resolution digital surface model (DSM) from RGB cameras which can be effective in investigating the 3-D structure of forests (e.g. Mohan et al., 2017). If coupled with the elevation of the ground surface (digital terrain models (DTM)), then canopy height models (CHM) can be calculated from which a variety of commonly used landscape and habitat metrics can be derived (Zhang et al., 2016; Mohan et al., 2017). However, because photogrammetric methods only capture the upper surface of the landscape, it can be very problematic to detect the ground surface in the case of closed canopy forests such as those commonly found in tropical rainforests (Lisein et al., 2013). While no literature has identified the percentage of canopy closure at which these techniques begin to fail, the amount of terrain visible between gaps in the canopy at Wasaunon was insufficient to see the ground surface.

Previous work attempting to solve this problem in closed canopy forests include a technique to manually collect ground surface points with a GPS and interpolate the ground surface (Isenberg, 2017). This method of collecting gridded GPS surface points was attempted at Wasaunon, however the extreme ruggedness of the terrain, very dense undergrowth, and low GPS signal under the forest canopy made this technique impractical beyond very small study areas. Ota et al. (2015) proposed a 10 × 10 m moving window method to recreate the terrain surface from gaps in the canopy, however this technique begins to fail if gaps are more than 10 m apart and was less accurate for terrain reconstruction than LiDAR. These challenges have meant that many researchers regard UAS as an ineffective tool for surveying closed canopy forests, despite their tremendous potential as a research tool.

4.1.2 A Novel Approach to Forest Structure Measurement from UAS

This project investigates a novel approach to the creation of a Canopy Height Model (CHM) from RGB aerial photogrammetry in three steps: 1) canopy gap identification, 2) interpolation of terrain surface from the lowest elevations of canopy gaps, and 3) the creation of a CHM from the interpolated terrain and canopy surface. The first step evaluated automated and manual techniques for identifying canopy gaps. Gaps in the forest canopy have long been recognized by ecologists as important features allowing light to penetrate the forest canopy and important in forest regeneration, nutrient cycling, biodiversity, and to invasive species (Schliemann & Bockheim, 2011). This study compared manual gap identification to an automated method adapted from Betts et al. (2005) using a high resolution Digital Elevation

Model from UAS imagery. The elevations of presumed ground surface points were extracted from the lowest points of the canopy gaps.

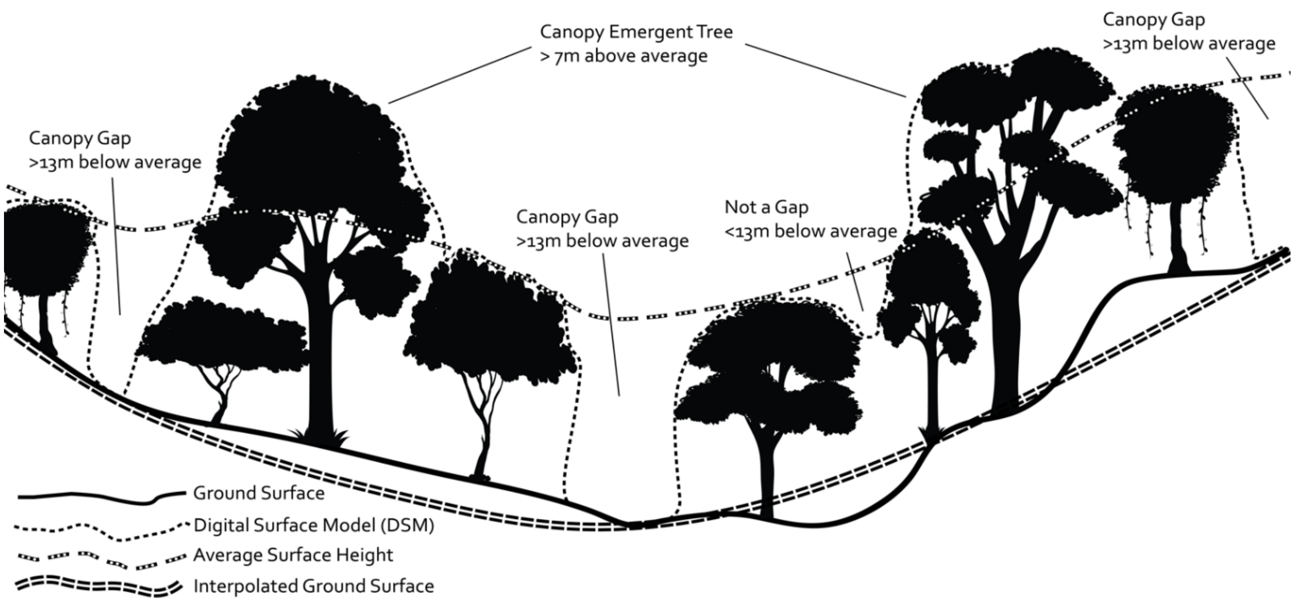


Figure 8. Conceptual representation of canopy structure and surfaces used for structure analysis. Differences between the digital surface model and interpolated ground surface were used to create a canopy height model.

The second step was to interpolate the terrain surface between canopy gap points. Many studies have investigated the use of different interpolation methods for terrain reconstruction from LiDAR ground returns, which generally have far higher point densities of ground returns than the method of terrain points from canopy gaps used here. Inverse Distance Weighting (IDW), a deterministic technique, is one of the most commonly used, however Lloyd and Atkinson (2002) found that Kriging, a geospatial statistical fitting method, has less error when reconstructing terrain from sparse LiDAR points, and recommend it for mountainous terrain. The ANUDEM technique, an iterative finite distance technique (Hutchinson, 1988; the algorithm used by the "Topo to Raster" Tool in ArcGIS), was specifically intended for terrain modeling and creates surfaces which are, "generally smooth and free of obvious artifacts", particularly when the drainage enforcement functions of this technique are not used (Bater & Coops, 2009). This project evaluated the reconstruction of terrain surface from IDW, Kriging, and ANUDEM techniques.

The third step was to subtract each of the interpolated terrain model from the Digital Surface Model to get a Canopy Height Model (CHM), which is the normalized height of each tree. The CHM allows for evaluation of tree height, texture, and other characteristics and is a standard method used by other papers investigating photogrammetric interpolation (e.g. Mohan et al., 2017).

4.2 Methods

4.2.1 Aerial Imagery Capture

Aerial mapping flights were conducted on two separate site visits with different equipment and settings approximately one year apart. Because there are few conventions for how to successfully map closed canopy tropical forests in rugged terrain, the techniques used during both trips and the relative success of each will be discussed.

In October 2017 a DJI Mavic Pro (DJI Science and Technology Co. Ltd., Shenzhen, China) was used controlled by Pix4D Capture (Pix4D SA) running on an iOS device. The camera on this aircraft is a 1/2.3” CMOS sensor with a rolling shutter that captures images of 4000×3000 pixels with a 78.8° Field of View (FOV). Pix4D Capture only records .jpeg images and does not offer terrain following, so flight height was manually set depending on the topographic variance of each separate grid mission. These ranged between 80-120 m AGL, and 80 – 350 m above the takeoff point, therefore image overlap ranged between 50-80% and Ground Sample Distance (GSD) varied depending on topography and flight altitude. The DJI

Mavic Pro has an advertised range of 7 km and flight duration of 27 min. Shutter speed and focus were controlled automatically by Pix4D Capture and flight speed was set to “fast”.

In October 2018, a DJI Mavic 2 Pro (DJI Science and Technology Co. Ltd., Shenzhen, China) was used controlled by the Map Pilot (Drones Made Easy, dronesmadeeasy.com) app running on an iOS device. This aircraft has a 1” CMOS sensor also with a rolling shutter that captures images of 5472 × 3648 pixels with a 77° FOV. It has an advertised flight range of 8 km and duration of 31 min. Map Pilot does allow for terrain following, and flight height was set to 122 m (400 ft), and a flight path overlap of 75% was used. Mapping missions must be pre-planned before leaving an internet connection to download terrain and basemap data because there is not cellular or internet connection at the field site. Importantly Map Pilot also allows for continuation of the mapping mission even with a temporary loss of connection to the controller.

4.2.2 Photogrammetry Processing

Images were processed using Pix4D Mapper (Pix4D) to develop 3-D forest canopy surface models and orthophotos. After the first step of processing and the generation of a sparse point cloud, the locations of 6 ground control points measured in the field with an Emlid Reach RS+ (Emlid Ltd.) were incorporated to georeferenced the imagery. Two iterations of processing were used for the generation of the densified point cloud and DSM: the first only required tie points to be identified in two images reconstruct finer details of the canopy surface (Figure 9A), the second required tie points to be visible in three images to remove noise in the canopy surface reconstruction that was present in the first round of processing (Figure 9B).

4.2.3 Canopy Structure Data Creation

Manual identification of canopy gaps was done using the photogrammetric DSM and orthoimage in ArcMap 10.6 (ESRI Inc.). This was a highly subjective process that relied substantially on local experience with forest canopy structure and terrain. A 13 m height difference between the surrounding canopy surface and the lowest point of the gap was used as a threshold for identifying gaps that reached fully through the canopy to the forest floor. This threshold was selected because the average canopy height is ~20 m, and the undergrowth on the forest floor often range from 2-5 m. There were several areas where depressions in the DEM aligned with gaps in the orthoimage but the difference to the surrounding canopy was <13 m indicating that the photogrammetry reconstruction had not successfully reconstructed down to the ground surface. These points were not selected as canopy gaps.

The automated gap-detection process from the DSM used a process modified from Betts et al. (2005). First a fill (Hydrology toolbox) was applied so that larger canopy gaps did not lower the average height of their surroundings and create artifacts when identifying canopy emergent trees. A 25 × 25 m mean moving window average was applied to smooth the canopy surface. The smoothed surface was then subtracted from the DSM to yield a raster that showed areas lower and higher than the mean. The raster calculator tool was used with a threshold of ≤13 m below the average being identified as a gap, and ≥7 m above the average being identified as a canopy emergent tree (Figure 8). These raster classes were converted to polygons and the zonal statistics tool was used to place points on the lowest elevation areas from the DSM inside each gap polygon. A 10 × 10 m standard deviation of roughness was also calculated to assess forest structure.

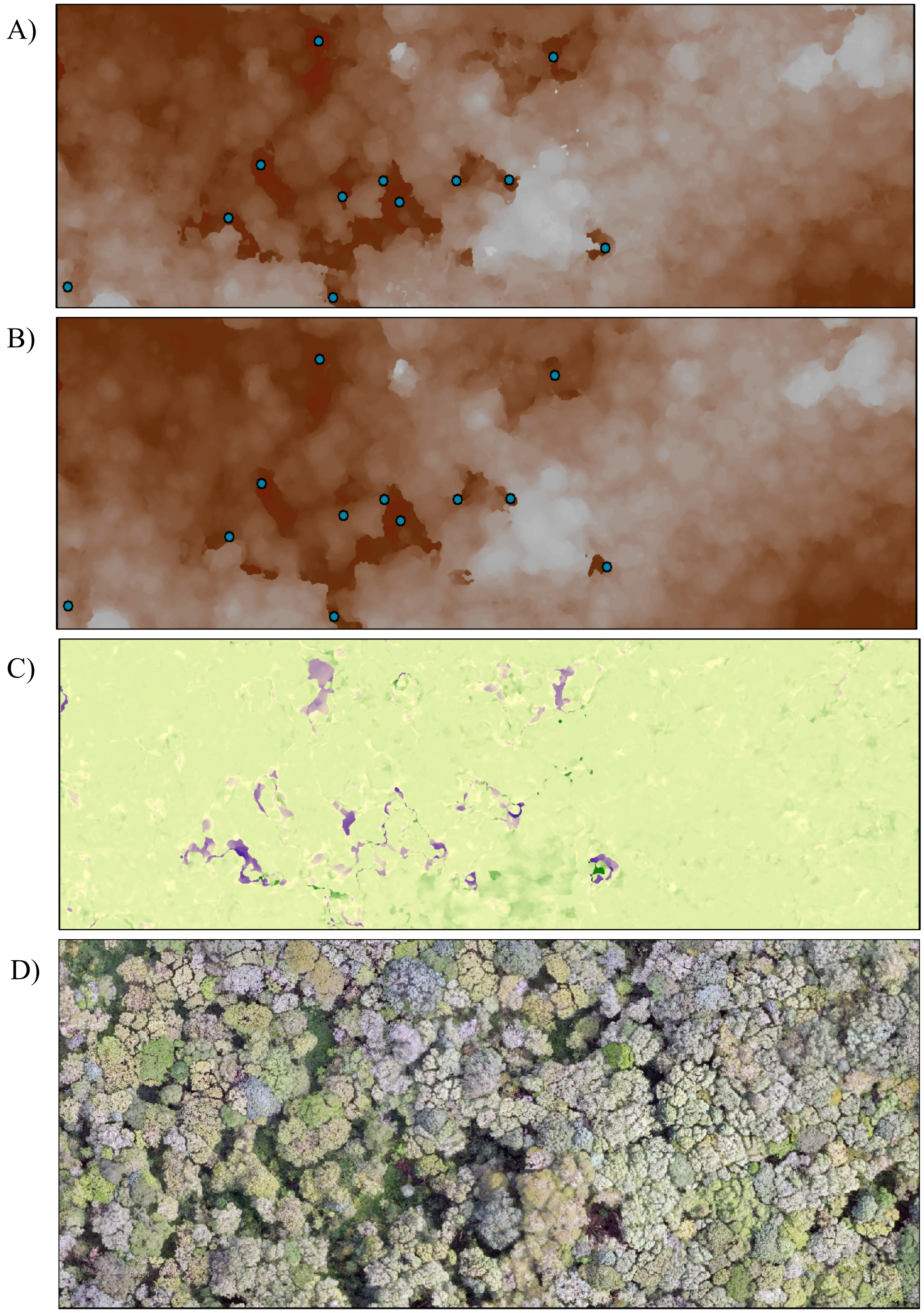


Figure 9. Photogrammetry processing technique comparison. A) Subset of the digital surface model elevation derived from the point cloud using a densification requiring two matches for points. Blue dots are manual canopy gap points. B) Digital surface model made requiring three matching points. This was used to calculate the canopy height model. There is a smoother canopy structure, reduced noise, and no canopy gap in upper left. C) Difference raster of the two methods–purple represents gaps not identified by B), and green represents noise introduced by A). D) Orthoimage of the same view.

4.2.4 Digital Terrain Model Interpolation

The original resolution of the DSM was ~5 cm, all products were down-sampled to 2 m because of computational limitations. The IDW interpolation used a power parameter of 5 to provide increased smoothing of the surface between measured points. The Kriging interpolation used ordinary kriging with a spherical model for the semi variogram. The ANUDEM method used a Threshold 1 value of 5 and a Threshold 2 value of 200. Sink filling and drainage enforcement functions were not used. The results of each interpolation method were clipped to a buffer 30 m inside of the original DSM to eliminate artifacts from low aerial photo overlap along the edges for CHM calculations.

4.2.5 Canopy Height Model Evaluation

Raster calculator was used to subtract the interpolated terrain from the original DSM to create the Canopy Height Model (CHM) for each interpolated terrain surface. Canopy height values were extracted from the resulting CHM rasters from comparison with measured canopy height values collected in the field by Byers (2018) using a laser rangefinder (Leupold RX-1300i TBR) and to those measured at animal locations in 2004 using a clinometer (Stabach, 2005).

4.3 Results

4.3.1 Aerial Imagery and Photogrammetry

In 2017, six flights over three non-consecutive days resulted in 864 photographs covering ~340 ha with an average GSD of ~8.5 cm. In 2018, three flights collected 546 images covering 194 ha with a GSD of 4.9 cm (Figure 10). The aerial imagery collected in 2017 proved to have systematic problems (including bad focus and low overlap) which prevented successful surface reconstruction at a resolution allowing the identification small canopy gaps. Additionally, signal interference limited flight range directionally to less than 2 km. In 2018, the new aircraft and change of flight control system was effective. While weather conditions were a challenge both years, the ability to opportunistically collect aerial imagery when it was clear in the morning was critical. Photogrammetric surface reconstruction using Pix4D proved to require a tremendous time investment as the available computer systems were not optimized for such large projects, and only imagery from flights conducted in 2018 was used for the remainder of these analyses.

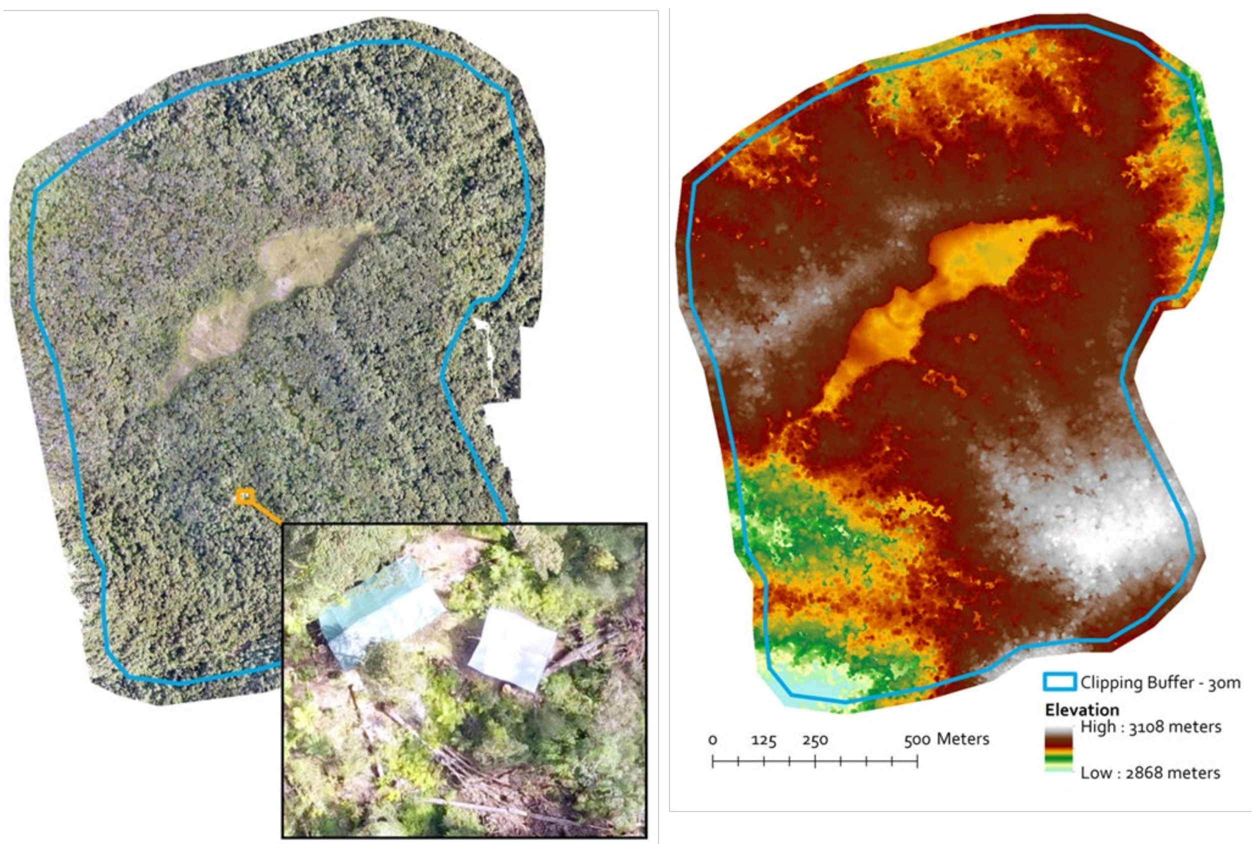


Figure 10. Resulting orthoimage and DSM of Wasaunon. Orthophoto of the aerial extent and inset of the research camp to illustrate resolution (left), and digital surface model (right) after processing. Insufficient overlap along the edges of the survey area reduced the accuracy of orthoimage merging and DSM and were trimmed (blue line).

4.3.2 Canopy Structure Analysis

While the manual method of canopy gap detection was tedious, the visual comparison between the orthoimage and the DSM was helpful in determining which gaps revealed the true terrain surface (Figure 9). The automated canopy gap detection method located more canopy gaps overall, and the largest distance between two points for interpolation was 83 m for the manual method and 150 m for the automated method (Figure 11A, B). The larger the distance between known terrain surface locations, the less likely the interpolation of that surface is to accurately represent the real terrain. The difference map (Figure 11C) reveals that gap detection techniques found contrasting results in different parts of the landscape–for example, in the lower elevation and lower left portion of the analysis area automatic gaps were closer together, and on the right side of the area in higher elevations the manual points were closer. No validation data was available to evaluate these further.

The distribution of canopy emergent trees resulting from the automated analysis shows broadly expected distribution, with no emergent trees detected in the open grassland (Figure 12). Similarly in pattern to the automated canopy gap detection, greater numbers of emergent trees were identified in the lower left (and lower elevation) portion of the study area. Because canopy emergent trees were only identified using the automatic thresholding method, there is no manual method from which to compare the effectiveness of the technique. The roughness analysis highlights the areas of large vertical change in canopy height, with a higher standard deviation of elevation along the edge of the grassland in the center of the analysis area, as well as the lower left part of the analysis area (Figure 13). No validation data was available to evaluate these further.

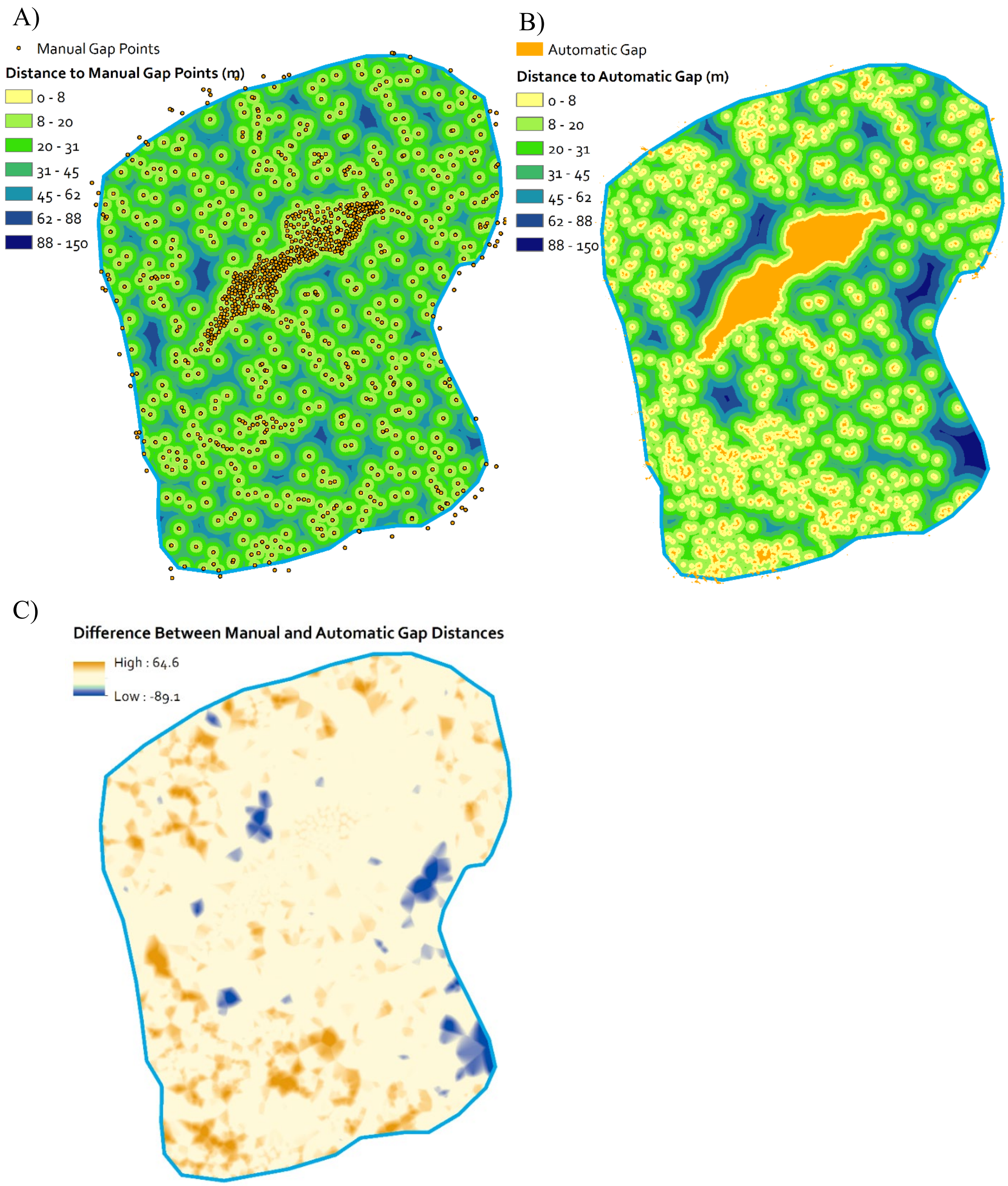


Figure 11. Maps of distance from canopy gaps by method. Canopy gaps identified A) using manual methods B) using automated methods. Color gradient is distance raster in meters from each point or polygon. C) Difference map of distance from canopy gaps determined from manual and automated methods meters. Orange is where the distance to automated gaps is closer and blue is where distance to manual gaps is closer.

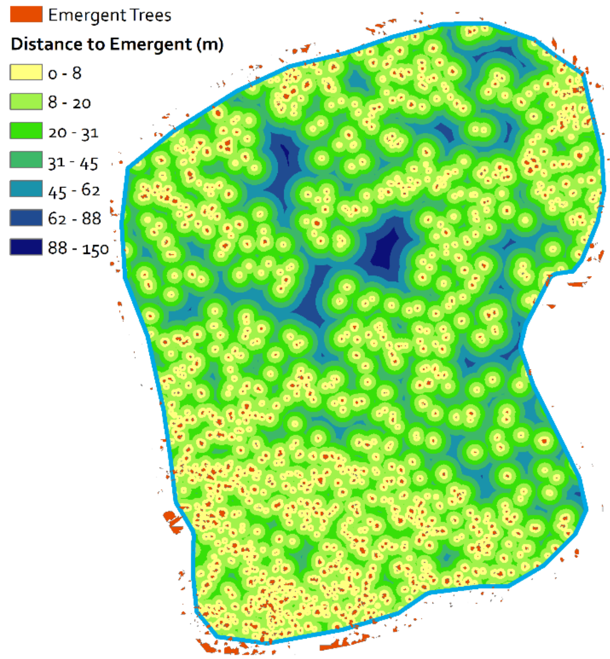


Figure 12. Map of distance from canopy emergent trees. Orange polygons represent emergent trees identified from automated thresholding and distance gradient is in meters.

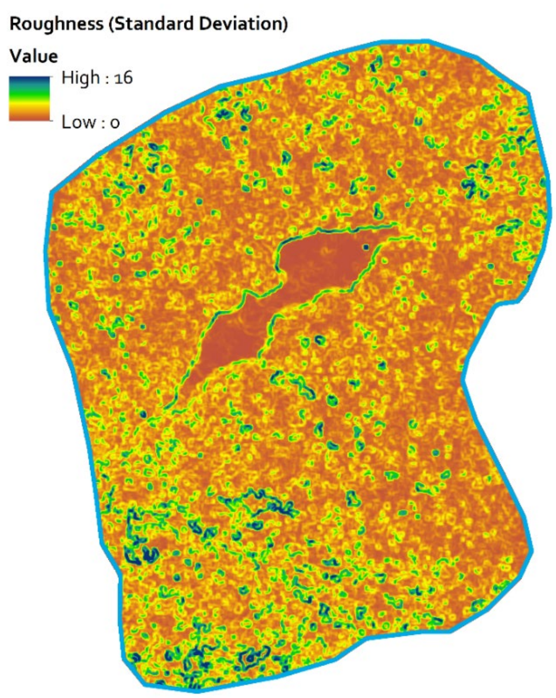


Figure 13. Map of canopy surface roughness. Calculated using the standard deviation of the canopy height model created using the ANUDEM method.

4.3.3 Terrain Interpolation Comparison

Of the three methods tried for terrain surface interpolation (Figures 14-16), the Topo to Raster (ANUDEM) method produced the most visually appealing and smoothest terrain surface (Figure 14). Kriging resulted in sharp stepwise changes of terrain surface in the larger gaps between points, but generally seems to represent the terrain (Figure 15). The IDW revealed characteristic bumps in the DTM, which translated to patches of artificially lower canopy height in the CHM (Figure 16).

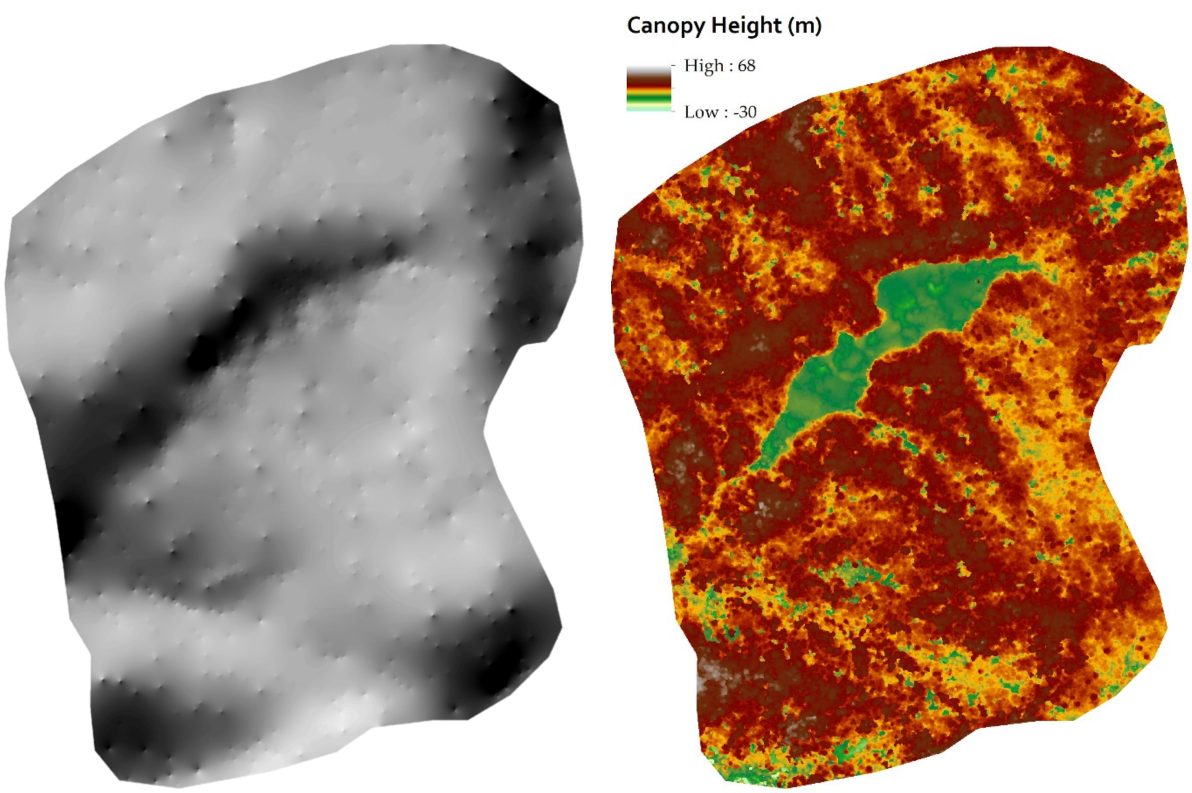


Figure 14. ANUDEM Hillshade and CHM. Hillshade of the DTM generated from the ANUDEM interpolation method (left) and resulting canopy height model (CHM; right, in meters above ground).

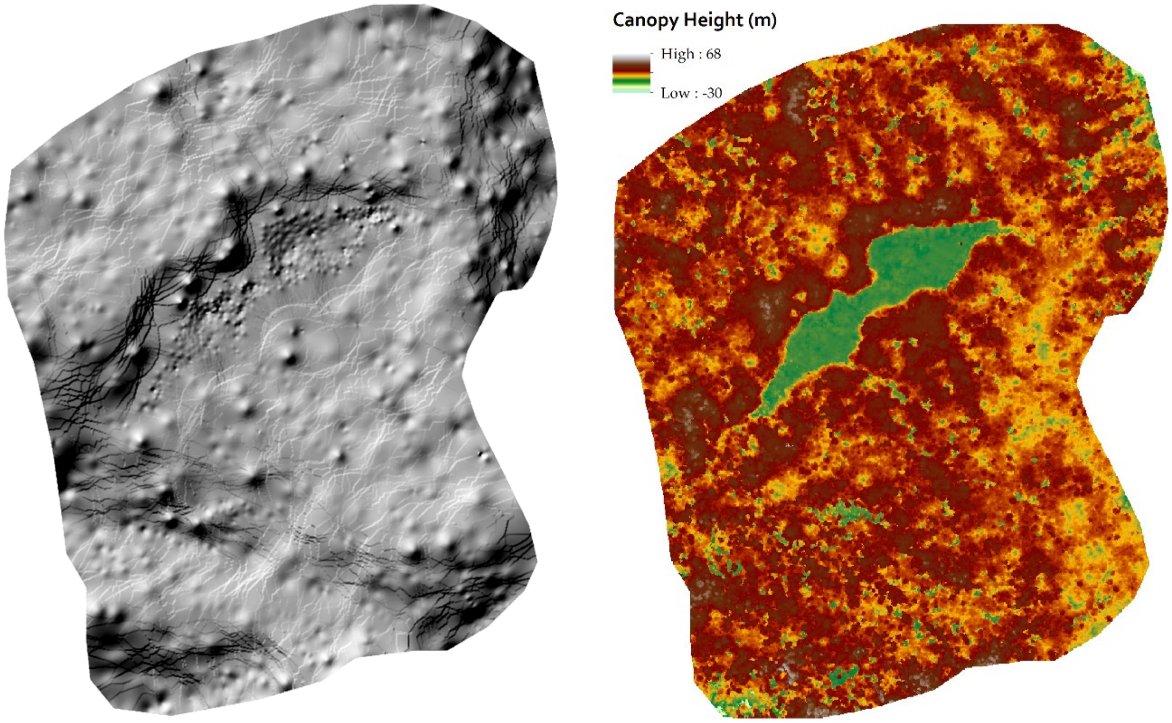


Figure 15. IDW hillshade and CHM. DTM from the IDW interpolation method (left) and resulting canopy height model (CHM; right, in meters above ground).

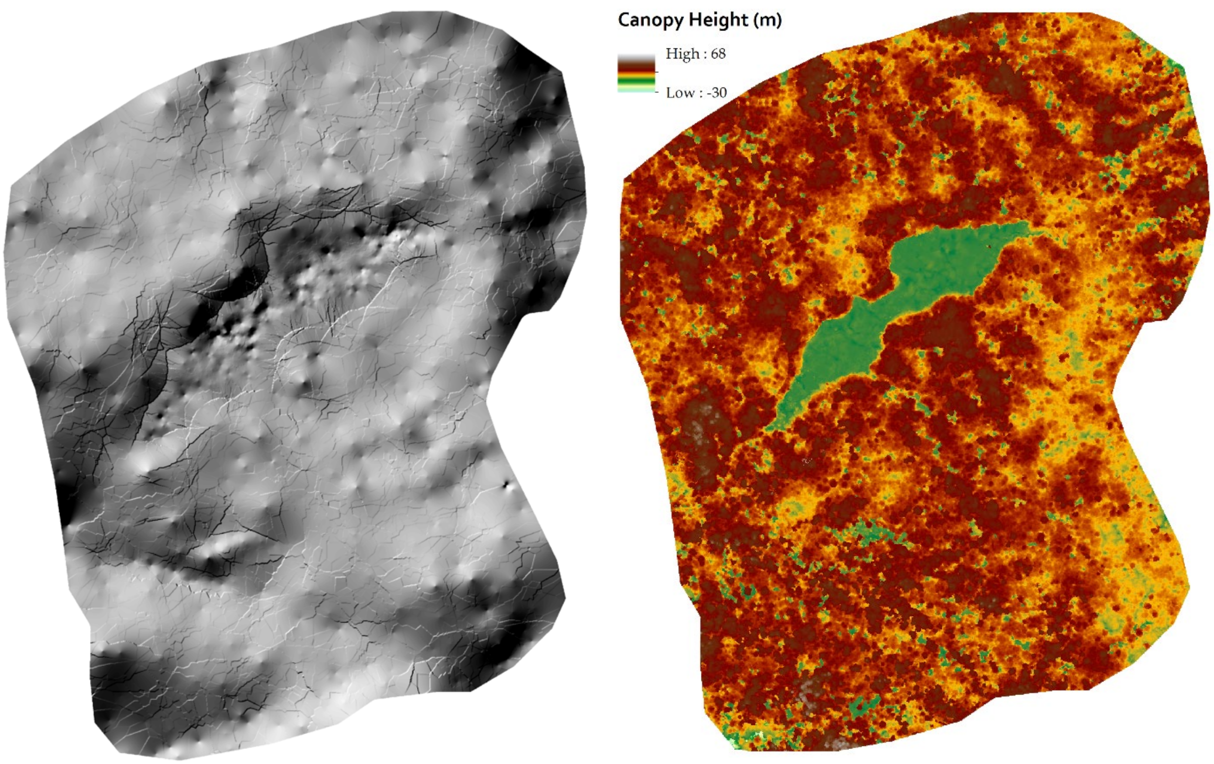


Figure 16. Kriging hillshade and CHM. DTM from the Kriging interpolation method (left) and resulting canopy height model (CHM; right, in meters above ground).

4.3.4 Evaluation of Canopy Height Models

The CHM developed from interpolation of the terrain surface using the technique proposed in this study and UAS photogrammetry consistently overestimated the height of the canopy compared to the measured canopy heights in 2018. The measured canopy height was on average 3.77 m lower than the Kriging interpolation, 6.89 m lower than the IDW interpolation, and 8.25 m lower than the ANUDEM interpolation (Figure 17). This contrasts with the height of the canopy measured by Stabach in 2004, who reported an average canopy height 4.2 m taller than the interpolated surfaces (Figure 18).

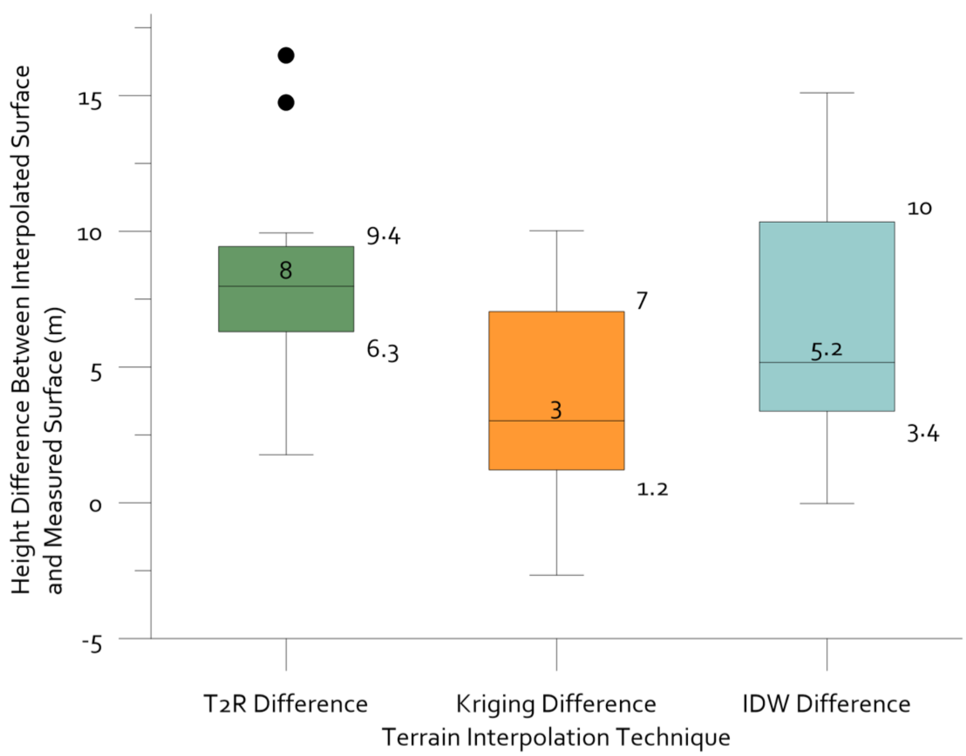


Figure 17. Plot of CHM and 2018 measured tree heights. Height differences between interpolated canopy heights and canopy heights measured in 2018 using DGPS location and direct laser rangefinder. Positive values indicate taller interpolated estimates.

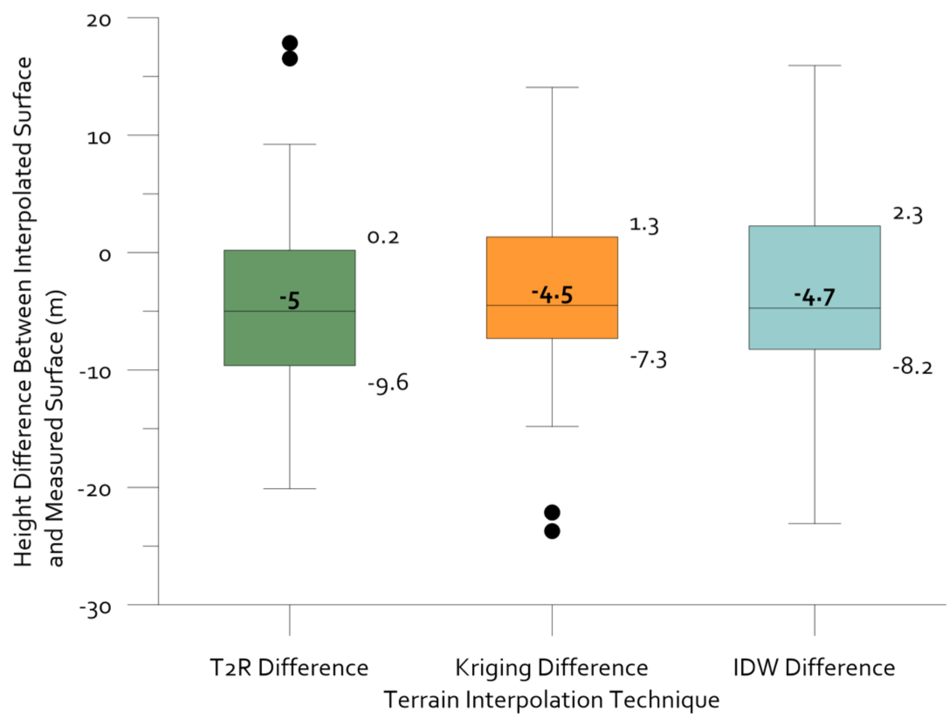


Figure 18. Plot of CHM and 2004 measured tree heights. Interpolated canopy heights compared to canopy heights measured by Stabach (2008) in 2004 using GPS location and trigonometry from clinometer angle/laser rangefinder distance.

4.4 Discussion

4.4.1 UAS Aerial Imagery and Photogrammetry of Tropical Cloud Forests

Throughout the process of data collection for this project, the process of aerial imagery data collection was the largest challenge. With any project attempting to use UAS for data collection, the implementation of imagery collection requires substantial knowledge of complex aircraft flight control, mission planning, camera system, and data processing techniques. Particularly in complex, forested terrain, aircraft safety is a top priority because locating and retrieval of a downed aircraft is effectively impossible. High contrast and large shadows in the early morning and evening can make imagery processing challenging, so flights could only be conducted between ~9 am–4 pm, however, most days the research area was fully cloud-covered by 10 am. Additionally, to reduce animal disturbance, no gasoline generators are used at the field site, and re-charging aircraft batteries with ~280 W solar panels proved to be very challenging given the cloud cover. Finally, the physical limitations of the site (a small forest clearing surrounded by 20+ m trees at ~3,000 m which must be accessed by walking ~5 km from the nearest village or by helicopter) limit the aircraft used to a small multirotor or hand-launched fixed wing.

The poor performance of aerial imagery collection in 2017 can be attributed to several factors. The lens-focusing issues from missions flown with Pix4D Capture meant that image matching in the processing stage produced lower precision images. Pix4D capture does not continue to capture photos when connection with the aircraft is lost, resulting in missions limited to less than 1.5 km from the takeoff point because of the high radio control attenuation of dense, wet tropical forest canopy. The inability to follow terrain resulted in low image overlap on ridges, causing photogrammetric reconstruction of these surfaces to fail. Additionally, fixed flight heights were set based on topographic maps of the area, plus an additional 20 m for forest canopy, however areas of tall forest canopy reduced image overlap as well.

Aerial imagery collection in 2018 using the Mavic 2 Pro and Map Pilot proved more successful, and would be recommended for future projects, however several challenges were encountered. Poor weather conditions in 2018 limited the number of opportunities for flying which prevented the acquisition of data over the entire area traversed by the collared animals.

Because of the computationally intensive nature of digital photogrammetry, each iteration of processing in Pix4D required 6-12 hours during which the computer was otherwise unavailable. This meant that each parameter change effectively required a full day of processing. Most workflows for photogrammetry processing from UAS were developed in temperate and semi-open forests, so finding the optimal settings for dense tropical forests required a substantial number of parameter changes. A 2016 MacBook Pro with an Intel i7 quad-core processor and 16GB RAM, and a PC desktop with an Intel i7 six-core processor and 32GB RAM failed while processing the densified point cloud with the original image resolution and failed to generate the 3D textured mesh at medium resolution. A computer designed for data processing and graphics intensive tasks would be recommended for future investigations, as currently available cloud computing services do not offer the parameter adjustment necessary to use these techniques.

4.4.2 Canopy Structure & Interpolation Methods

The results of the interpolation between canopy gaps technique were encouraging because the forest canopy coverage at Wasaunon is very high. Despite this, the structure of the treefall gaps allowed for ground points to be found. Because this is an intact old growth forest, there are large trees to clear the gaps necessary for this technique to be successful when they fall. It seems likely that a disturbed forest or an area of recent regrowth might not have enough gaps for this technique to work. Manually collecting the locations of canopy emergent trees from the ground is nearly impossible because the closed canopy obscures the tops of the trees. While this makes validation difficult, it also highlights the value of airborne LiDAR or UAS imagery to map this important habitat structure that cannot be measured from the ground.

Collecting additional GPS points under the forest canopy would be necessary to fully assess the accuracy of the canopy height models from the interpolation methods. A combination of manual terrain point collection and interpolation from gaps could prove an ideal balance, particularly if areas that are far from gaps could be identified in advance and targeted for additional point collection. The sharp edges around a few of the canopy gap elevation points visible in the hillshade visualizations of the DTM indicate that these were likely not representative of the true terrain surface.

The averaging method used to automatically identify canopy gaps and canopy emergent trees appeared to overall be and effective technique, although it appears to be less accurate in areas of high structural variability. As seen in the lower left of Figures 11-13, the higher roughness areas mean that the average canopy height is lower which then would lead to a larger number of trees being identified as canopy emergent. Setting higher threshold values or using a larger moving window for height averaging could address this issue. The larger problem with this technique is that it is impossible to see the tops of canopy emergent trees from the ground to validate height measurements and canopy emergent status.

4.5 Conclusions

UAS can successfully be used to acquire far higher resolution imagery on demand quickly and less expensively than other sources, however, the wider utilization of UAS in ecology has been limited by many of the challenges encountered here. With effective preparation, aircraft selection, and mission planning, high resolution imagery can be collected in the most remote places on earth. It is understandable why many studies of forest structure from photogrammetry rely on LiDAR as a comparison because of the more regularly spaced ground returns. However, the need to map high resolution forest structure in areas where LiDAR data does not exist or is impractical to collect will continue to drive researchers towards using photogrammetry techniques.

The different interpolation methods appear to generally represent the underlying terrain but it could be oversimplifying the terrain. This can be seen in Figure 14 where the linear patterns of ridges and valleys are seen in the canopy height model. While there may be differences in canopy height between ridges and valleys, these patterns could also be explained by the interpolated terrain model oversimplifying the terrain. While a conservative threshold of 13 m below the average canopy height was used for the automated gap detection it appears to overestimate the number of gaps, particularly in areas of higher slope. Without measurements of the terrain surface across the entire study area it is difficult to accurately assess the interpolation methods used in this analysis. The manually collected locations and canopy heights provide some comparison but the difference in technique and 14 year time difference between the data collection introduce uncertainties.

Despite these uncertainties, this data will be essential in evaluating the altitude and location data from the redesigned collars deployed in 2018-2019. Because they record corrected barometric altitude, the height of the animal below the canopy surface can be known from the DSM, and the interpolated DTM will provide a lower boundary to know whether the animal was traveling on the ground. Additionally, because the altitude data is collected every minute, as opposed to the 4-hour intervals of the GPS locations, it could potentially even be used to constrain the probable movement pathways between measured GPS locations.

This study proves that interpolation of terrain from canopy gaps is a feasible technique to create a DTM from which a CHM can be calculated, however further assessment of this technique in closed canopy forests with existing LiDAR coverage would be needed to assess the accuracy of this method. This understanding of the 3D forest structure at Wasaunon provides an ideal foundation to use the corrected barometric altitude data from the currently deployed GPS collars to understand the importance of forest structure for these elusive animals.

5 EVALUATING FOREST STRUCTURE PREFERENCES FROM GPS POINTS

5.1 Connecting Location to Structure

While manually locating animals using VHF collars provided the opportunity for researchers to collect habitat information *in situ* while taking the observation for each location, the vastly larger number of locations from GPS collars invites using remote sensing to measure habitat variables over even larger numbers of locations. While species composition of habitat is commonly investigated from available satellite data, our ability to assess forest structure on a landscape scale relies primarily on LiDAR (e.g. Chambers et al., 2007). For many species, the structure of a forest is important in determining their movement pathways, food resources, and shelter (Davies et al., 2017; McLean et al., 2016), but for some researchers, LiDAR data is not available or feasible. The synthesis of habitat structure data from UAS photogrammetry and habitat utilization from GPS points has the possibility to provide an effective tool to investigate habitat utilization that is far more accessible than LiDAR.

Anecdotally, *D. matschiei* use different parts of the forest canopy depending on environmental conditions. During field tracking individuals were known to move quickly away from trackers on the ground or remain motionless in the canopy in response to human disturbance. During times of bad weather and high wind they are believed to remain lower in the shelter of the forest canopy, but when it is sunny, they move into the higher canopy to dry out and warm up (N. Wari, personal communication). Stabach (2008) found that *D. matschiei* were found in trees that were taller than the overall average (26.1 m) but suggested that accurately assessing the habitat preferences of *D. matschiei* has always proved to be challenging because it required assessing the forest structure manually. By combining the location and behavior from the GPS collars with complete forest structure data from aerial photogrammetry, the habitat characteristics of any point can be known without requiring in situ measurement allowing larger areas to be studied in higher resolution.

5.2 Methods

For this analysis, the number of separate visits (*nsv*) values from T-LoCoH were exported from R. Areas with a high number of separate visits can be interpreted as areas of importance to *D. matschiei* (Lyons et al, 2013). The raster values of habitat structure metrics of distance from canopy emergent trees, distance to manually and automatically identified canopy gaps, canopy height, and canopy roughness were extracted for each GPS location. The distance to emergent trees and/or gaps was used instead of whether they were inside or outside the polygon of an emergent tree or gap to account for potential GPS inaccuracies. The mean values of these points for each animal, and for all animals combined were compared to the overall average of that orthoimage to examine differences. The areal extent of the UAS orthoimage and DSM did not cover the entire areas used by MTK 2 and 3, therefore only the locations from those animals falling inside the area covered by the CHM were used. This resulted in a subset of 948 locations, or 70% of the total GPS points collected. One-tailed T-tests were conducted for all animals combined to assess the significance of correlation between locations and habitat variables. The hypothesized habitat preferences are that the distances between *D. matschiei* locations and canopy emergent trees would be lower than average, that distance to canopy gaps would be lower than average as GPS fixes are more likely in less dense canopy cover, and that canopy height and roughness would be higher than average.

An assessment of the number of GPS locations contained within the polygons of automatically identified canopy gaps and emergent trees, and within buffers of 5, 10, and 15m was conducted to assess the importance of these variables and potentially minimize the effects of inaccurate GPS locations on habitat correlations.

5.3 Results & Discussion

The general findings of this comparison support the hypothesis that some variables of canopy structure are important for the habitat utilization of *D. matschiei.* There appears to be no reliable trend in their distance from manually or automatically identified canopy gaps; the mean distance was lower using the automatically identified gaps and greater than the orthoimage using the manually identified gaps, and individual TKs had contrasting means (Figures 19 and 20; Table 4). The significance of correlation between tree-kangaroo locations and automatically generated canopy gaps is questionable since there is no significant correlation with manually identified gaps and the automatic method identified far higher numbers of gaps in some areas of the study site (Figure 11; Table 4). The GPS-collared tree-kangaroos were most often located substantially (13.7 m) and significantly closer to canopy emergent trees than the mean (21.5 m) within the study area, especially MTK 1 and MTK 3 (Figure 21; Table 4). MTK 2 did not show this trend clearly, but this may have been due to the few GPS points (58 of 376) located within the orthoimage compared to the other animals. Overall, 78% of the GPS positions located were within 15 m of the polygon defining an emergent tree (Table 5) and while the accuracy of the GPS positions is unknown, it seems probably that it is less than the 15m buffer used here.

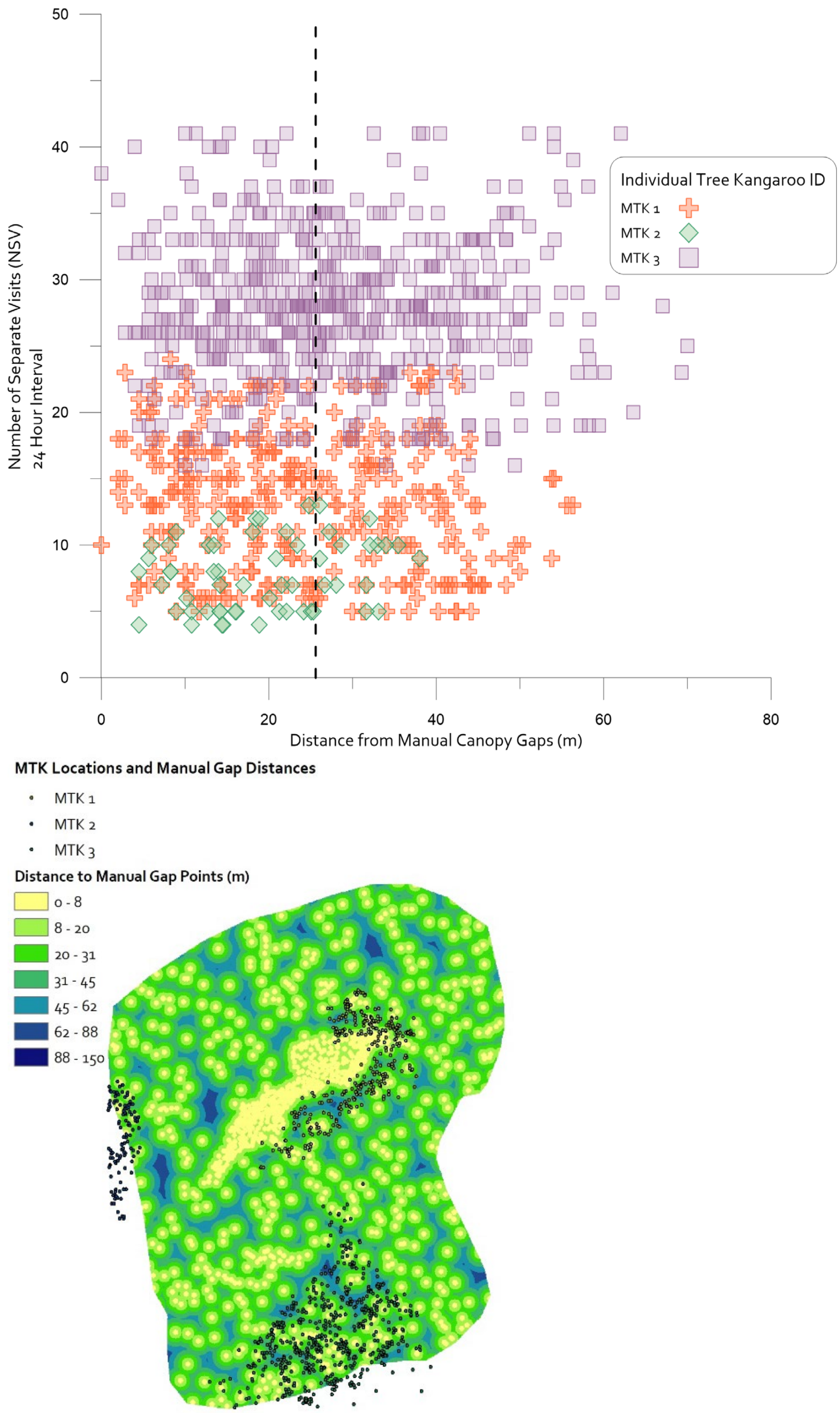
All tree-kangaroos were found at locations with slightly, but significantly, taller canopy heights (23.1 vs. 21.2 m averages; Figure 22; Table 4). MTK 3 was found in areas with more than mean canopy roughness, but MTK 1 and 2 were observed in areas with average roughness (Figure 23; Table 4). There were no distinct patterns apparent between habitat variables and revisitation rate. An assessment of percentage of locations contained within buffers of different distances from canopy emergent trees and from canopy gaps confirms the importance of emergent trees (Table 5).

Further investigation should be made of the structural patterns within each animal's home range and using different utilization metrics, however additional collared animals and complete areal coverage is needed. Statistical tests comparing the distributions (e.g. Kolmogorv-Smirnov) and ones designed specifically for spatial dataset instead of t-tests comparing the mean characteristics should also be explored. The fact that the CHM did not cover the entire areas traversed by the collared animals was disappointing, but provides opportunities for synthesis with future high-resolution height models or future aerial mapping flights over larger areas.

Mean values	**MTK 1**	**MTK 2**	**MTK 3**	**All Locations**	**Ortho-image**	**One tailed t-test**	**P-Value**
Distance from manual canopy gaps (m)	23.9	19.2	27.9	26.0	25.6	.99	0.32
Distance from automatic canopy gaps (m)	22.9	19.3	18.4	20.0	22.7	**-6.39**	2.47^{-10}
Distance from canopy emergent trees (m)	18.8	21.5	9.8	13.7	21.5	**-19.96**	2.56^{-74}
Canopy height (m)	22.1	22.9	23.6	23.1	21.2	**6.80**	1.82^{-11}
Roughness	2.6	2.6	3.5	3.1	2.6	**8.08**	1.95^{-15}
Count	329	58	561	948			

Table 4. Mean values of canopy structure for each tree-kangaroo compared to average values for the entire study area. T-test critical value of 1.96 for n-1 sample size. Bold values indicate significance lower than 0.01 p-value threshold.

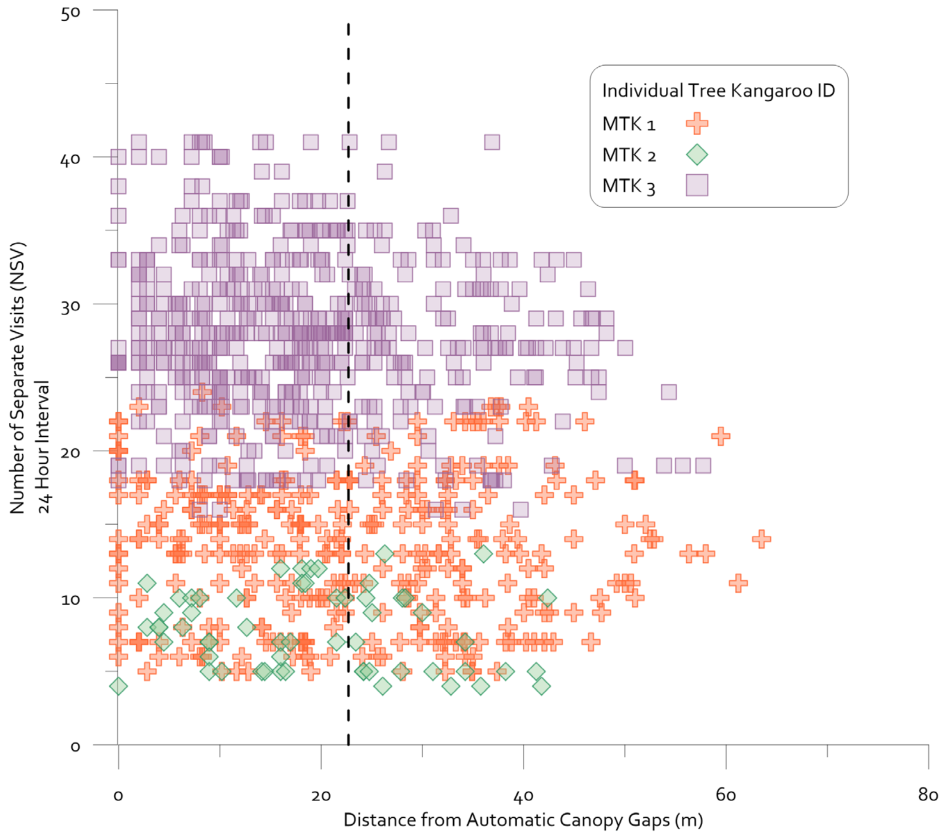
A)



B)

Figure 19. Distance from manual gap by revisitation rate. A) Scatterplot of distance from manually identified canopy gaps (in m) by the *nsv* value from T-LoCoH. The black dashed line shows the average distance from a manually identified canopy gap. B) Map of GPS collar locations and distance to manually identified canopy gap points in meters.

A)



B)

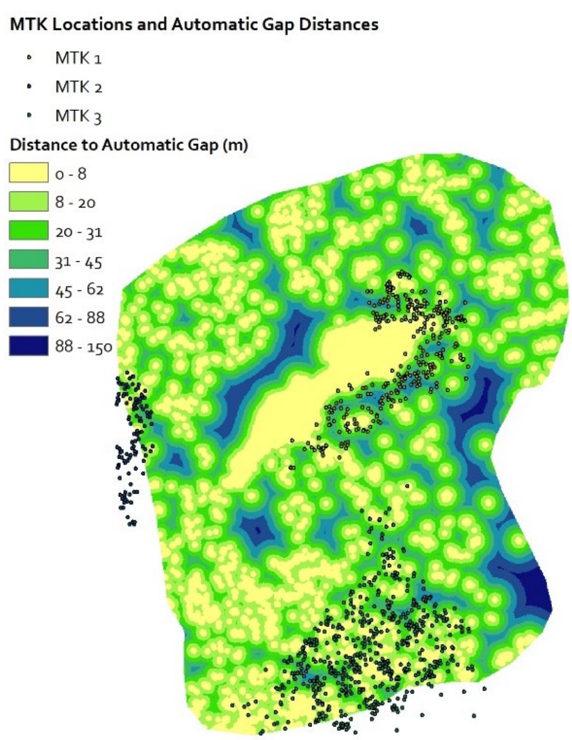
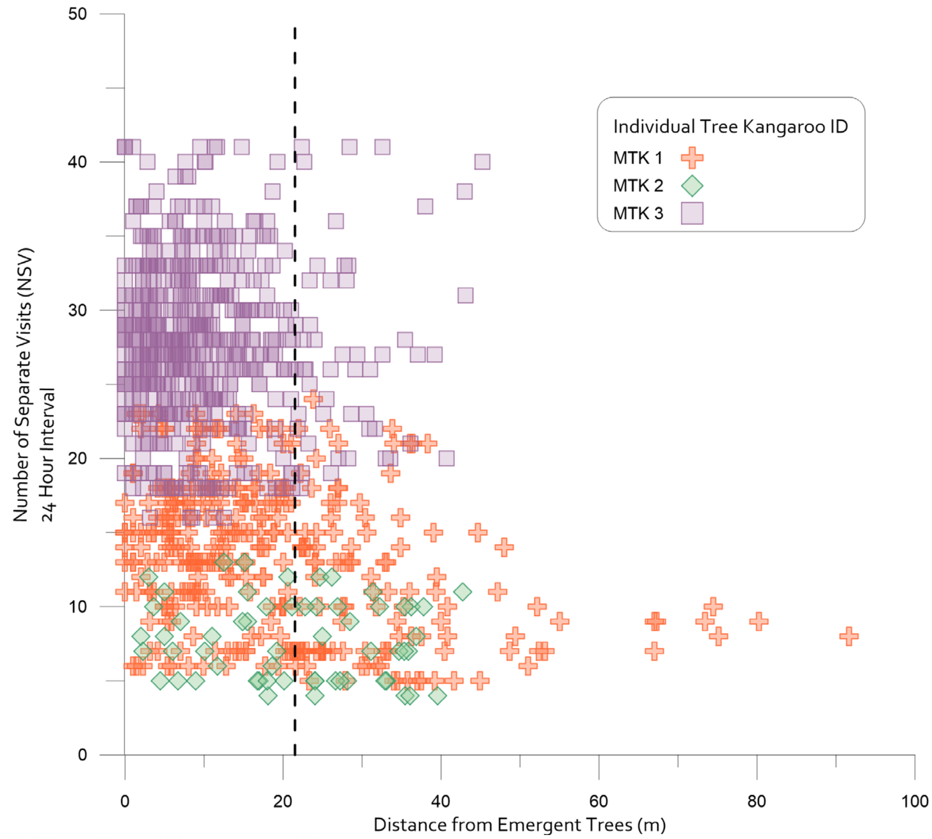


Figure 20. Distance from automatic gap by revisitation rate. A) Scatterplot of distance from automatic canopy gaps (in m) by the *nsv* value from T-LoCoH. The black dashed line shows the average distance from an automatic gap. Note zero distance values are points within the polygon defining the automatic gap. B) Map of GPS collar locations and distance to automatically identified canopy gap points (in m).

A)



B)

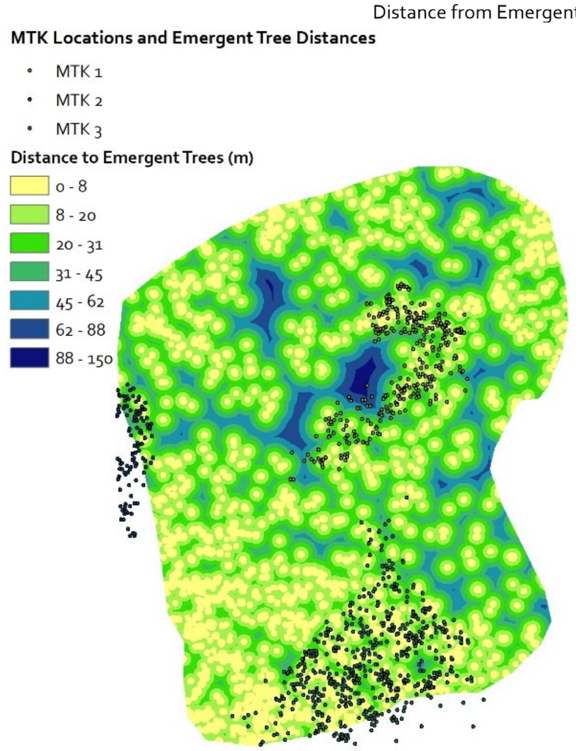
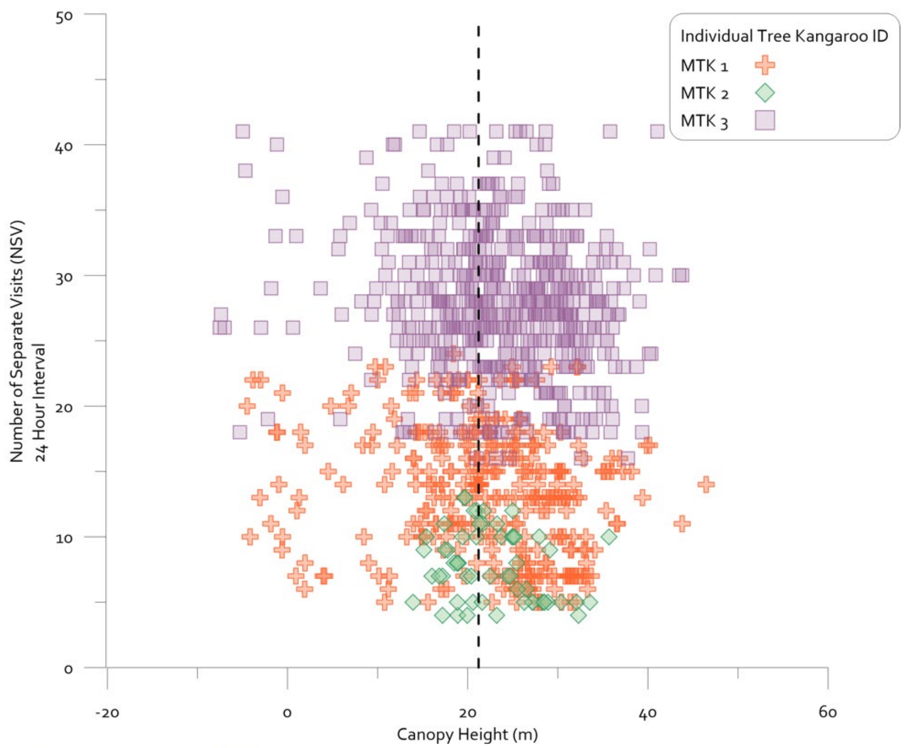


Figure 21. Distance from emergent trees by revisitation rate A) Scatterplot of distance from emergent trees (m) by the *nsv* value from T-LoCoH. The black dashed line shows the mean distance from a canopy emergent tree. Zero values are points within the polygon of the canopy emergent tree. B) GPS collar locations and distance to canopy emergent trees (in m).

% of GPS Locations	Canopy Emergent Tree	Canopy Gap
Contained Within	2.0%	1.7%
Within 5 m:	15.2%	7.3%
Within 10 m:	43.1%	23.6%
Within 15 m:	78.4%	44.3%

Table 5. GPS locations within and near emergent trees and canopy gaps. Percentage of TK GPS locations that were located within a polygon of an automatically identified canopy emergent tree or canopy gap, as well as those locations within buffered distances of 5, 10, and 15 m from those polygons.

A)



B)

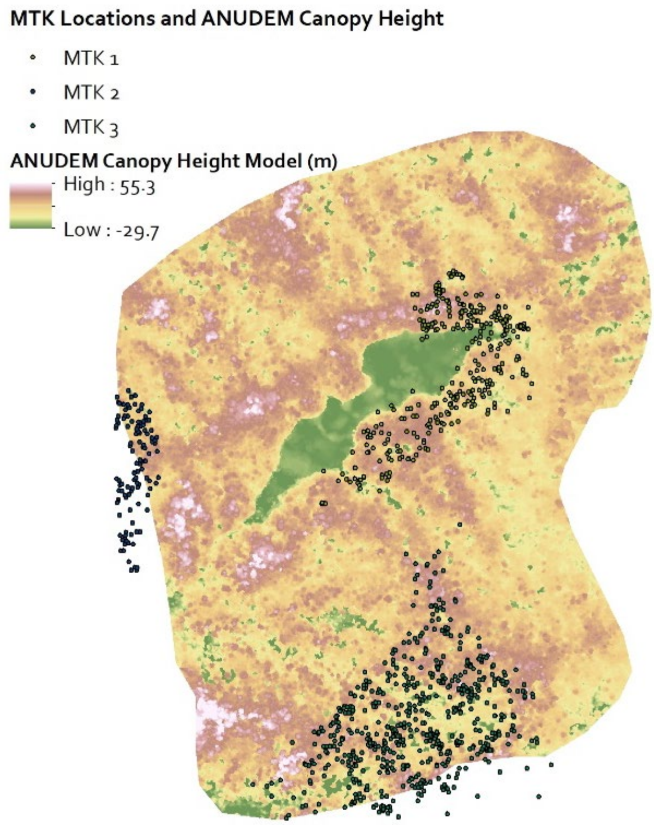


Figure 22. Canopy height by revisitation rate. A) Scatterplot of canopy height at GPS points from the ANUDEM interpolation CHM. The black dashed line shows the average canopy height across the study area. B) Map of GPS collar locations overlaid on ANUDEM CHM.

A)

B)

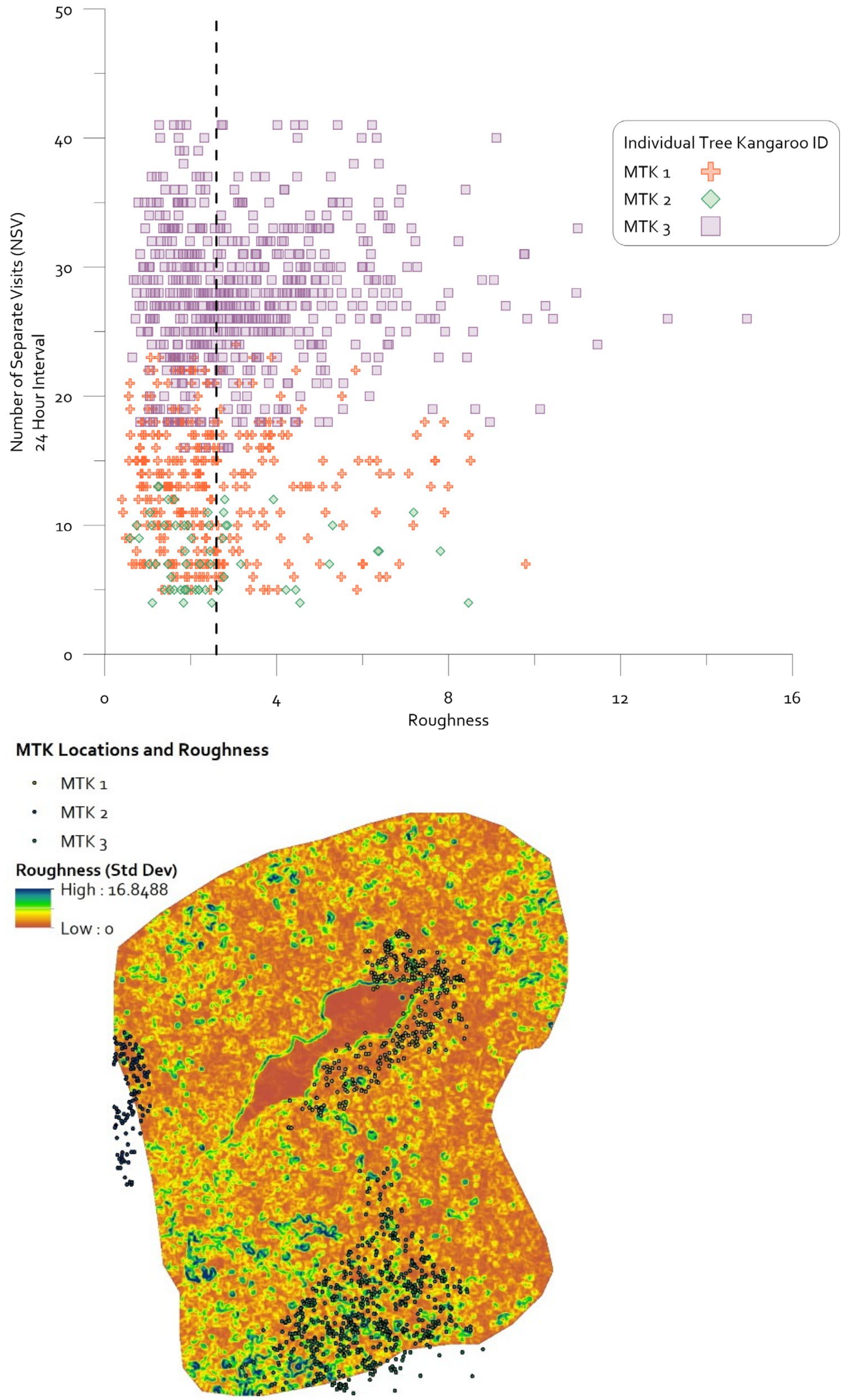


Figure 23. Canopy roughness by revisitation rate. A) Scatterplot of canopy roughness by the *nsv* value from T-LoCoH. The black dashed line shows the average canopy roughness across the raster layer. B) Map of GPS collar locations overlaid on roughness.

5.3 Conclusion

These results support the hypothesis that the structural complexity of the forest, particularly canopy emergent trees and taller canopies are important to *D. matschiei,* and validate the results found by Stabach (2008) that *D. matschiei* are commonly found in trees that are taller than the forest canopy average. Further investigation in needed, however, to validate the accuracy of the structural metrics developed, expand the area covered by the UAS orthoimagery, and increase the sample size of GPS collared animals.

The importance of habitat structural complexity is useful for conservation management and planning as the removal of structural complexity through selective logging or fires would negatively impact tree-kangaroo habitat. To provide sound management advice for local community landowners, further investigation of these patterns at different elevations and in different forest species compositions would be necessary.

This analysis proves the viability of remotely interpreting canopy structure at animal GPS collar locations from UAS aerial imagery in closed canopy forests. While further evaluations and refinement of aspects of data collecting and processing are necessary, including additional ground sampling and validation and refinement of interpolation techniques, the techniques demonstrate here can provide a valuable framework to help answer challenging questions in similar habitats. Plans for continued refinement of these techniques are already in place and will be used to assess results from the 8 collars deployed in 2018-2019 and provides a better foundation for building on further investigations of 3D habitat utilization and movement.

6 CONCLUSIONS AND FUTURE RESEARCH

6.1 The Importance of Forest Structure for Tree-kangaroos

As an arboreal animal, forest structure provides the framework of where and how tree-kangaroos move. The results of this study support the hypothesis that TK's are not habitat generalists and had some locations (emergent canopy) frequently visited while grasslands were rarely traversed. Whether these patterns of movement are driven more by forest species composition or more by forest structure remains undetermined. The destruction of complex forest at higher elevations from climate change associated fires and frosts, and at lower elevations from population expansion and swidden agriculture poise substantial threats if indeed the complex structure of primary cloud forests is necessary for *D. matschiei*.

Despite the low sample size, each individual animal exhibited interesting differences in movement pattern, velocity, and habitat use. *D. matschiei* appear to be very sensitive to the vertical structure of their habitat, with no evidence of them crossing forest clearings, which has significant implications however movement data were of insufficient resolution to see if they similarly avoid forest gaps. The far larger 100% MCP sizes from the VHF data than the GPS data add evidence to the argument that VHF data overestimates the area in which individual tree-kangaroos are found due to sampling error or disturbance by trackers.

While this project shows photogrammetric height reconstruction of closed canopy forest structure is possible, validation of forest height using LiDAR data would still be valuable. The NASA Global Ecosystem Dynamics Investigation (GEDI) spaceborne LiDAR that deployed to the International Space Station successfully in December 2018 has the potential to provide forest canopy and terrain surface measurements at 60 m intervals, with a 500 m/pixel output. Combined with high resolution radar data such as TAN DEM-x (2 m/pixel) this may provide high resolution accurate forest structure and biomass measurements in the tropics. (Qi & Dubayah, 2016). Having very high-resolution 3D forest structure data from UAS could be used to increase the spatial resolution of the data provided by GEDI, while simultaneously providing a validation of the representativeness of GEDI data of localized forest types and structure. The rapid developments of powerful new tools in animal-attached remote sensing, Unmanned Aircraft Systems (UAS), satellite sensors, and computational methods indicate rapidly increasing new possibilities to understand the natural world.

6.1.2 Animal-Attached Remote Sensing

The GPS collars deployed during this study proved to be far more capable of collecting regular GPS locations in the dense forests at Wasaunon than previously deployed collars and collected far more location information than VHF tracking has provided. This deployment was an effective test of a new collar design and the lessons learned have been applied to the redesigned collars that were deployed October 2018 to April 2019. The temporally correlated nature of this location data requires new processing techniques which produce a higher resolution picture of the spatial and temporal use of habitat by *D. matschiei.*

The experiences gained from this project have already been applied to a redesign of GPS collars for redeployment with the objective of implementing novel 3D movement and probability distribution for an arboreal organism. A number of other directions of investigation would be interesting including: integration of still cameras with motion and/or altitude triggers into the GPS collars to have the animals themselves photogrammetrically map the 3D structure of their habitat, broad deployment of motion triggered cameras in the forest canopy to observe movement patterns, collaring efforts with GPS in different forest types and across altitudinal gradients where previous VHF studies proved to be too challenging, or the incorporation of small solar panels and the use of low power inertial sensors for GPS-corrected dead-reckoning modules to get continual motion and location pathways without the high power requirements of high frequency GPS tracking. Of all of those, the dead-reckoning technique combined with machine learning has the most potential in GPS limited environments such as tropical forests (Dewhirst et al., 2016), and has already begun to revolutionize animal movement research particularly in marine organisms.

6.1.3 Applications of UAS

Despite the widespread espousal that UAS has the potential to revolutionize ecology, the logistical and technical challenges in deploying these systems in the field, particularly high-altitude tropical cloud forests, remain high. However, the conclusions presented here represent the limits of the capabilities of inexpensive commercially available systems in 2018, and these technologies continue to advance rapidly in capability and ease of use. UAS mapping projects need to be planned with knowledge of aircraft system and environmental limitations. Terrain following is essential for both data collection (to maintain a consistent GSD, and avoid uncontrolled flight into terrain), and regulatory reasons (maintain legal flight altitudes). Off-the-shelf solutions such as the DJI Mavic aircraft used here often prove to be insufficient for large areas because of radio-signal attenuation but can provide otherwise unobtainable data about the vertical structure of the forest.

One of the challenges of UAS are their limited spatial coverage. While they can collect raster data at far higher resolution, the flight times of the longest duration multi-rotors are less than 30 minutes. Flying at 120 m AGL with 75% overlap, this results in a maximum area covered per flight of about 80 ha. In the case of Wasaunon, it is possible to fly five or six 80 ha areas and cover sufficient areas to gather habitat information about the collared animals but this would not be sufficient when working with larger numbers of animals. Also, as this study found, 2.4 GHz control radios are limited to ranges far shorter than their theoretical maximum because of the high radio attenuation in dense, wet forest canopies.

The ideal UAS for this type of work would be a hand-launchable fixed wing capable of carrying a multispectral sensor with high accuracy DGPS image geotagging with flight times of ~1 hour, and 1.2 GHz long range control and telemetry radios. Fortunately, this aircraft has already been built and deployed during field research in October 2018 supported by the funding of a Conservation Technologies grant from the National Geographic Society. The canopy structure data presented by this study is an ideal foundation to continue testing and validating new techniques in being able to understand forest habitat using UAS.

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