2020-01-01

Development On Of An Unmanned Aerial Vehicle-Based Orangutan Population Assessment And Monitoring Method For The Multifunctional Landscape Of East Kalimantan, Indonesia

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DEVELOPMENT ON OF AN UNMANNED AERIAL VEHICLE-BASED ORANGUTAN POPULATION ASSESSMENT AND MONITORING METHOD FOR THE MULTIFUNCTIONAL LANDSCAPE OF EAST KALIMANTAN, INDONESIA

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THE MULTIFUNCTIONAL LANDSCAPE OF

EAST KALIMANTAN, INDONESIA

by

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THESIS

Presented to the Faculty of the Graduate School of

The University of Texas at El Paso

in Partial Fulfillment

of the Requirements

for the Degree of

MASTER OF SCIENCE

Department of Geological Sciences

THE UNIVERSITY OF TEXAS AT EL PASO

December 2020

Acknowledgments

It would be not possible for me to finish all my schoolwork and my thesis project without the help of many people who support me in different ways. I would like to thank my advisors Dr. Craig Tweedie, Dr. Yaya Rayadin, Dr. Vanessa Lougheed, and Dr. Stacey Sowards for their encouragement, guidance, and help in developing my project. I would like to thank all students and staff from the Systems Ecology Laboratory at UTEP, especially Sergio, Steven, Marguerite, and Gesuri, for all the help throughout my project. I also would like to thank Bapak Supriyono, Bapak Supriatno, and Bapak Dolly Priatna from the Sinarmas Group, Bapak Mujito from the Surya Hutani Jaya Timber Company, Bapak Dudu and Bapak Pardi from the Sumalindo Hutani Jaya Timber Company, Bapak Sanjaya Immanuel Maneje, Bapak Kris Parnoto, Bapak Niko, and Bapak Deni from the Kaltim Prima Coal Company, and all the crews who supported our fieldwork. I would like to thank my friends, Indra Hadiyana, Muhammad Rofik, Firman, and Guruh Putusyurowo, who accompanied me as field assistants – it would be so hard doing all the work without you guys with me in the field. I also would like to thank the System Ecology Lab UTEP and ECOSITROP for financing the logistical and equipment support needed for this project. Last, but certainly not least, I would like to thank all my friends and family for their support, patience, and unconditional love that has made me persist throughout the challenges in life. More importantly, I am thankful for my Mom and my Dad, to whom I dedicate this thesis. I love you beyond words can express.

Abstract

Deforestation, habitat degradation, and other forms of land conversion are threatening the existence of orangutans (*Pongo spp.*), the critically endangered great apes that only live on the two large Sunda-shelf islands of Sumatra and Borneo. Currently, orangutan populations persist not only within conservation or protected areas but also in other functional landscapes such as forest/acacia plantations, oil palm plantations, and mining concessions. The presence of orangutan populations in this recently modified multifunctional landscape has the potential to exacerbate human-orangutan conflict, which could further threaten orangutan populations. Lack of information about the distribution and size of orangutan populations hampers long term conservation efforts on local to regional scales.

Habitat-specific orangutan population data are crucial for effective conservation planning as such information can be used to more adequately assess population-level threats, set conservation priorities, and establish and/or maintain monitoring. Traditionally, orangutan distribution and density are assessed by conducting ground-based nest surveys, which are expensive, time-consuming, require an experienced survey team, and generally have a limited sampling area compared to the home of orangutan. This study focused on evaluating the utility of Unmanned Aerial Vehicle (UAV)-based image analysis for detecting orangutan nests in a range of multifunctional landscapes throughout East Kalimantan. Specifically, the study compared nest data derived from UAV and ground-based surveys conducted in the multifunctional landscape of East Kalimantan, Indonesia, assess what factors limit nest detectability in UAV imagery, and developed models to correct UAV-based methods to ground-based surveys. From this research, UAV flight protocols for orangutan nest detection were developed for the multifunctional landscapes inhabited by orangutans in East Kalimantan.

Summary total of 15, 250 to 600-meter-long coupled ground/UAV transect surveys were conducted at different localities in three multifunctional landscape units (6,800 m surveys in total). We detected a total of 205 nests from the ground surveys and 45.37% of these nests were detected in UAV images: 82.50% in timber plantations, 45.83% in the post-mining rehabilitation areas, and 32.48% in secondary forests. UAV-based surveys failed to detect nests that were not detected in ground-based surveys, highlighting the high accuracy of ground-based surveys. Canopy openness and nest site location were key determinants of nest detectability in UAV imagery. We tested three different interactions for predictive models, which showed that models predicting ground-based nest counts from UAV imagery were strongest when a two-way interaction with average transect UAV-derived crown spread was accounted for. Although fewer nests were detected in UAV imagery compared to ground-based surveys, UAV surveys required significantly less time for a smaller field team to execute. Given that UAV-derived attributes of forest structure could be used in a single model to effectively approximate ground-based survey results, this study concludes that UAV-based survey methods are an effective complement to ground-based survey methods that could enhance orangutan population surveys of the multifunctional landscape of East Kalimantan, and therefore, the protection and conservation management of orangutan.

Table of Contents

Acknowledgments ... iv

Abstract ... v

Table of Contents ... vii

List of Tables ... ix

List of Figures ... x

List of Illustrations ... xi

Chapter 1: Introduction ... 1

1.1. Background and Rationale ... 1

1.1.1. Nest count method ... 3

Line transect technique ... 3

Plot technique ... 4

1.1.2. Spatial capture-recapture (SCR) method using camera traps ... 5

1.1.3. Aerial-based surveys ... 5

1.2. Goal and Objectives ... 7

Chapter 2: Assess orangutan populations with UAVs across the multifunctional landscapes of East Kalimantan, Indonesia. ... 9

2.1. Introduction ... 9

2.2. Methods ... 11

2.2.1. Study area ... 11

2.2.2. Field data collection ... 16

Ground nest surveys ... 16

Aerial nest surveys ... 17

2.2.3. Image processing ... 18

2.2.4. Nest detection ... 19

2.2.5. Statistical analysis ... 20

2.3. Results ... 20

2.3.1. Ground and aerial surveys ... 20

2.3.2. Nest detection ... 22

2.3.3. Factors influencing nest detectability ... 24

2.3.4. Predicting ground-based nest counts from UAV imagery 26
2.3.5. Testing the predictive models 29
2.4. Discussion 30
2.5. Conclusion 34
Chapter 3: Developing UAV flight protocols suitable for orangutan nest surveys in the multifunctional landscapes of East Kalimantan 36
3.1. Introduction 36
3.1.1. Background and motivation 36
3.1.2. UAV-based vs. ground-based nest survey 38
3.2. UAV Platforms 39
3.3. Site Selection 41
3.4. Data Collection 44
3.4.1. Field orientation 44
3.4.2. Aerial-based nest survey 44
3.4.3. Mission planning 49
Mission planning protocols 50
Image quality 52
3.5. Metadata and Data Management 53
3.6. Post-processing 55
References 57
Vita 69

List of Tables

Table 2.1: The orangutan nest data from the ground-based and aerial-based surveys 12

Table 2.2: Summary of orangutan nest counts from ground-based and UAV-based surveys .. 21

Table 2.3: The ratio of nests detected by UAV for each study site 23

Table 2.4: All models ranked by AIC 26

Table 2.5: The results of multiple regression with interaction, the LOOCV, and AIC tests of all three predictive models 27

Table 2.6: Results of adjusted multiple regression models with interaction with tree crown spread, the LOOCV (*and the results of the Model 1 and Model 2*)......................... 29

Table 2.7: The predicted values of the test dataset using two new models: Diff = difference value of predicted value (Fit) and the ground data (Ground), Diff (%) = percentage of different value.. 30

Table 3.1: Fieldwork effort and data collection comparison of UAV-based and ground-based nest survey 38

List of Figures

Figure 2.1: Map showing orangutan presence (derived from Rayadin et al. nest surveys from 2006 to 2019, unpubl.) and the three primary study locations in mid-east, East Kalimantan, Indonesia 12

Figure 2.2: Habitat use of orangutan in timber plantation; (a) orangutan nest on young acacia trees that also the inner bark had been eaten by orangutan, (b) orangutan nests on *Eucalyptus pellita* trees 14

Figure 2.3: 2-year-old *Paraserianthes falcataria* that the inner bark had been eaten by an orangutan........ 15

Figure 2.4: Nest site location (OT = at top of tree crown; MS = at the main stem; EB = at the end of branch; O = open; C = closed) 17

Figure 2.5: Orthomosaics of a transect for each landcover type; (a) 3-year-old *A. crasicarpa* plantation, (b) 7-year-old *E. pellita*, (c) 2-year-old post-mining rehabilitation area, (d) 20-year-old post-mining rehabilitation area, (e) secondary forest 19

Figure 2.6: Box plots showing results for ground (a) and UAV (b) nest densities recorded for the different land cover types, and results of both surveys overall (c) 22

Figure 2.7: Predicted values of ground survey nest on certain level of predictor variable: (a) Model 1, predictor variable = landcover type; (b) Model 2, predictor variable = tree crown spread in meter 28

Figure 3.1: (a) a fixed-wing drone 'Conservation Drone Penguin', (b) a multirotor drone 'DJI Phantom 4 Pro ver. 1' 41

Figure 3.2: Drone images highlighting examples of vegetation variation as observed with orangutan nest (red circle) by tree-age within non-protected areas: (a) 3-year-old *Acacia crasicarpa* plantation, (b) 7-year-old *Eucalyptus pellita* plantation mix with pioneer species trees, (c) 2-year-old, and (d) 20-year-old post-mining rehabilitation area 43

Figure 3.3: Example of a flight log sheet for aerial-based nest surveys 54

List of Illustrations

Illustration 2.1: Design of the nest line transect survey 16

Illustration 3.1: Illustration of how different altitudes on drone surveys affect GSD, GSA, and overall mission configuration; (a) at a lower altitude, (b) at higher altitude 46

Illustration 3.2: Illustration of flight mission on the study area with significant topographic variation; (a) using terrain following feature, (b) using default flat altitude 47

Illustration 3.3: Illustration of different overlapping configuration on the flight mission; (a) front and side-overlap at 40%, (b) front and side-overlap at 80% 48

Chapter 1: Introduction

1.1. Background and Rationale

Orangutans are the only great ape found outside of Africa and are a member of the Family Hominidae, which also includes three other great apes ~ gorilla, chimpanzee, and bonobo (Rijksen and Meijaard 1999; Delgado and van Schaik, 2000). Deforestation and habitat degradation due to anthropogenic change have threatened orangutan populations and the biodiversity of both Borneo and Sumatra islands for the past half-century (Margono et al., 2014; Wich et al., 2016a; Turubanova et al., 2018; Voigt et al., 2018; Ministry of Forestry, 2007). Orangutan populations occur not only within protected or conservation forests but also in other functional landscapes such as timber plantations, oil palm plantations, and mining concessions (Wich et al., 2008; Wich et al., 2012a; Spehar & Rayadin, 2017; Voigt et al., 2018). Today, all three orangutan species (*Pongo pygmaeus*, *P. abelii*, and *P. tapanuliensis*) are classified by the IUCN as critically endangered (IUCN, 2016; 2017a; 2017b).

Orangutans are a 'flagship species' for biodiversity conservation efforts in the tropical forests of Indonesia (Meijaard et al., 2012; Marshall et al., 2016; Ministry of Forestry, 2007). The name orangutan stems from the Malay language where 'orang' means 'person' and 'hutan' means 'forest', literally translating to 'orangutan' or 'person of the forest' (Rijksen and Meijaard 1999). The conservation of orangutans is thought to ensure the protection of the habitat that they share with other species (Ministry of Forestry, 2007). Orangutans are predominantly found in dry lowland and hill forests, alluvial forests, and freshwater/peat-swamp forests, which are also a prime habitat for commercially valuable timber species, and mineral and coal resources (Husson et al., 2009; Rijksen and Meijaard 1999). The exploitation of natural resources and land use landcover change in Bornean forests has limited the availability of natural habitat for orangutans

(Rayadin et al., 2013). Historically, orangutans had been assumed to be ecological specialists that rely on the forest and could not cope with anthropogenic change to the natural landscape (Spehar & Rayadin 2017). Several studies over the past decade, however, have highlighted how orangutan are using plantations (Meijaard et al., 2010; Rayadin & Spehar, 2015; Ancrenaz et al., 2015), agricultural areas (Campbell-Smith et al., 2011), and even mining concessions (Rayadin et al., 2013; Niningsih et al., 2017). The dietary and behavioral ecology of orangutan make them highly adapted to habitat change (Marshall et al., 2009); nesting in oil palms (Ancrenaz et al., 2015), and terrestrial movement (Ancrenaz et al., 2014; Loken et al., 2013; 2015), which facilitates the exploitation of garden crops and fruits, the cambium of *Acacia mangium* and *Paraceriantes falcataria* trees, the pith of immature oil palm trees, and oil palm fruit (Ancrenaz et al. 2015; Rayadin & Spehar, 2015; Rayadin et al., 2013). Of the plethora of orangutan population and distribution studies that have been conducted thus far, few have been carried out in non-protected areas and/or have examined how orangutan persist in human-dominated habitats, highlighting the loose understanding of how these critically endangered species are adapting to anthropogenic-induced landscape changes (Campbell-smith et al., 2011; Meijaard et al., 2010). The presence of orangutan populations in these recently modified landscapes could increase the potential of hunting and human-orangutan conflict, which pose further risk to orangutan populations (Wich et al., 2012b; Abram et al., 2015).

Lack of information about the distribution and size of orangutan populations hampers long-term conservation efforts on a broader scale (Ancrenaz et al., 2004b; Seaman et al., 2019). Orangutan population data and their habitat use are crucial for effective conservation planning, as such information can be used to more adequately assess threats to populations and species, set conservation priorities, and monitor populations (Spehar et al., 2015; Rahman et al., 2019; Rayadin et al., 2013). A significant body of research has developed, tested, and refined techniques for acquiring orangutan population data and distribution. Following is a summary of some of the most well-accepted methods for assessing orangutan populations and habitat use:

1.1.1. Nest count method

Line transect technique

In wildlife studies, the line transect method has been developed to rely on the sign left by animals (nests in orangutan case) along a buffered line transect instead of relying on encounters with animals, which is a common survey method employed by Brockelman and Ali (1987) for estimating forest primate densities. This technique focuses on counting all visible nests within a specified distance from a line transect and records the perpendicular distance between the transect and each nest to estimate the width of the survey strip, which is then converted into nest densities with the general equation:

$$d = \frac{N}{L\ x\ w\ x\ 2}$$

where d is the nest density (number/km^2), N is the number of nests counted along the line transect, L is the length of the transect line (km), and w is the estimated strip width (km). Nest densities are then converted into orangutan density using:

$$D = \frac{d}{p * r * t}$$

where D is the orangutan density (individuals/km^2), p is the proportion of nest builders in the population, r is the rate of nest production (n/day/individual), and t is the rate of nest decay or time during which a nest remains visible (in days).

There are some problems that result in underestimating the orangutan density and this challenge has been addressed in several studies (van Schaik et al., 1995; Buij et al., 2003;

Mathewson et al., 2008). Briefly, these errors arise from: i) the underestimation of nest builders (p) and rate of nest production, which may vary between different populations since nesting can depend on the age and sex composition of a given population (Buij et al., 2003; Mathewson et al., 2008); ii) estimation of t, which requires a long period of data collection and may also vary between orangutan habitats due to differential nest decay rates related to climatic factors, altitude, nest height, tree species and the different purpose for which the nest was constructed (van Schaik et al., 1995; Ancrenaz et al., 2004c; Johnson et al., 2005; Mathewson et al., 2008); iii) the likelihood of observers missing a nest above or near the transect line, and/or overestimate the strip width (w) or perpendicular distance between the transect line and nest (van Schaik et al., 1995; Buij et al., 2003). Despite these problems, most orangutan researchers express confidence in this method (van Schaik et al., 1995; Russon et al., 2001; Buij et al., 2003; Morrogh-Bernard et al., 2003; Johnson et al., 2005; van Schaik et al., 2005; Mathewson et al., 2008). Importantly, this survey method tends to be expensive, time-consuming, requires an experienced survey team, and is generally limited to a small survey area (Buij et al., 2003; Ancrenaz et al., 2004a; Wich et al., 2016b; Wich, 2015).

Plot technique

The plot method basically follows similar procedures to the line transect method except that the plot technique counts orangutan nests within the area of specified plot instead of along a line transect (van Schaik et al., 2005). Van Schaik et al. (2005) experimented to show that the plot method results in higher nest counts than the line transect method, did not take much more time, and resulted in better estimates, even though it needed a relatively larger number of plots to reach similar confidence as the line transect method. Another advantage with this method is the size and shape of plots can be adjusted to the area spanned by a given forest as long as the plots are sufficiently separated from each other to avoid sampling in the same cluster of nests or similar habitats.

1.1.2. Spatial capture-recapture (SCR) method using camera traps

Spatial capture-recapture, or SCR, is a technique to estimate population density from 'captures' of individual animals obtained using camera traps (Borchers & Efford, 2008; Royle et al., 2015; Spehar et al., 2015). To estimate abundance and population density using SCR modeling, animals must be individually identifiable from the camera trap photographs, which is possible for orangutans that have identifiable facial characteristics and other features that can be recognized from photographs (Spehar et al., 2015). Second, the animals need to be captured and recaptured by camera traps that are often easier to place on the ground than in an arboreal location (Royle et al., 2015; Spehar et al., 2015). This is possible for Bornean orangutans because recent studies have shown Bornean orangutans move on the ground more so than the Sumatran orangutan (Loken et al., 2013; 2015; Ancrenaz et al., 2014).

The comparison study of the SCR method and plot nest count method by Spehar et al. (2015) in primary-secondary forests of Wehea Forest showed that the SCR provided lower population estimates than the plot method in the same location, and a much lower density than reports for other relatively undisturbed sites in Borneo (Husson et al., 2009). The SCR method also has a much higher cost than the nest survey method because of the vast amount of equipment needed (~$15,000 vs. ~$2,000), even though SCR requires less effort in the field than line transect-based nest surveys (Spehar et al., 2015).

1.1.3. Aerial-based surveys

The first reported aerial orangutan nest surveys were conducted from a helicopter by Ancrenaz et al. (2004a; 2004b), in Sabah, Malaysia. This nest survey technique used the same basic concept as the line transect method; counting nests around a line transect from a helicopter from which observers estimated the average strip width needed to calculate the orangutan nest densities using parameters p, r, and t (described in section 1.1.1.) and converted nest densities into individual densities (Ancrenaz et al., 2004a; 2004b). Ancrenaz et al. (2004a; 2004b) were motivated to design their helicopter survey based on the premise that ground-based nest surveys typically cover very small census areas that may not be representative of the population status and the variety of habitats and human disturbances that persist over the home range of a given orangutan population, which can more adequately be sampled from helicopters. Helicopter-based surveys are extremely expensive and are limited by the availability of pilots and flight infrastructure (Wich et al., 2016b; Ancrenaz et al., 2004a; 2004b).

Another aerial nest survey to assess orangutan distribution and density was conducted by Wich et al. (2016), using an unmanned aerial vehicle or UAV. Aerial nest surveys with UAV offer similar advantages to helicopters in that they can cover much larger survey areas and reach remote habitats relative to ground-based surveys at a cost that is less than that of a helicopter. UAV surveys also have the capacity to reduce survey costs and field time compared to ground-based nest surveys (Wich et al., 2016b; Wich, 2015). In the past 20 years, UAVs have become cheaper and more widely available (Wich, 2015), and have been utilized for a range of wildlife studies and conservation purposes. These include but are not limited to arboreal surveys (Wich et al., 2016b; van Andel et al., 2017; Bonnin et al., 2018; Spaan et al., 2019), terrestrial surveys, (Vermeulen et al., 2013; Mulero-Pazmany et al., 2014) and surveys of various aquatic systems (Oliveira-de-Costa et al., 2019; Frouin-mouy et al., 2020). With the rapid development of UAV technologies and image processing techniques over the past decade that has been coupled to a range of advances in population surveys for other biota, there is an urgency to develop and test a UAV-based survey method for orangutan that spans the range of habitat they utilize (Buij et al., 2003; Mathewson et al., 2008; Seaman et al., 2019; Wich et al., 2016b; Margono et al., 2014; Turubanova et al., 2018).

1.2. Goal and Objectives

The goal of this study was to develop and test the use of Unmanned Aerial Vehicles (UAVs) and various analytical routines for improving orangutan population assessments in the multifunctional landscapes of East Kalimantan. To meet this goal, the study addressed the following objectives and underlying questions:

Objective 1: Assess orangutan populations with UAVs across the multifunctional landscapes of East Kalimantan, Indonesia.

- How accurately can nests be identified from UAV imagery?
- Do differences in landscape/landcover type affect the visibility of nests in UAV imagery?
- What factors most influence the detection of orangutan nests in UAV imagery?
- How well do models predict ground-based nest surveys from UAV surveys?
- What are the relative strengths and weaknesses of UAV and ground-based surveys?
- What are the implications of orangutan nest surveys using UAV for orangutan conservation?

Objective 2: Develop UAV flight protocols suitable for orangutan nest surveys in the multifunctional landscapes of East Kalimantan, Indonesia.

- What UAV platform works best for the orangutan nest survey?
- How to maximize the effectiveness of aerial-based surveys on orangutan nest detection from drone imagery?

- What software/program is needed for the image processing and spatial analysis of the aerial-based nest surveys?
- What are the challenges of conducting orangutan nest surveys using drones in different landscape types?

Chapter 2: Assess orangutan populations with UAVs across the multifunctional landscapes of East Kalimantan, Indonesia.

2.1. INTRODUCTION

Orangutans are the only great apes found outside of Africa and occur on the two large Sunda-shelf islands of Sumatra and Borneo (Delgado and van Schaik, 2000). All orangutan species (Bornean, Sumatran, and Tapanuli orangutan) are classified by the IUCN as critically endangered (IUCN, 2016; 2017a; 2017b). Their population has been threatened over the last few decades by habitat loss, degradation, and fragmentation due to logging, fire, and forest conversion (Rijksen & Meijaard, 1999; Marshall et al., 2009; Meijaard et al., 2012; Wich et al., 2008; 2012a; 2016a; Voigt et al., 2018). Currently, orangutan populations persist not only within conservation or protected areas but also in other functional landscapes such as timber plantations, oil palm plantations, and mining concessions (Rayadin & Spehar, 2015; Spehar & Rayadin, 2017; Ancrenaz et al., 2015; Meijaard et al., 2010; Seaman et al., 2019). The presence of orangutan populations in these recently modified landscapes have increased the potential of orangutan-human conflict (Wich et al., 2012b; Davis et al., 2013; Abram et al., 2015; Rayadin & Spehar, 2015; Ancrenaz et al., 2015).

Lack of information about the distribution and size of orangutan populations hampers long-term conservation efforts on a broader scale (Ancrenaz et al., 2004b; Seaman et al., 2019). Many orangutan population and distribution studies have been conducted thus far, but few studies have been carried out in non-protected areas and/or have examined how orangutan persist in human-dominated habitats, highlighting the loose understanding of how these critically endangered species are adapting to anthropogenic-induced landscape changes (Meijaard et al., 2010; Campbell-Smith et al., 2011; Seaman et al., 2019). This circumstance establishes a knowledge gap for orangutan population and habitat use assessments and remains a detriment to orangutan conservation planning efforts (Rahman et al., 2019; Spehar & Rayadin, 2017).

Orangutan population density is traditionally estimated from nest census along ground-based line transects (van Schaik et al., 1995, Buij et al., 2003), which are expensive and time-consuming (Wich et al., 2016b, Wich, 2015). Ground surveys are also prone to challenges associated with traversing difficult, remote, and often mountainous or peat swamp terrain (Wich et al., 2016b; Ancrenaz et al. 2004a). Accordingly, the size of most ground-based sampling areas is relatively small relative to the home range of orangutan, and the representativeness of such methods has persisted for some time (Buij et al., 2003, Ancrenaz et al., 2004a).

Unmanned Aerial Vehicles (UAVs) or drones have been used for a range of wildlife studies and conservation purposes (Wich, 2016). These include but are not limited to arboreal surveys (van Andel et al., 2015; Bonnan et al., 2018; Spaan et al., 2019; Szantoi et al., 2017), terrestrial surveys (Mulero-Pázmány et al., 2014; Whitehead, et al. 2014; Vermeulen, et al. 2013), and surveys of various aquatic systems (Oliveira-da-Costa et al., 2019; Frouin-Mouy et al., 2020). Specifically, in a study of orangutan populations, Wich, et al. (2016) successfully used UAVs for assessing orangutan distribution and density in Sumatra. The results of these studies indicate that UAVs have the potential to increase the efficiency and reduce the cost of orangutan nest surveys, which is one of the main challenges of ground-based nest surveys (Wich et al., 2016b; Wich, 2015). Like the majority of orangutan studies, however, all of the published UAV-based studies to date appear to have been conducted in conservation forests and the efficacy of UAV methods remain untested in other landscape types.

In this study, we evaluate the utility of UAV-based imagery for detecting orangutan nests in a range of multifunctional landscapes throughout East Kalimantan, Indonesia. Specifically, we compare nest data derived from UAV and ground-based surveys, assess what factors limit nest detectability in UAV imagery, and develop models to correct UAV-based methods to ground-based surveys. In doing so, we are motivated by the challenge to develop a standardized protocol for UAV-based surveys that can be applied across the full range of multifunctional landscapes that are inhabited by orangutans in Borneo and thereby develop an improved survey capacity for the conservation of this critically endangered species.

2.2. METHODS

2.2.1. Study area

Field studies were conducted over a 1-month period in June and July 2018 and were focused on three primary study areas on company concessions, each with different land cover types (Figure 2.1, Table 2.1). The three company concessions included two forest plantations managed by the Surya Hutani Jaya Timber Company and Sumalindo Hutani Jaya Timber Company (both owned by Sinar Mas Forestry) respectively, and post-mining rehabilitation stands and secondary forest managed by the Kaltim Prima Coal Company.

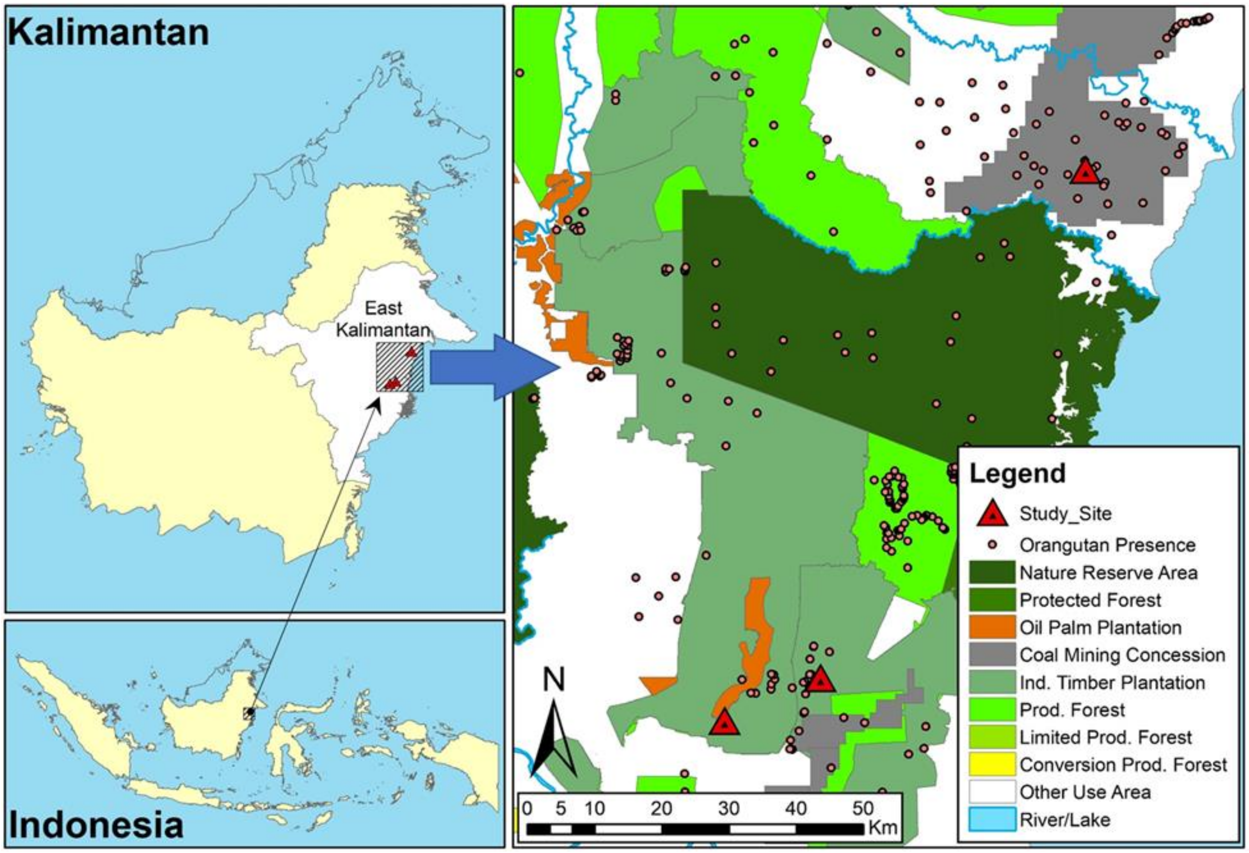

Figure 2.1: Map showing orangutan presence (derived from Rayadin et al. nest surveys from 2006 to 2019, unpubl.) and the three primary study locations in mid-east, East Kalimantan, Indonesia.

Table 2.1: The orangutan nest data from the ground-based and aerial-based surveys.

Company	Landscape type	Landcover/vegetation type	Tree height
Surya Hutani Jaya	Ind. timber plantation	3-year-old *Acacia crasicarpa*	5 - 9.7 m
Sumalindo Hutani Jaya	Ind. timber plantation	7-year-old *Eucalyptus pellita*	16 - 26 m
Kaltim Prima Coal	Mining concession	2-year-old post-mining rehab. area	3 - 6 m
		20-year-old post-mining rehab. area	10 - 23 m
		Young secondary forest	8 - 34 m

The first study site was the timber plantation concession managed by Surya Hutani Jaya Timber Company and Sumalindo Hutani Jaya Timber Company located in the East Kutai and Kutai Kartanegara districts, East Kalimantan. These two companies manage a combined ~259,000 ha of land planted with three different tree species: *Acacia mangium*, *Acacia crasicarpa*, and *Eucalyptus pellita*. In the 1990s, the companies developed *A. mangium* as the main tree species (which is currently being replaced by *E. pellita*), but due to the conversion of natural forest to timber plantation, orangutan lost their natural habitat and lived in small patches of forest in the middle of the plantation (Rayadin & Spehar, 2015; Spehar & Rayadin, 2017; Rayadin et al., 2013). Over time, orangutans have acclimated to eating the inner bark of young planted acacia trees (Figure 2.2), which has become one of their main food resources due to lack of natural food and forest (Rayadin & Spehar, 2015; Spehar & Rayadin, 2017; Rayadin 2013). Following these events, the companies began to develop an action plan for orangutan conservation such as establishing conservation areas for orangutan in their concession areas, monitoring orangutan populations, and collaborating with government conservation agencies and Kutai National Park in orangutan rescue and relocation to natural forests when they were encountered in the concessions (Rayadin & Spehar, 2015; Spehar & Rayadin, 2017). In this study, nest surveys were conducted on plantations of 3-year-old *Acacia crasicarpa* plantation and 7-year-old *Eucalyptus pellita* where tree height ranged from 5 to 26 meters (Table 2.1). Both plantations had been unmanaged by the companies due to the presence of orangutans in those areas. Thus, plantation vegetation dominated but was inter-mixed with native pioneer species.

Figure 2.2: Habitat use of orangutan in timber plantation; (a) orangutan nest on young acacia trees that also the inner bark had been eaten by orangutan, (b) orangutan nests on *Eucalyptus pellita* trees.

The second location of this project is a coal mining concession owned by Kaltim Prima Coal Company, located in the East Kutai district of East Kalimantan. This company had also been carrying out long-term orangutan and other wildlife conservation efforts in and around its concession by collaborating with government conservation agencies and Kutai National Park. Similar to the timber plantation, after the forest area was opened for mining activities, orangutans stayed in the fragmented forest areas and also in the post-mining rehabilitation areas (Niningsih et al., 2017; Rayadin et al., 2013). The post-mining rehabilitation program is mandated by the government whereby the mining companies are required to restore the post-mining area to its original land use so that the land can function again to its designation (Ministry of Energy and Mineral Resources, 2014). However, due to the loss of natural habitat, orangutans started to use young trees of fast-growing species that were planted by the company such as Sengon Laut (*Paraserianthes falcataria*), and Akasia (*Acacia mangium*) as their primary food resource by eating the inner bark of the planted trees (Rayadin et al., 2013, Figure 2.3). This phenomenon has led to the failure of many rehabilitation efforts.

Figure 2.3: 2-year-old *Paraserianthes falcataria* that the inner bark had been eaten by an orangutan.

In this study site, nest surveys were conducted on 2- and 20-year-old stand ages of post-mining rehabilitation areas where tree height ranged from 3 to 23 meters (Table 2.1). Both rehabilitation areas were planted with various fast-growing species such as *Paraserianthes falcataria, Cassia siamea, Samanea saman, Gmelina arborea,* and several other fast-growing species. Several pioneer species such as *Macaranga* spp. and *Ficus* spp. were present but less dominant than species planted for rehabilitation. We also conducted a survey in a young secondary forest close to the rehabilitation survey area. This secondary forest had been designated by the company as a conservation area and has been named the Pinang Dome Conservation Forest, which is approximately 1000 ha in size and dominated by pioneer species with mixed open areas dominated by shrubs. The tree height of the Pinang Dome forest generally ranged from 8 to 34 meters (Table 2.1).

2.2.2. Field data collection

Ground nest surveys

The ground survey was conducted along the same line transects as the aerial survey, following the established line-transect protocol developed by van Schaik et al. (1995). In this method, the perpendicular distance between the transect line and each nest is recorded to estimate the width of the survey strip (van Schaik et al., 1995). These nest count data can be used to estimate nest density, which can then be used in models incorporating nest decay rate, nest construction rate, and the proportion of nest builders in the orangutan population, to estimate population density (van Schaik et al., 1995, Buij et al. 2003).

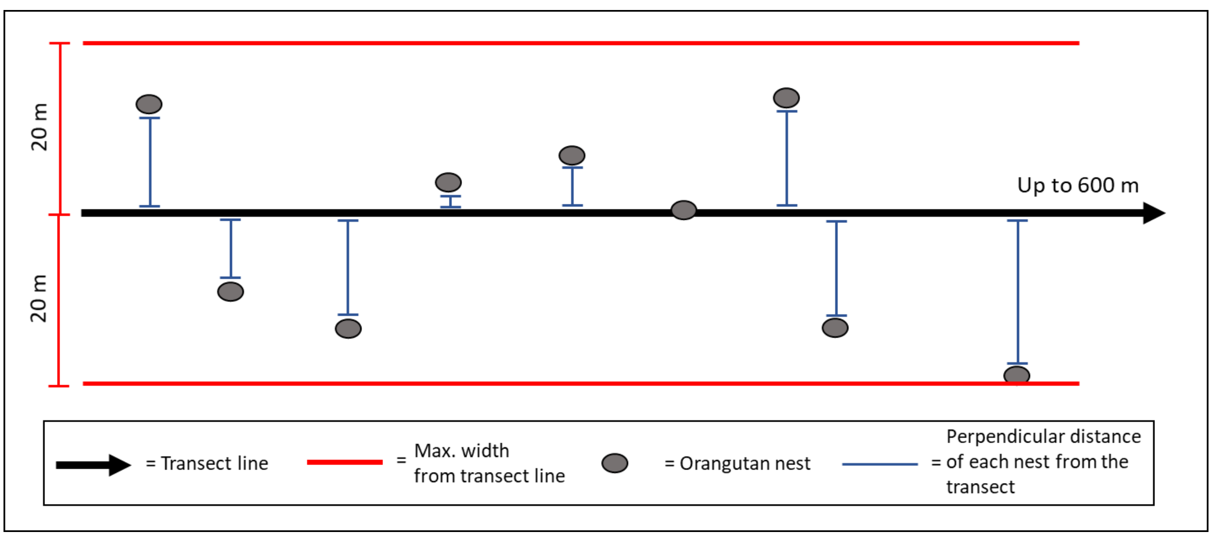

Illustration 2.1: Design of the nest line transect survey

Along each transect, trained observers walked slowly and recorded all observable nests 20 meters either side of the primary transect line (15 meters either side of the transect line was for the young plantation sites because of more limited visibility of the canopy that prevailed at this survey site). The location of each nest was recorded with a hand-held GPS, as was the distance along the transect and the distance perpendicular to the transect line (Illustration 2.1). The following features were recorded for each nest encountered on the ground surveys: nest tree circumference, estimated nest height, tree height, and height to the lowest branch location in the tree (at top of tree crown; at the main stem, or the end of branch), whether the nest is closed (covered by one or more tree crown layers) or open (not so covered) (Rayadin and Saitoh 2009, Figure 2.4). We also assessed the decay stage of each nest in a five-class system: (A) fresh, leaves still green; (B) fairly fresh, mix of green and brown leaves; (C) nest is brown but remains intact; (D) leaves missing and holes appearing in nest; (E) leaves are gone, only branch structure of nest remains (Spehar et al, 2010).

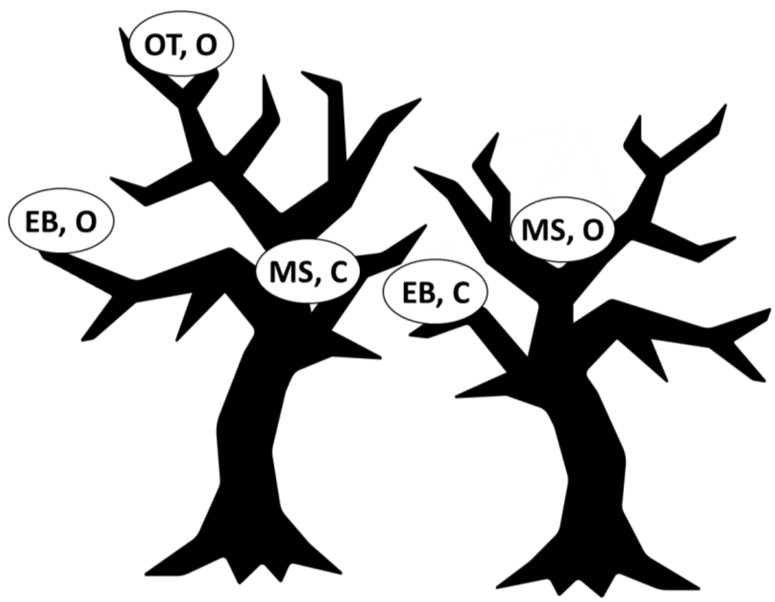

Figure 2.4: Nest site location (OT = at top of tree crown; MS = at the main stem; EB = at the end of branch; O = open; C = closed).

Aerial nest surveys

The UAV chosen for this study was a "DJI Phantom 4 Pro" quadcopter with an onboard 1" CMOS 20-megapixel camera. The UAV was flown over the same transects sampled by ground-based surveys. The mobile application *Pix4DCapture* (https://www.pix4d.com/) was used on an android tablet for flight planning. The UAV was flown at a speed of approximately 6 m/s over a 'lawnmower' flight path that ensured 80% image overlap, and at an altitude of 30 – 80 m above ground level, depending on the vegetation structure and topography of the study site.

Aerial surveys on fifteen line transects were made in total over a 1-month period, and included field orientation and survey planning, pre-flight preparation, UAV calibration, and ground nest surveys. Survey transects had varying lengths of 250 to 600 meters with a mean of 460 meters. Each aerial survey captured approximately 174 aerial images at nadir and required approximately 18 minutes of flight time over a total flight distance of approximately 2 – 3.5 km. All UAV surveys were conducted on the same day as ground surveys to avoid the chance of capturing a newly made nest because of the orangutans present in the study site. In some instances, poor weather required next-day UAV sampling to resolve poor image quality.

2.2.3. Image processing

We produced a total of 90.41 ha of orthomosaiced imagery (Figure 2.5) from 1568 aerial images, that had an average ground resolution of ~3.6 cm/pixel. Orthomosaics were produced with Agisoft Metashape software version 1.5.5 (https://agisoft.com/) and the DroneDeploy mapping tool (https://dronedeploy.com). For each survey transect, a measure of average tree crown spread was estimated from digitizing the crown area for 20 trees using Editor tools in ArcMap ArcGIS desktop software (https://desktop.arcgis.com/).

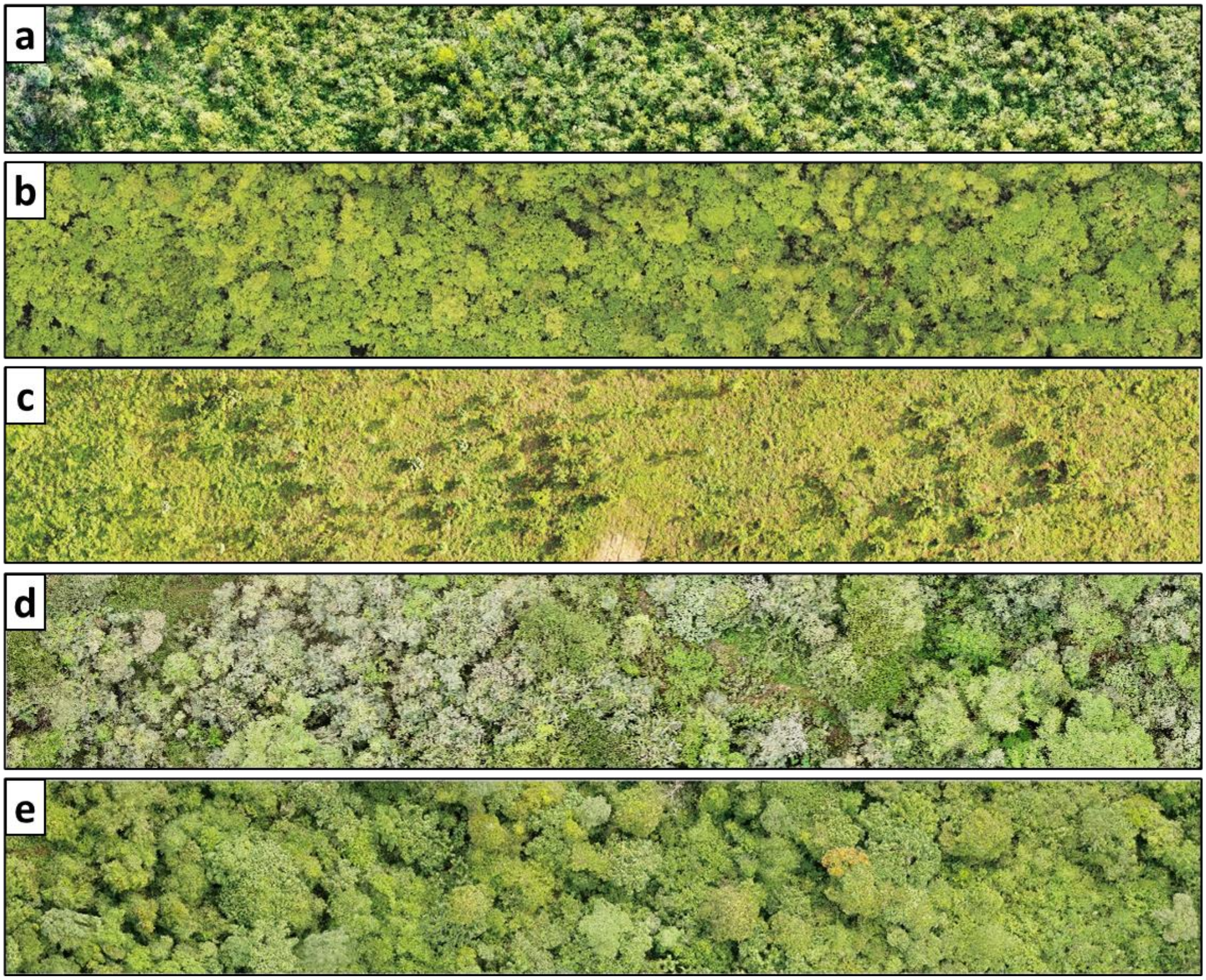

Figure 2.5: Orthomosaics of a transect for each landcover type; (a) 3-year-old *A. crasicarpa* plantation, (b) 7-year-old *E. pellita*, (c) 2-year-old post-mining rehabilitation area, (d) 20-year-old post-mining rehabilitation area, (e) secondary forest.

2.2.4. Nest detection

Three observers carefully and manually examining all the UAV imagery for the nests and determined the locations in the orthomosaics, whether the nests were located within the maximum width of the line transect and also within a 15-meter buffer/footprint of GPS nest data from ground-based surveys. The main features that were used to detect orangutan nests were the distinguishing color and unique shape of bent branches on the tree canopy.

2.2.5. Statistical analysis

All statistical analyses were conducted using RStudio software version 1.3.959. Data descriptors such as mean, median, and range for nest relative density are presented. A Wilcoxon and Kendall's tests were used to compare the nest density of ground and UAV surveys since data were not normally distributed. Logistic regression was used to evaluate which of the predictors (nest height, nest location, canopy openness, and nest decay) influenced the detectability of orangutan nests in UAV imagery. Possible combinations of predictors in the model were examined and then ranked using the Akaike Information Criterion (AIC). The likelihood ratio test (lmtest package, Zeileis & Hothorn, 2002) was also used to calculate the significance of the models. Multiple regression with interaction was used to develop models that predict the number of nests from UAV data. The Leave One Out Cross Validation (LOOCV caret package, Kuhn, 2020) method was used for model validation. The AIC was used to compare all the predictive models. We also used the marginal effects of regression models (ggeffects package, Lüdecke, 2020) to calculate the predicted value, the standard error, and the 95% confidence interval of the predicted value.

2.3. RESULTS

2.3.1. Ground and aerial surveys

We located of total 205 nests during ground surveys along 15 line transects that had a total length of 6.8 km and spanned an area of 26.4 ha. A total of 93 nests were detected in UAV imagery. Nest density varied between 8 nests/km to 80 nests/km (median = 24 nests/km; mean = 29.6nests/km; n = 15) for the ground survey, while for UAV survey, nest density varied between 2/km to 26.7/km (median = 12.5 nests/km; mean = 14.6 nests/km; n = 15, Figure 3). The number of nests that were identified from the UAV survey was significantly less than the number of observed nests from the ground survey (Wilcoxon test; $V = 120$; p-value < 0.05; n = 15) but there was a marginally significant positive correlation between the two surveys (Spearman's $\rho = 0.33$; p-value = 0.055; n = 15). Although some nests observed in ground-based surveys could not be identified on UAV imagery, there were no cases where a nest was observed in UAV imagery and not in ground-based surveys. Only 45.37% of nests observed from ground-based surveys could be detected from the UAV survey (Table 2.2). However, successful nest detection from the aerial survey varied between landcover types, which also had significantly different mean tree crown spread: 82.50% for timber plantation with 3.65 m crown spread, 45.83% for post-mining rehabilitation area with 6.20 m crown spread, and 32.58% for the secondary forest with 9.48 m crown spread (Table 2.2).

Table 2.2: Summary of orangutan nest counts from ground-based and UAV-based surveys.

Landcover type	Transect		n Nest		Nest/km		Nest Drone	Avg.
	n	Length (m)	Ground	Drone	Ground	Drone	Detection	Crown
Ind. Timber Plantation	4	1800	40	33	26.3	21.8	82.50	3.65
- 3 years old sites	2	800	19	16	63	53	84.21	2.59
- 7 years old sites	2	1000	21	17	42	34	80.95	4.71
Post Mining Rehab. Area	6	2400	48	22	20.1	10.1	45.83	6.20
- 2 years old sites	2	500	9	7	36	28	77.78	2.55
- 20 years old sites	4	1900	39	15	85	33	38.46	8.02
Secondary Forest	5	2600	117	38	43.6	14.2	32.48	9.48
Total	15	6800	205	93			45.37	

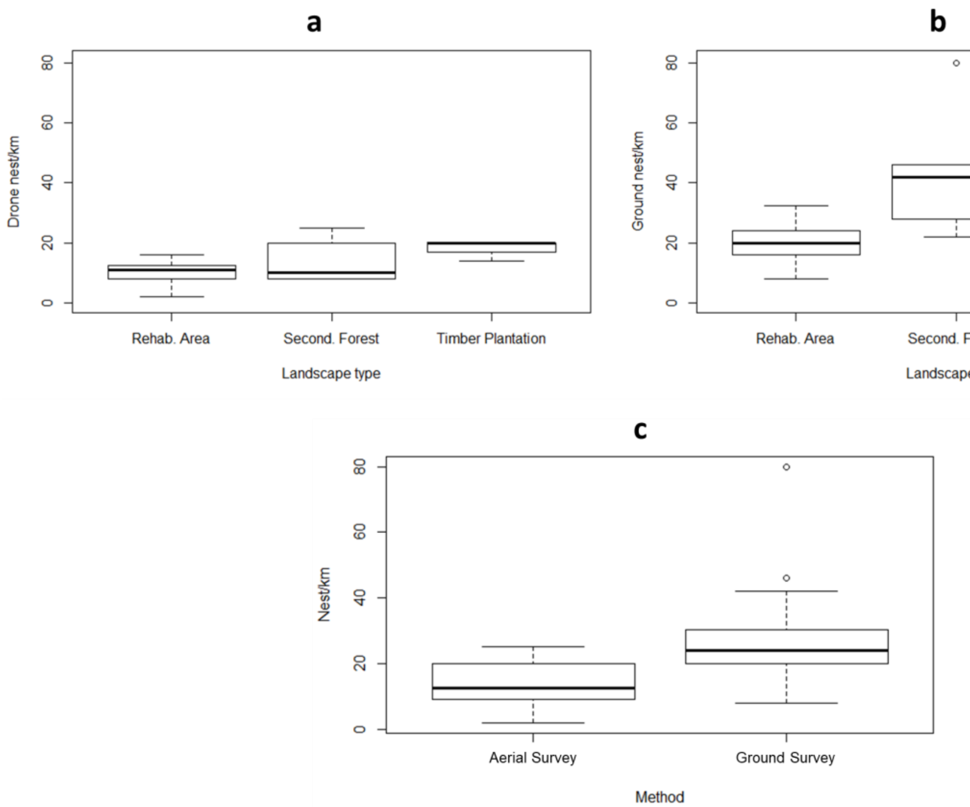

Figure 2.6: Box plots showing results for ground (a) and UAV (b) nest densities recorded for the different land cover types, and results of both surveys overall (c)

2.3.2. Nest detection

Nest height in timber plantations and post-mining rehabilitation sites varied depending on the age of the plantation. The average height of nests located on the ground in the 3-year-old timber plantation site and the 2-year-old rehabilitation site was 6.44 ± SD 1.43 m and 2.27 ± SD 0.53 m respectively. The nests detected in the UAV imagery occurred at heights of 6.62 ± SD 1.47 m for the 3-year-old timber plantation and 2.27 ± SD 0.59 m for the 2-year-old rehabilitation site, and the nests not detected in the UAV imagery were at heights of 5.50 ± SD 0.75 m and 2.25 ± SD 0.35 m, respectively. For the older stands, the average height of nests located on the ground was 19.62 ± SD 3.11 m for the 7-year-old plantation site and 13.21 ± SD 2.99 m for the 20-year-old rehabilitation site. The nests detected in the UAV imagery occurred at height 19.94 ± SD 2.95 m for the 7-year-old plantation site and 14.93 ± SD 1.72 m for the 20-year-old rehabilitation site were detected in the UAV imagery, and nests at height 18.25 ± SD 3.86 m and 12.13 ± SD 3.13 m were not detected in UAV imagery, respectively. Almost all nests located at a height below 10 m were found in the younger stands where more than 75% of the nests were detected from UAV imagery (Table 2.3). All nests at a height above 10 m were found in the older stands, where 71% and 45% of the nests were detected from UAV imagery in the 7-year-old timber plantation and 20-year-old rehabilitation area, respectively (Table 2.3). In the secondary forest, all nests observed from the ground survey were at the average height of 16.18 ± SD 4.19 m; nests located at height 18.78 ± SD 4.38 m were detected in UAV imagery, and nests located at height 14.93 ± SD 3.49 m were not detected in UAV survey. There were no nests below 10 m height in secondary forest sites that were detected from UAV imagery, 26% of nests located at 10 to 20m, and 64% at ≥ 20m were detected from UAV imagery respectively (Table 2.3).

Table 2.3: The ratio of nests detected by UAV for each study site.

Landcover type	Nest height			Canopy openness		Nest site location			Nest decay stage				
	<10m	10 to < 20m	≥ 20m	Closed	Open	MS	TC	EB	A	B	C	D	E
1. Industrial Timber Plantation													
- 3 years old	19 (16)	0 (0)	0 (0)	1 (0)	18 (16)	5 (2)	14 (14)	0 (0)	0 (0)	1 (1)	13 (11)	5 (4)	0 (0)
Ratio of nest detected by UAV	84%	0%	0%	0%	89%	40%	100%	0%	0%	100%	85%	80%	0%
- 7 years old	0 (0)	7 (5)	14 (12)	0 (0)	21 (17)	8 (4)	13 (13)	0 (0)	0 (0)	0 (0)	16 (13)	3 (3)	2 (1)
Ratio of nest detected by UAV	0%	71%	86%	0%	81%	50%	100%	0%	0%	0%	81%	100%	50%
Ratio of all nest detected by UAV	84%	71%	86%	0%	85%	46%	100%	0%	0%	100%	83%	88%	50%
2. Post Mining Rehabilitation Area													
- 2 years old	9 (7)	0 (0)	0 (0)	1 (0)	8 (7)	1 (1)	7 (6)	1 (0)	0 (0)	0 (0)	7 (6)	2 (1)	0 (0)
Ratio of nest detected by UAV	78%	0%	0%	0%	88%	100%	86%	0%	0%	0%	86%	50%	0%
- 20 years old	6 (0)	33 (15)	0 (0)	16 (0)	23 (15)	17 (0)	18 (13)	4 (2)	0 (0)	2 (1)	23 (7)	11 (6)	3 (1)
Ratio of nest detected by UAV	0%	45%	0%	0%	65%	0%	72%	50%	0%	50%	30%	55%	33%
Ratio of all nest detected by UAV	47%	45%	0%	0%	71%	6%	76%	40%	0%	50%	43%	54%	33%
3. Secondary Forest	6 (0)	86 (22)	25 (16)	55 (0)	62 (38)	45 (2)	41 (29)	31 (7)	1 (0)	3 (1)	76 (24)	27 (11)	9 (1)
Ratio of nest detected by UAV	0%	26%	64%	0%	61%	4%	71%	23%	0%	33%	32%	41%	20%
Ratio of nest detected by UAV in all sites	58%	33%	72%	0%	70%	12%	81%	25%	0%	50%	45%	52%	27%

Nest site location: MS = main stem; TC = top of crown; EB = end of branch (Rayadin & Saitoh, 2009)
Nest decay stage: A = fresh, leaves still green; B = fairly fresh, mix of green and brown leaves; C = nest Is brown but remains intact; D = leaves missing and holes appearing in nest; E = leaves are gone, only branch structure of nest remains (Spehar et al., 2010)

There were no nests classified as being in a '*closed'* location observed in the UAV imagery (Table 2.3). The lowest nest detection ratio for '*open'* nest locations was in the secondary forest with 61%, followed by the post-mining rehabilitation area with 71% and the timber plantation at 85% (Table 2.3). The nest site location '*top of the crown'* or 'TC', had the highest incidence of nest detection in all three landcover types, 81% nest detection compared to 12% of '*main stem'* (or 'MS') nest and 25% of '*end of branch*' (or 'EB') nests. Most of the nests found at the top of the crown were also located in the open area of the canopy, and most of the nests found in the main stem location were also located in the closed area of the canopy except in the timber plantation sites and 2-year-old rehabilitation area. This exception reflected the detectability of nests located at the main stem in these locations; 46% '*main stem*' nests (6 of 13 nests) were detected from UAV imagery in timber plantation sites, and 100% nests (1 of 1 nest) were detected in the 2-year-old rehabilitation site. From UAV imagery, 50% of stage B nests, 45% of stage C, 52% of stage D, and 27% of stage E were observable. No very new/fresh nests or stage A were detected in UAV imagery, in fact, only one 'stage A' nest was observed in all sites (Table 2.3).

2.3.3. Factors influencing nest detectability

Five nest characteristics were used as predictors of UAV image detection using logistic regression: 'landcover type' (classes: plantation, rehabilitation area, secondary forest), 'nest height' (classes: <10 m, 10 to < 20 m, ≥ 20m), 'nest site location' (classes: at the main stem or MS, at the top of the crown or TC, at the end of branch or EB), 'canopy openness' (classes: closed, open), and 'nest decay stage' (classes: A, B, C, D, E). The best model with the lowest AIC was the model with combination predictors of 'canopy openness', 'nest site location', and 'nest decay' (Model 1, Table 2.4). The AIC score of the models with a combination of two or more predictors increased drastically when there was no 'canopy openness' and 'nest site location' in the models (Model 18 to Model 19, Table 2.4). The single predictor models 'canopy openness' (Model 10) and 'nest site location' (Model 17) also had the lowest AIC score (AIC: canopy openness = 164.24, nest site location = 193.17) compared to the other three single predictor models (Table 2.4). The likelihood ratio test of models with only the predictor ‘canopy openness’ and ‘nest site location’ showed that these two models had a very significant influence on nest detectability in UAV imagery (canopy openness: $\chi^2 = 122.19$, p-value < 0.05; nest site location: $\chi^2 = 95.26$, p-value < 0.05). These two predictors determined whether the nests were in a location that could be captured by the UAV camera from above. The models with the lowest AIC were the single predictor model ‘nest height’ (Model 23: AIC = 284.48), ‘nest decay’ (Model 25: AIC = 288.07), and the model with the combination of these two predictors (Model 24; AIC = 287.37, Table 2.4). The likelihood ratio test of these two single predictor models also showed weak results on influencing nest detectability (nest height: $\chi^2 = 1.95$, p-value = 0.16; nest decay: $\chi^2 = 4.36$, p-value = 0.36).

Table 2.4: All models ranked by AIC.

No	Model	AIC
1	nest detection ~ nest_site_location + canopy_openness + nest_decay	138.37
2	nest detection ~ landcover_type + nest_height + nest_site_location + canopy_openness + nest_decay	139.96
3	nest detection ~ nest_height + nest_site_location + canopy_openness + nest_decay	140.27
4	nest detection ~ landcover_type + nest_height + nest_site_location + canopy_openness	147.29
5	nest detection ~ nest_site_location + canopy_openness	147.89
6	nest detection ~ nest_height + nest_site_location + canopy_openness	149.81
7	nest detection ~ canopy_openness + nest_decay	155.18
8	nest detection ~ landcover_type + canopy_openness	161.60
9	nest detection ~ landcover_type + nest_height + canopy_openness	163.20
10	nest detection ~ canopy_openness	164.24
11	nest detection ~ nest_height + canopy_openness	166.15
12	nest detection ~ landcover_type + nest_height + nest_site_location + nest_decay	166.61
13	nest detection ~ landcover_type + nest_height + nest_site_location	168.72
14	nest detection ~ landcover_type + nest_site_location	170.25
15	nest detection ~ nest_site_location + nest_decay	190.64
16	nest detection ~ nest_height + nest_site_location + nest_decay	191.31
17	nest detection ~ nest_site_location	193.17
18	nest detection ~ nest_height + nest_site_location	194.08
19	nest detection ~ landcover_type + nest_height	249.43
20	nest detection ~ landcover_type + nest_height + nest_decay	252.30
21	nest detection ~ landcover_type	256.83
22	nest detection ~ landcover_type + nest_decay	260.90
23	nest detection ~ nest_height	284.48
24	nest detection ~ nest_height + nest_decay	287.37
25	nest detection ~ nest_decay	288.07

Nest predictors:
- landcover type : industrial timber plantation, post-mining rehabilitation area, secondary forest
- nest height : <10 m, 10 to <20 m, ≥20 m
- nest site location : main steam, top of crown, end of branch (Rayadin & Saitoh, 2009)
- canopy openness : open, closed (Rayadin & Saitoh, 2009)
- nest decay : A = fresh, leaves still green; B = fairly fresh, mix of green and brown leaves; C = nest is brown but remains intact; D = leaves missing and holes appearing in nest; E = leaves are gone, only branch structure of nest remains (Spehar et al., 2010)

2.3.4. Predicting ground-based nest counts from UAV imagery

Because UAV nest identification failed to discover nests that were observed in ground-based surveys, we regarded the ground-based surveys to be the most accurate measure of nest presence. However, developing models to accurately predict nest density using UAVs would be highly beneficial. Accordingly, and knowing that specific nest features appear to limit detectability in UAV imagery, we explored how mixed models could offer the potential to correct UAV-surveys to best match ground-based studies using features extractable from UAV imagery alone. Two predictor variables were used for the predictive models: landcover type, which was habitat based, and tree crown spread, which was easily acquired from the aerial photos. These two predictor variables were chosen for model development because they can be derived from UAV imagery and are thus a test of how well UAV-only derived variables can be used to approximate results from ground-based surveys. With these two variables, we tested three different multiple regression models to predict ground-based nest density: Model 1 explored the two-way interaction of UAV-identified nests with landcover type; Model 2, two-way interaction of UAV-identified nests with tree crown spread; and Model 3, three-way interaction of UAV-identified nest, landcover type, and crown spread. We used a total of 15 datasets from all the study sites for developing the models. The best predictive model was Model 2 which had a high R^2 score and lower error both for the full model (Adjusted R^2 = 0.92, Residual SE = 3.13, AIC = 82.23) and LOOCV test (Predicted R^2 = 0.81, RMSE = 4.76, MAE = 3.53, Table 2.5). Model 3 had the highest adjusted R^2 score (0.95), the lowest residual SE (2.35), and lowest AIC score (70.04) compared to the other two models but had a lower predicted R^2 (0.30), and very high RMSE (49.91) and MAE (26.78) in the LOOCV test (Table 2.5). These results suggest that Model 3 could be overfitting because the model was too complex.

Table 2.5: The results of multiple regression with interaction, the LOOCV, and AIC tests of all three predictive models.

Model	Full Model			LOOCV			AIC
	Residual SE	Adj. R^2	p-value	RMSE	Pred. R^2	MAE	
Model 1	3.92	0.87	0.0001	5.99	0.69	4.3	89.55
Model 2	3.13	0.92	< 0.0001	4.76	0.81	3.53	82.23
Model 3	2.35	0.95	0.001	49.91	0.3	26.78	70.04

We calculated the predicted values, SE, and 95% CI using Model 1 and Model 2 to see how well the predictors and the outcome of the models were associated. The average crown spread of each landcover type (Table 2.2) was used in Model 2 as the level group for the predictor variable to calculate the predicted values. Model 2 had a much narrower range of 95% CI for each predicted value compared to Model 1, especially for the timber plantation and rehabilitation area (Figure 2.7).

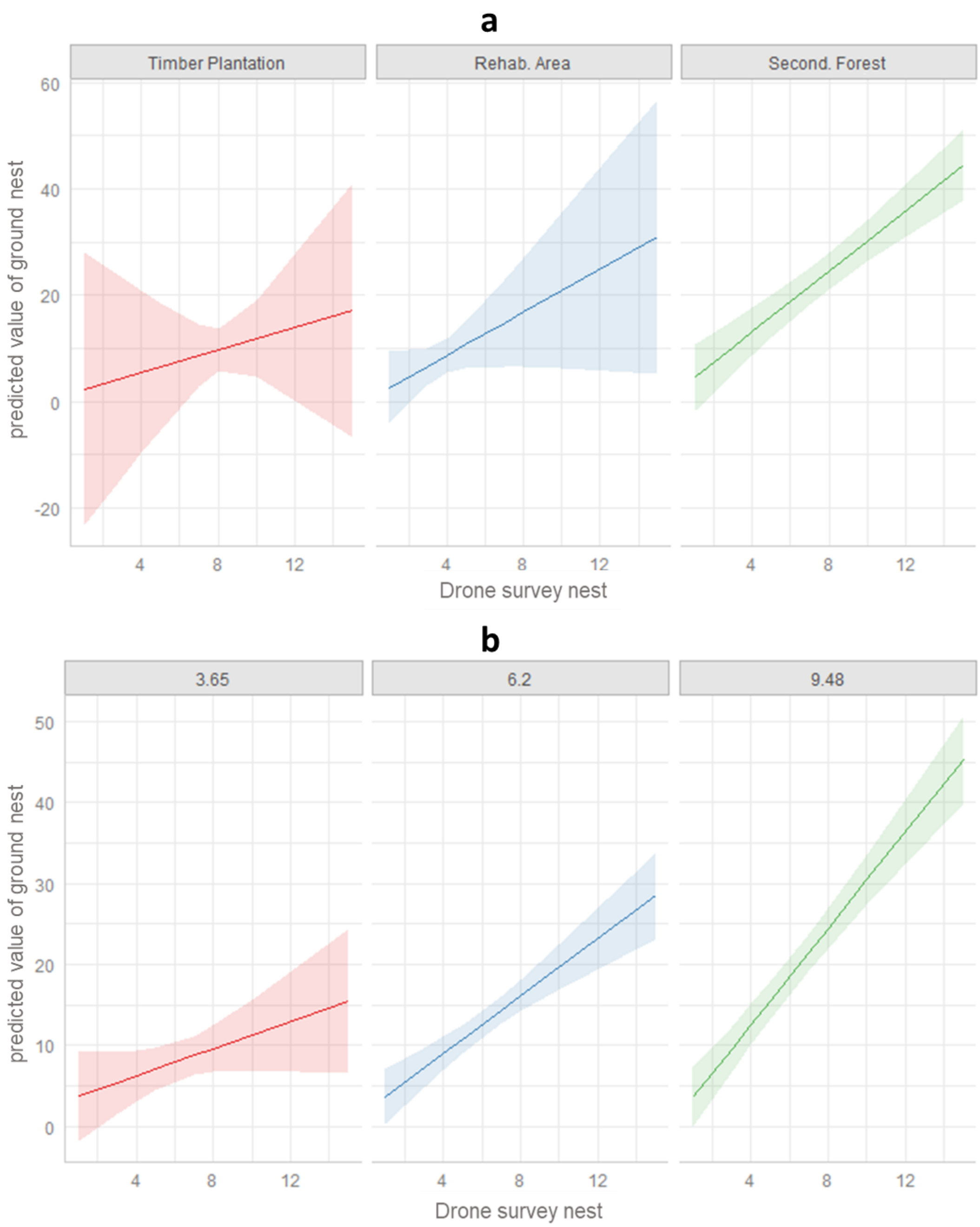

Figure 2.7: Predicted values of ground survey nest on certain level of predictor variable: (a) Model 1, predictor variable = landcover type; (b) Model 2, predictor variable = tree crown spread in meter.

2.3.5. Testing the predictive models

We randomly split the original dataset into two datasets and established a training dataset, and a validation dataset. Following, we reran the multiple regression models and the LOOCV with the training dataset. Results suggest there is little difference in these adjusted models compared to the original Models 1 and 2 (Table 2.6).

Table 2.6: Results of adjusted multiple regression models with interaction with tree crown spread, the LOOCV (*and the results of the Model 1 and Model 2*).

Model	Full Model			LOOCV		
	Residual SE	Adj. R^2	p-value	RMSE	Pred. R^2	MAE
Adj. Model 1	3.81	0.9	0.001	6.55	0.69	4.74
Adj. Model 2	3.09	0.93	< 0.0001	5.28	0.8	3.69
Model 1	*3.92*	*0.87*	*0.0001*	*5.99*	*0.69*	*4.3*
Model 2	*3.13*	*0.92*	*< 0.0001*	*4.76*	*0.81*	*3.53*

The predicted values of the test datasets were then estimated. For both adjusted models, a greater number of nests were predicted for the survey area than what was observed in UAV imagery alone. The predicted value (Fit) was mostly underestimated nest counts observed in ground surveys, except for the timber plantation sample data with Adjusted Model 2 (Table 2.7). The best model for predicting the nest count from ground surveys was Adjusted Model 2, with a total difference of -6.8 or 16.19% less than the number of nests observed in ground surveys. Adjusted Model 1 had a bigger total difference with a value of -11.68 or 27.81% less than the number of nests observed in ground surveys. The equation of the original Model 2 is: $Y = 4.3263 + (-0.4951*X_1) + (-0.3893*X_2) + (0.3661*X_1*X_2)$, where Y is ground nest count, X_1 is UAV nest count, and X_2 is average tree crown spread.

Table 2.7: The predicted values of the test dataset using two new models: Diff = difference value of predicted value (Fit) and the ground data (Ground), Diff (%) = percentage of different value.

Landcover type	Crown spread (m)	Nest Observed			Nests Predicted					
					Adj. Model 1			Adj. Model 2		
		Ground	Drone	% Nest Loss	Fit	Diff	Diff (%)	Fit	Diff	Diff (%)
Ind. Timber Plantation	4.44	9	7	22.22	8.25	-0.75	-8.33	10.55	1.55	17.22
Post-mining Rehab. Area	7.03	12	4	66.67	7.96	-4.04	-33.67	9.2	-2.8	-23.33
Secondary Forest	10.34	21	5	76.19	14.11	-6.89	-32.81	15.45	-5.55	-26.43
Total		42	16	61.90	30.16	-11.68	-27.81	35.55	-6.8	-16.19

Adjusted Model 1 equation:
- Ind. timber plantation: $Y = -0.5 + 1.25 * X$
- Post-mining rehab. area: $Y = (-0.5+0.8214) + (1.25+0.6607) * X$
- Secondary forest: $Y = (-0.5+-0.615) + (1.25+1.7942) * X$

Adjusted Model 2 equation: $Y = 4.8787 + (-0.4435*X_1) + (-0.6116*X_2) + (0.3697*X_1*X_2)$

Where; Y = ground nest count, X or X_1 = UAV nest count, X_2 = Average tree crown spread

2.4. Discussion

This study showed that the detectability of orangutan nests in UAV imagery depended on the landscape type and canopy structure of the survey area. There were no cases of nests being identified in UAV imagery that were not recorded in ground-based surveys. Nest detectability was greatest for timber plantations (82.50%). Timber plantations also had the smallest average crown spread compared to other landscape types. Among the planted stands surveyed, nest detection was lowest in the post-mining rehabilitation area (45.83%), which had a larger mean crown spread than the timber plantation. In the timber plantation, there was no difference in nest detection between the younger and older sites; both had more than 80% nest detection rates in UAV imagery. These results were somewhat expected because timber plantations, irrespective of their age, have relatively small and unconnected canopies that readily expose orangutan nests in UAV imagery. At the post-mining rehabilitation sites, results were dissimilar to the plantation site. Here, 2-year-old rehabilitation sites had a higher nest detectability (77.78%) than the 20-year-old sites (38.48%). The 20-year-old sites had a bigger average tree crown spread and much more established canopy structure than the 2-year-old rehabilitation site, which resulted in a higher degree of variation in nest location within the canopy that made nests more difficult to detect in UAV imagery. Secondary forests had the lowest nest detectability of all the landscapes surveyed (32.48%). Not only did the secondary forest sites have a larger average crown spread than the post-mining rehabilitation area, but the secondary forest sites also had a more complex canopy structure, which challenged nest detectability in UAV imagery.

The nest detection rate of all three landcover types combined was 45.37%, which is higher than that documented for a comparable study in Sumatra (Wich et al. 2016) that documented a detectability of 17.4%. These results differences are likely due to a combination of different flight altitudes and camera system, which affected the spatial resolution of UAV images. In our study, we used a camera system with a larger image sensor and resolution (DJI Phantom 4 Pro in-build camera; 20 megapixels, 1" CMOS sensor) compared to the camera system used in Wich et al. study for Sumatran orangutan (Canon S100; 12.1 megapixels, 1/1.7" CMOS sensor). We also flew the UAV at various altitudes but mostly at 60 m above ground level, which was lower than in Wich et al. study at 80 m above ground level. In our study, we used a multirotor drone that had smaller flight time capacities but could fly at a lower altitude. This hypothesis is supported by a study on the aerial survey for chimpanzee nests in Tanzania (Bonnin et al., 2018), in which a higher probability of nest detection was associated with the higher-resolution camera and at a lower flight altitude above ground level, due to the better spatial resolution images. In the Wich et al. study (2016), orangutan nests were extracted from UAV imagery without the aid of GPS'd locations recorded during ground surveys as was the case in this study. As such, this study and that of Wich et al. (2016) likely presented the best- and worst-case scenario for orangutan nest detection using UAV imagery. A chimpanzee nest study (van Andel et al., 2015) used a similar approach to this study for ground-truthing UAV nest surveys, which resulted in a ~39% nest detection rate.

Locating orangutan nests from aerial imagery with the GPS location from the ground survey seemed to increase the probability of nest detection in UAV imagery.

Nest features and canopy complexity appear to best explain the detectability of orangutan nests from UAV images. ’Canopy openness’ had the lowest AIC score among the other single predictor models, which compares well with a comparable study of chimpanzee nests (van Andel et al., 2015) in the Loango National Park, Gabon. in the Loango National Park, Gabon. Another single predictor model showed that ‘nest site location’ was also a good determinant of nest detectability although canopy openness and nest site location are likely to be autocorrelated. All nests located at top of the tree crown were also open, making them much easier to detect in UAV imagery than nests located at the main stem of a tree or where nests are covered by the canopy. We could not locate almost all the nests at the main stem position in the UAV imagery because all the nests were also in the closed position. The only exception for nests located in the ‘main stem’ position, were nests found in the young timber plantation or young rehabilitation area. The nest site position was also related to landscape type and orangutan nesting behavior. Generally, orangutans prefer to build a nest at the main stem and at the top of the crown, which has a more stable location capable of supporting their large body mass, especially for flanged males and adult females (Rayadin and Saitoh, 2009).

Because our ground-based surveys detected more nests than the UAV, we created a model to predict ground-level nests from UAVs. The multiple regression model that included a measure of UAV-derived tree crown spread (Model 2) performed statistically better, yet consistently under-predicted ground-based nest counts, compared to two other models that included landcover type and the combination of trees crown spread and landcover type, respectively. While, we suggest that the mixed models presented in this study require further refinement prior to their widespread use, we are optimistic given that the success of this mixed model approach based on a sample size of 15 transects.

This study demonstrates a promising potential for UAV surveys to be used to rapidly assess orangutan nest densities and enhance conservation management of this critically endangered species. Based on our experience in the field, the UAV nest surveys could be executed in about 80-85 % less time than ground-based surveys with a smaller survey team. Importantly, however, the accuracy of ground-based surveys cannot be matched by UAV surveys and UAV surveys also require similarly highly trained personnel to ground-based, where there is arguably a greater emphasis on post-survey image and data processing than is typical for ground-based surveys. An optimal approach likely requires the combination of selective ground surveys to establish baseline datasets to characterize landscape variability at a given location from which correction factors can be modeled and applied to UAV-based surveys that span a larger area than those of ground-based surveys.

UAV nest survey techniques used the same basic concept as the line transect method employed by ground-based nest surveys. However, besides counting nests from the UAV imagery, which detected fewer nests than ground surveys, the estimation of several additional parameters (p, r, and t) are required in order to convert nest density into estimates of individual density (van Schaik et al., 1995; Johnson et al., 2005). The proportion of nest builders in the population (p) and the rate of nest production (r) must be based on observed values from known populations and may vary for different locations (Buij et al., 2003; Johnson et al., 2005). The rate of nest decay (t) must also be based on observations of nest longevity in the area (Buij et al., 2003; Mathewson et al., 2008). Based on our observation, UAV imagery can provide a good detail to identify the nest decay stage if we can fly the UAV closed enough to the forest canopy. The most accurate way to estimate *t* is by nest monitoring that requires laborious effort and can take years for data collection (Russon et al., 2001; Buij et al., 2003; Morrogh-Bernard et al., 2003; Johnson et al., 2005; Mathewson et al., 2008). This could be another opportunity of using UAV for nest monitoring to estimate *t*, especially in study sites such as mining concessions or timber plantations that have very limited data and information about orangutan populations and habitat use.

UAV-based nest surveys have a high initial investment due to the cost of equipment, software, training for flight operations, maintenance, and data analysis. Over time and with increasing survey area, the return on initial investment increases. Thus, we believe that the development of UAV nest survey methods is essential for the research, management, and conservation of orangutan populations in the multifunctional landscapes of East Kalimantan, other areas of Sumatra and Borneo. Beyond the need to further test our modeling approach in a greater variety of landscapes and locations, we also suggest that further research exploring the utility of machine learning to automatically detect orangutan nests from UAV imagery and exploring how nests could be detected with hyperspectral or thermal imagery using a classification-based approach could further enhance opportunities for assessing orangutan population using UAV-based approaches.

2.5. CONCLUSION

We evaluated the use of UAVs for orangutan nest surveys in the multifunctional landscapes of East Kalimantan. A total of 205 nests were observed from the ground survey and 45.37% of these nests were detected in UAV images: 82.50% in timber plantations, 45.83% in the post-mining rehabilitation areas, and 32.48% in secondary forests. The key determinants of nest detectability in UAV imagery are canopy openness (χ^2 = 122.5, p-value < 0.05) and nest site location (χ^2 = 99.01, p-value < 0.05), which both had the lowest AIC value than other predictors.

We also tested three predictive models with three different interactions of the two predictor variables landcover type and average crown spread. The two-way interaction models with average crown spread, or Model 2, were the strongest than the other two models (full dataset Model 2: R^2 = 0.81, RMSE = 4.76; Adjusted Model 2: R^2 = 0.80, RMSE = 5.28). The drone nest counts were increased when we applied the adjusted Model 2 to the test datasets, although the model consistently underestimated the nest counts from ground-based surveys. These tests show the potential of using UAV survey data to assess orangutan distribution and densities. More tests with other predictor variables and more samples need to be explored to further develop models.

Chapter 3: Developing UAV flight protocols suitable for orangutan nest surveys in the multifunctional landscapes of East Kalimantan

3.1. INTRODUCTION

3.1.1. Background and motivation

Orangutans are a 'flagship species' for biodiversity conservation efforts and habitat protection in the tropical forests in Indonesia where their existence has been threatened by habitat loss and fragmentation due to logging, fire, and forest conversion for coal mining, and oil palm and timber plantations (Marshall et al., 2009; Meijaard et al., 2012; Ministry of Forestry, 2007; Wich et al., 2008). Currently, over 75% of Indonesian Bornean orangutans exist outside of protected or conservation areas (Wich et al., 2008; Wich et al., 2012a). Many orangutan population and distribution studies have been conducted thus far, but few studies have been carried out in the non-protected areas and/or have examined how orangutan persist in human-dominated habitats, highlighting the loose understanding of how these critically endangered species are adapting to anthropogenic-induced landscape changes (Campbell-smith et al., 2011; Meijaard et al., 2010). This circumstance establishes a knowledge gap for orangutan population and habitat use assessments and remains a detriment to orangutan conservation planning efforts (Rahman et al., 2019; Seaman et al., 2019; Spehar et al., 2017).

Orangutan population density is traditionally estimated from nest census along ground-based line transects and a well-developed method that has been used extensively for decades (van Schaik et al., 1995; Buij et al., 2003; Husson et al., 2009). Although this method yields excellent results, surveys tend to be expensive, time-consuming, require an experienced survey team, and are generally limited to a small survey area (Ancrenaz et al., 2004a; 2004b; Wich et al., 2016b; Wich, 2015). Motivated by such limitations, alternative ground-based methods for estimating orangutan populations have been tested and include plot nest surveys (van Schaik et al, 2005) and spatial capture-recapture (SCR) methods using camera traps (Spehar et al., 2015). In all cases, these methods appear to have only partially resolved the challenges addressed above. Ancrenaz et al. (2004a; 2004b) were able to increase the size of the sampling areas significantly and reached remote areas that were not accessible from the ground by conducting aerial nest surveys using a helicopter, but such surveys were extremely expensive and limited by the availability of pilots and flight infrastructure.

Another aerial-based orangutan nest survey was tested by Wich et al. (2016), using unmanned aerial vehicles (UAVs, or drones) and structure from motion (SfM) photogrammetric techniques to generate georeferenced mosaics of the study area/line transects. This study demonstrated that this drones are able to not only reach remote habitats and cover much larger areas compared to ground-based nest surveys but also could potentially reduce survey costs and fieldwork time. Drones have also been used successfully to detect chimpanzee nests in Africa (Bonnin et al., 2018; van Andel et al., 2016). Drones can help fill the data gap of not only the distributions of orangutan populations but also gain a better understanding of habitat use within the multifunctional landscape.

The main purpose of developing the protocols below is to guide interested parties (i.e. researchers, conservation workers, or even company management) in utilizing UAV approaches for monitoring and mapping orangutan populations and distributions. These protocols were developed based on aerial nest surveys using a multirotor UAV but could serve as a guide for use with other types of drone platforms (e.g. fixed-wing, vertical take-off and landing, balloons, etc.).

3.1.2. UAV-based vs. ground-based nest survey

Before more discussion about the technicality of UAV nest survey protocols, it is appropriate to compare the fieldwork effort and data collection of the UAV nest survey method to the well-accepted ground-based nest survey method.

Table 3.1: Fieldwork effort and data collection comparison of UAV-based and ground-based nest survey.

Nest survey methods	Ground-based[1]	UAV-based[1]
Field operational/fieldwork		
- Fieldwork cost	very expensive[2]	much less cost
- Equipment	standard survey equipment	UAV, high initiation investment
- Field time	1- 2 km transect/day	500m - 1km transect/battery (15-50 minutes flight time, depending on the UAV platform, the mission planning, and the terrain/vegetation of study area)
- Personnel	at least 4 or 5 observers	minimal 2 person
- Sample size	relatively small[3,4]	can cover much larger survey area[3,4]
Data collection		
- Nest count	more accurate	less accurate/fewer number of nest[4]
- Nest features	Able to identify all the features[5]	limited to what capture in the images
- Vegetation structure & composition	Able to collect much detail vegetation data; tree density, species, etc. [6,7]	limited, can measure tree crown spread from orthos, or identify habitat type in general

[1]based on our field experience; [2]Wich, 2015; [3]Ancrenaz, 2004b; [4]Wich et al., 2016b; [5]Rayadin & Saitoh, 2009; [6]Rayadin et al., 2013; [7]Onrizal & Bahar, 2019.

As shown in Table 3.1, the UAV-based method has the advantage of being more time and cost efficient than ground-based methods but less accurate on nest counts and nest characterization (decay stage, canopy position, etc). On the other hand, the ground-based survey method offers a means to more accurately detect orangutan nests in the forest and document additional nest features and nesting behavior (Rayadin & Saitoh, 2009; Prasetyo et al., 2009); vegetation structure and composition that is important for food resource determination and habitat preference (van Schaik et al., 1995; Onrizal & Bahar, 2019); and nest decay stage (Russon et al., 2001; Buij et al., 2003; Mathewson et al., 2008). However, most modern UAV imagery is of sufficiently high resolution and to detail nest decay classification and in some cases tree species identification. UAVs and the sensor packages they can host are developing rapidly, offering enormous potential for orangutan and other survey applications following rigorous testing.

3.2. UAV PLATFORMS

There are two common UAV platforms: multirotor or fixed-wing drones (Figure 3.1). Multirotor drones are the most common and have a wide range of uses including recreation, cinematography, photogrammetry, and land mapping proposes. Multirotor drones usually have four, six, or eight rotors to control the vehicle's motion. On the other hand, fixed-wing drones have a more traditional aircraft design – a single or double propeller with a pair of wings that allow the aircraft to remain flying once in the air. Fixed-wing drones are commonly used for only large-scale land mapping and surveys and are generally more complex to operate than multirotor drones (DroneDeploy, 2017).

These two platforms have been successfully tested for aerial-based nest surveys (van Andel et al., 2015; Wich et al., 2016b; Bonnin et al., 2017; Hanggito et al., unpublished) and most vehicles of both platforms are qualified as small unmanned aircraft system and applicable for recreational and research purposes, based on regulation from Minister of Transportation, Indonesia (Minister of Transportation, 2015). But, there are some pros and cons to consider between these two platforms related to the aerial-based nest survey:

- *Take off/landing zone*. Multirotor drones can perform vertical takeoffs and landings (VTOL) while fixed-wing drones require a large takeoff and landing zone for flight. For aerial nest surveys, multirotor drones give more flexibility to fly the drone even in limited spaces, which is needed for applications such as monitoring roads of a natural forest in mining concession or those between plantation blocks.

- *Survey range*. Fixed-wing drones can cover a larger geographic survey area with a single battery cycle, due to a faster flight speed and longer flight time. Multirotor drones can fly slower at low altitude to capture higher spatial resolution data. Both platforms can work very well for drone nest surveys. With fixed-wing drones, we can create a mission plan that can cover multiple transects in one large study area. And with multirotor drones, we may need at least two or three extra batteries to be able to do multiple flight missions in the study area.
- *Flight operations*. Operating fixed-wing drones requires more training and experience, especially for takeoff and landing operations. Additionally, the increased survey range of a fixed-wing drone introduces potential issues to maintain visual line-of-sight (VLOS) between the operator and the drone. Based on Indonesian regulations for operating UAV, "Civil Aviation Safety Regulation Part 107 Small Unmanned Aircraft System", it is a requirement to maintain VLOS throughout the entire flight (Ministry of Transportation, 2015) for flight safety, but it seems most likely not a problem when conducting drone nest surveys in the forest or free-ranging areas. On the other hand, multirotor drones are easier to fly – after a relatively short training session and a little practice for mastering both manual and autonomous flight, most pilots adapt and can competently complete most flight missions.
- *Price*. The price of both platforms is comparable but largely depends on the build specifications. ConservationDrones.org provides good information about drone options and how to build the drone, especially fixed-wing aircraft for conservation-related

applications. In our study, we used a DJI Phantom 4 Pro version 1 bundle that costs around $2500 with an onboard 1-inch 20-megapixel sensor camera and 3-axis stabilization gimbal (detail product/specs: https://www.dji.com/phantom-4-pro/info#specs). We chose this drone system because it was more suitable for our study site and research purposes, which required a high degree of adaptability for takeoff and landing, and a capacity to fly at low altitudes and capture high-quality images. Another quadcopter drone from DJI with a lower price than the Phantom series is the DJI Mavic 2 which costs $988. The drone is equipped with a 48 MP RGB camera sensor and includes a total of 3 flight batteries and 6 pairs of propellers. The best drone system for aerial nest surveying is likely to be limited by budget and operational limitations or conditions of the study area.

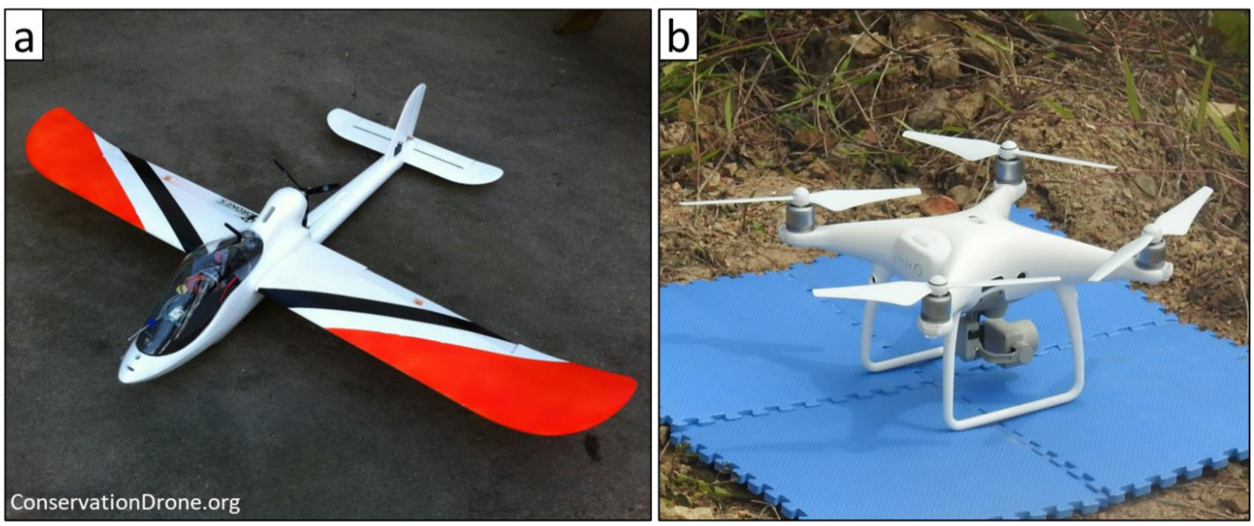

Figure 3.1: (a) a fixed-wing drone ‘Conservation Drone Penguin’, (b) a multirotor drone ‘DJI Phantom 4 Pro ver. 1’.

3.3. Site Selection

A crucial step in the monitoring of orangutan populations across multifunctional landscapes is the proper selection of study site locations. These can be based on parameters such as land cover type and vegetation composition or variation. In natural forests, sources of variation can include forest type (e.g. young secondary, old secondary, and primary forest). In non-protected areas such as industrial timber plantations or coal mining concessions, sources of variation can include tree species and stand age differences (Figure 3.2), or intensive and selective logging concessions. Considering these site variations will help with adequately sampling each vegetation or landcover type and variations therein within the study area and underpin analyses of orangutan distribution and population size.

Flat terrain is preferable for drone nest surveys, although slight topographic variations can be managed by adjusting the flight altitude, or using 'terrain following' features if the study site or the transect has a significant variation of topography/elevation (more detail will be discussed in Section 3.4.2 below). Another important factor to consider during site selection is the accessibility of the study site. In industrial concession areas, companies tend to establish roads for easy access, which can be used to reach a wider range of areas for conducting the aerial nest surveys. Roads also provide a flat and stable surface free from obstacles that can be used for the drone's takeoff and landing spot if there is no other relatively flat surface available. It is always better to discuss fieldwork plans with officials or land managers who might understand the landscape better and could be a useful source of information for site accessibility.

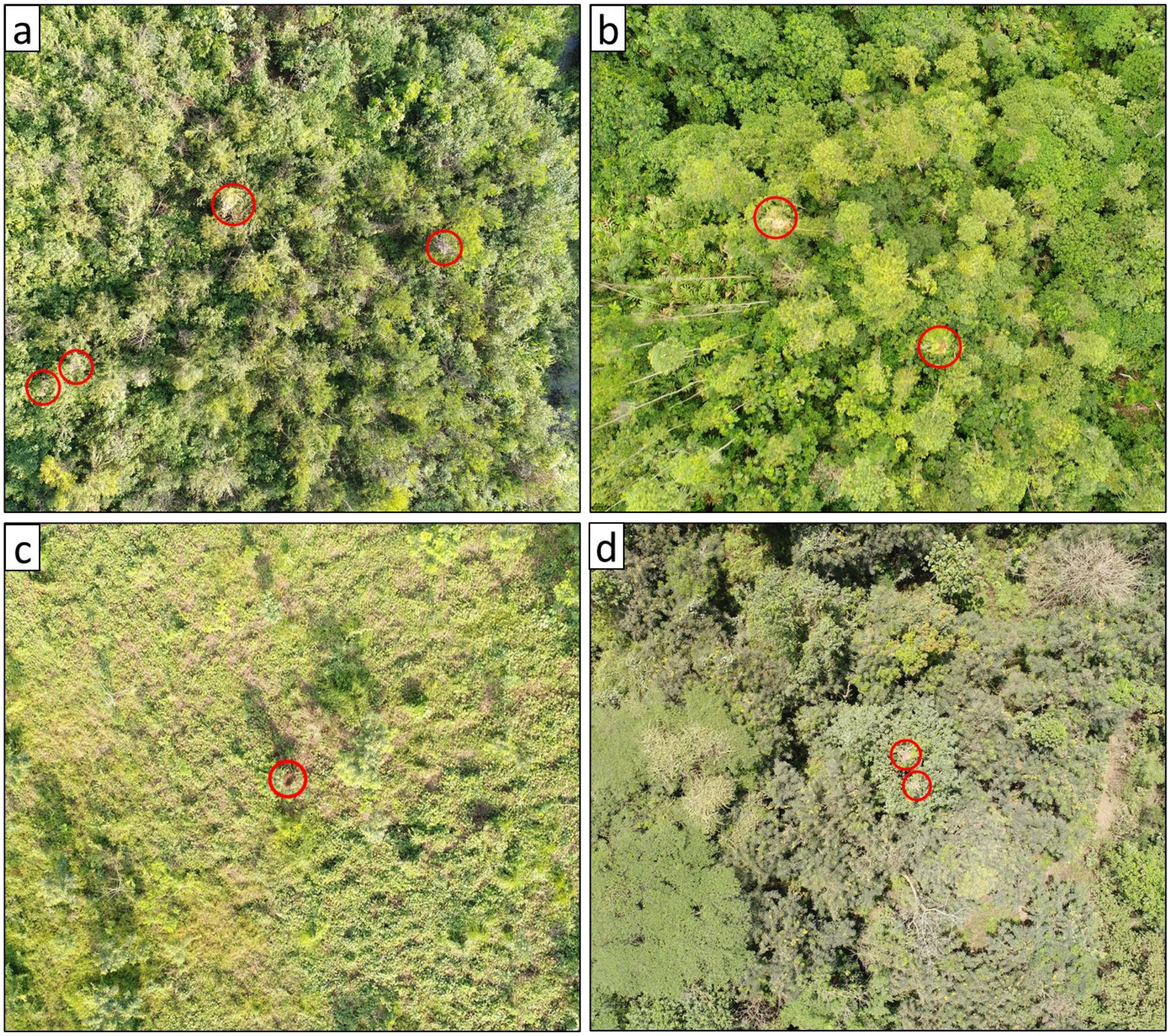

Figure 3.2: Drone images highlighting examples of vegetation variation as observed with orangutan nest (red circle) by tree-age within non-protected areas: (a) 3-year-old *Acacia crasicarpa* plantation, (b) 7-year-old *Eucalyptus pellita* plantation mix with pioneer species trees, (c) 2-year-old, and (d) 20-year-old post-mining rehabilitation area.

In Indonesia, a valid research permit from the Indonesian Government is required for foreign researchers conducting environmental research, but not for local/domestic researchers. For local/domestic researchers, only permission from local officials (in the case of government areas) or the land managers (in the case of company concessions) is required for research. The research permit from the Indonesian Government can be very hard to get for foreign researchers, but one of the key points of the permit approval is a research partnership with researchers from a local university or research institution (Rayadin 2020, personal communication). It is very important to collaborate with local researchers, not only as a requirement for the research permit but also for maximizing the effectiveness of the research because of the value of local knowledge and the relationship between local researchers and government officials and/or land managers. These restrictions and practicalities highlight the importance of foreign national researchers sharing their knowledge and training local researchers or conservation practicians about UAV-based survey methods.

3.4. Data Collection

3.4.1. Field orientation

It is very important to conduct field orientation or pre-survey flight planning and collect as much information as possible for determining the design of aerial nest surveys. Field orientation can be assessed by flying the drone over the target study site to visualize and assess landscape conditions like topography, vegetation cover, surface hydrology, and gauge the general presence of orangutan nests in the area of interest. Collection of handheld GPS data and/or geotagged drone imagery during field orientation flights can be used to help create regions of interest or bounding boxes for subsequent flight planning efforts.

3.4.2. Aerial-based nest survey

The aerial-based nest surveys, in many respects, uses the same concept as the ground-based transect line survey method, in that the main idea is to quantify orangutan nests within a 15 – 20 m width around the midline of a line transect. The length of the transect can vary between 500 m to 1 km, depending on factors such as topography, battery capacity, flight mission setup, and drone-related safety measures. The altitude of the drone survey can also be adjusted depending on the vegetation cover or height, and topography of the study site, but in most cases surveys to be conducted 50 – 80 m above ground level (AGL). In our tests, a drone was flown once at a lower altitude, 30 m AGL over the 3-year-old acacia plantation to have better imagery for the purpose of detecting orangutan nests on the 5 – 9 m height trees. There is a trade-off that occurs when flying survey missions both at low and high altitudes, especially for orangutan nest survey. At the lower altitude, the drone camera will be able to capture higher spatial resolution images and more detail can generally be discerned because drones fly closer to the forest canopy, enabling higher detect nests detectability. But the trade-off is, having a lower ground sampling distance (GSD) and lower ground sampling area (GSA) due to a lower altitude, which will increase the flight path length which directly affects the flight time and power budgeting (Illustration 3.1). Missions flown at a higher altitude can cover the same amount area/ROI with less pictures and therefore in a shorter amount of time because of a larger ground sampling area, but the images will have lower spatial resolution and nest detectability can be more difficult.

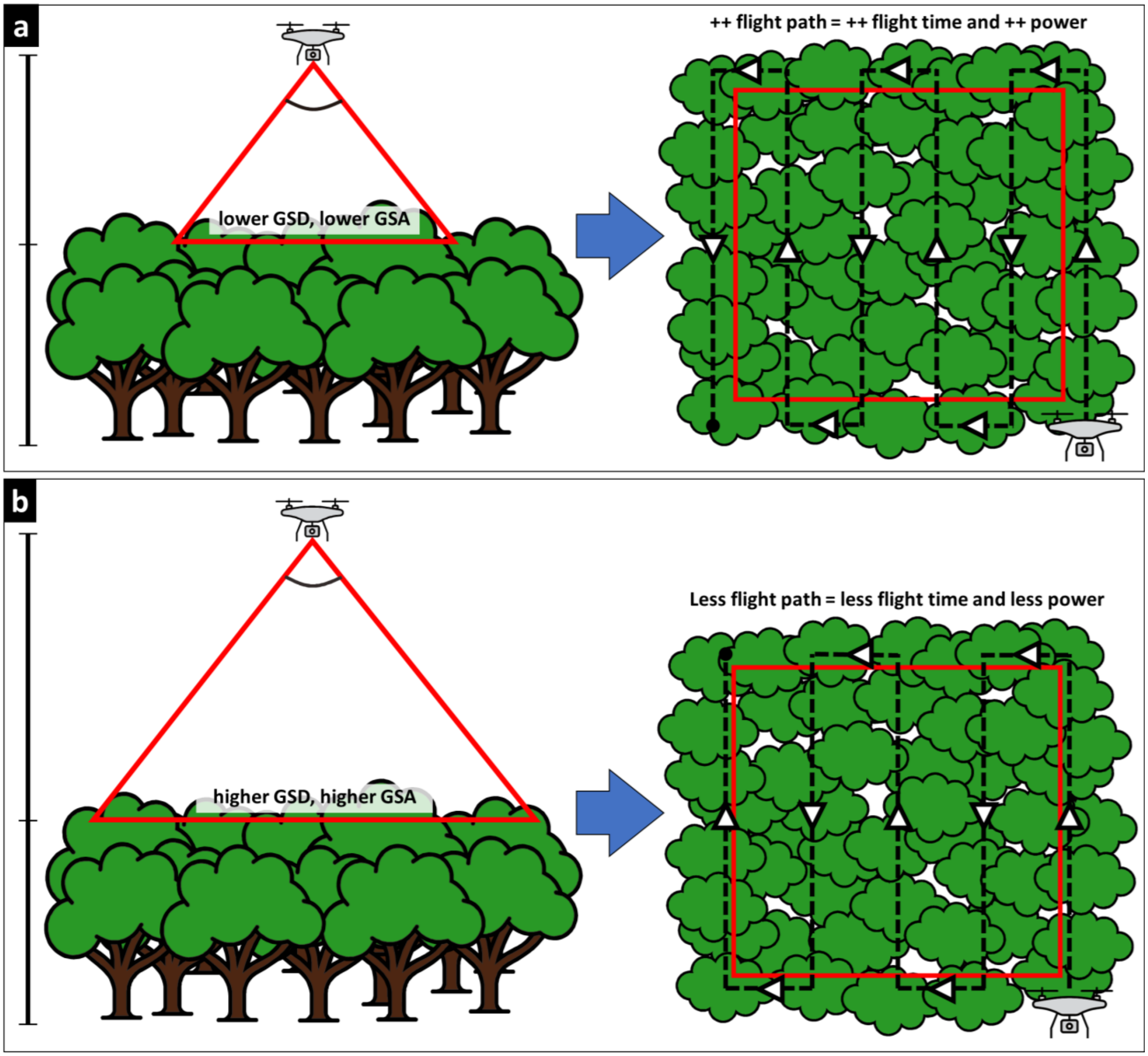

Illustration 3.1: Illustration of how different altitudes on drone surveys affect GSD, GSA, and overall mission configuration; (a) at a lower altitude, (b) at a higher altitude.

As mentioned in Section 3.3 above, there is a feature called 'terrain following' that can be used for surveys where the study area has a significant variation of elevation. This feature uses terrain datasets to allow the drones to adjust altitude during flights based on current elevation and ensures uniform drone flying altitude relative to the canopy height at any given section of the survey area (Illustration 3.2). This method also ensures that the spatial resolution of derived imagery is of even quality and resolution for the entire study area. However, there is some limitation that must be considered with this feature. Some mission planning software, like Measure Ground Control (https://www.measure.com/help/terrain) or DroneDeploy (https://support.dronedeploy.com/docs/terrain-awareness), requires an internet connection to download the terrain dataset, which can be difficult to get when conducting survey in remote locations. These apps also only can be worked with drones and/or camera specific such as DJI or Skydio, which is a multirotor UAV platform. The ArduPilot autopilot system allows us to download the terrain database and load it to the MicroSD card on the autopilot hardware so the aircraft can use the terrain height data in the location to maintain the same altitude during the flight (technical detail: https://ardupilot.org/plane/docs/common-terrain-following.html#common-terrain-following). Another limitation is that the terrain database maybe not be perfect for some regions including Indonesia because terrain following typically uses data from the NASA Shutter Radar Topography Mission (SRTM) database, which only includes high-resolution data for certain areas such as the USA, Europe, and Australia.

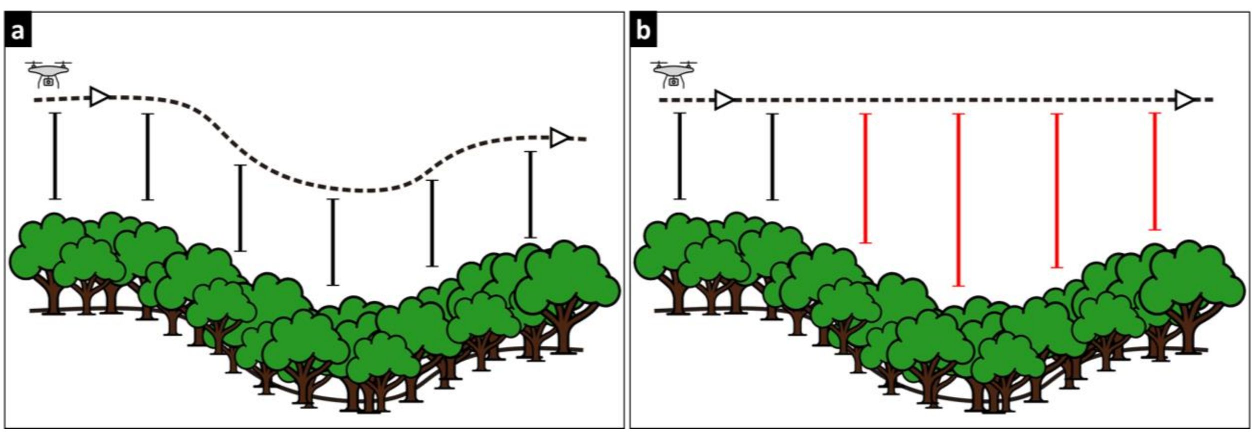

Illustration 3.2: Illustration of flight mission on the study area with significant topographic variation; (a) using terrain following feature, (b) using default flat altitude.

Another crucial setting for drone surveys is optimizing image overlap for the nature of the survey being conducted. Image overlap is very important for structure-from-motion (SfM) photogrammetric surveying, especially for image point matching and for the model reconstruction phase of image post-processing (Geinko and Terry, 2014). A higher percentage of image overlap will generate better results in structural models and orthomosaics, even though the camera will capture more images (Illustration 3.3). However, such approaches increase image storage requirements, also add more path and flight time to the mission. Our experience suggests that nest survey missions should be programmed to have at least has 80% front and side-overlap between images so the photogrammetric software can locate the same features across images and georeferenced and mosaic all images accurately.

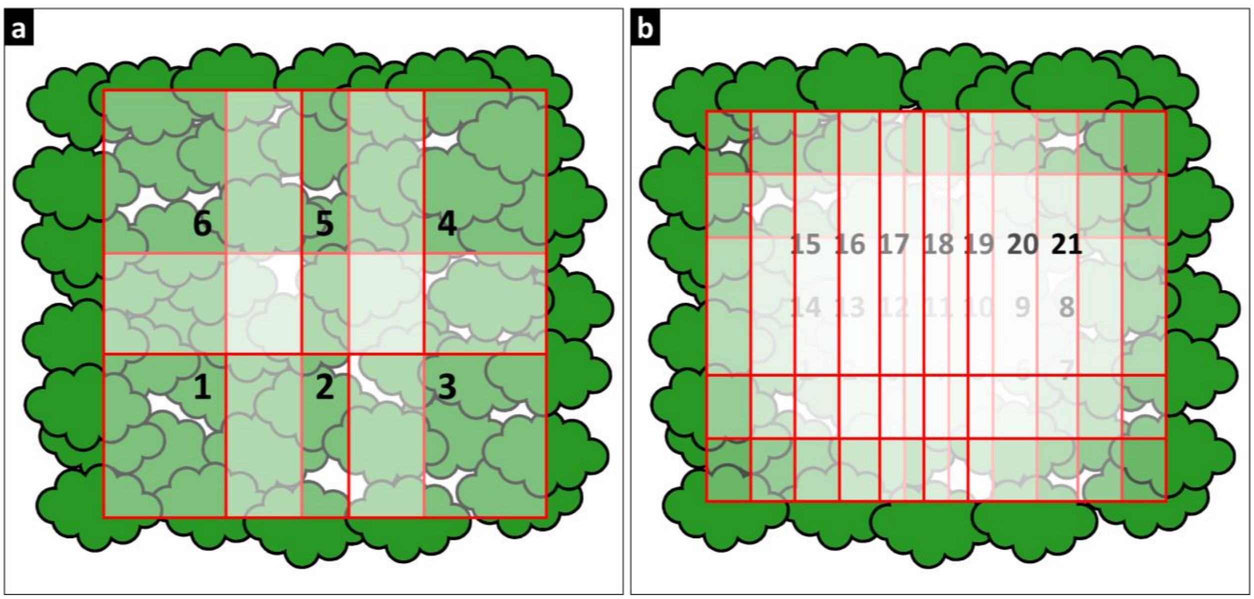

Illustration 3.3: Illustration of different overlapping configurations on the flight mission; (a) front and side-overlap at 40%, (b) front and side-overlap at 80%.

Around midday is always the best time for drone surveys for avoiding excessive shadowing from low sun angle illumination, but in our test in the tropics, we were able to conduct drone surveys effectively between 9 am to 3 pm. Sometimes the sky condition in tropical areas can be very cloudy all day but still provide a substantial diffuse light (if dark rain clouds do not persist) and consistent lighting conditions. Flight operation should avoid high wind days as this can cause the UAV to become unstable and influence the clarity of the images (i.e. create blurry images and impact image alignment). Additionally, windy days can have a motion blurring effect on the tree canopy, especially on a study site with small, unconnected tree canopies such as timber plantations or young rehabilitation areas. This motion blur can hinder the photogrammetric process where computer vision algorithms attempt to match distinct features from one image to the next. The maximum wind speed resistance for the drones can vary, but for drone safety, it is recommended to not fly the drone when the wind speed is more than 30 km/h. Also, it can be quite difficult to measure wind speed from the ground because the wind speed above the canopy will often be greater than that experienced on the ground. The movement of tree canopies should be assessed from below if possible, to roughly measure if the wind above the canopy is strong or not.

3.4.3. Mission planning

Depending on the drone and computer system used for aerial nest surveying, there are numerous mobile apps or PC software options that can be used for mission planning. A good mission planning app must have the capability to create a flight plan with proper settings for image quality, image overlap, above ground level, image exposure/camera settings, consistent application of mission, and have manual/semi-manual flight controls for safety reasons. Here are some mission planner apps that can work with most drone platforms and manufacturer products:

- Pix4DCapture (https://www.pix4d.com/product/pix4dcapture), Measure Ground Control (https://www.measure.com/), DroneDeploy (https://www.dronedeploy.com/), for both Android OS and iOS mobile device
- DJI GS Pro (https://www.dji.com/ground-station-pro) for DJI system, available only on iOS
- Mission Planner (https://ardupilot.org/planner/index.html) for Pixhawk/3DR system (ArduPilot autopilot), available only on PC.

Each of these apps has different compatibilities but in general, they work in a similar manner to generate the desired flight plan. Many tutorials exist on YouTube about specific details of how to operate the drone system with different combinations of hardware and software/apps.

Mission planning protocols

As mentioned in the previous section, field orientation is very important to gather data and information for optimizing drone nest survey planning. We can import the field orientation data (the GPS coordinate points) to a Geographic Information System (GIS) software like ArcMap or Google Earth Pro (or other GIS software) and create ROIs/polygons of the line transects in the target study area. When planning the flight missions, it is better to extend the ROI at least 20 meters beyond the desired mapping area to prevent stitching errors on the edges of orthomosaics, where there is often insufficient image overlap. For example, if the transect length is 500m and the width is 30m for each side of the transect line (total 60m), the ROI should be 540 m x 100m. We can import the ROI of the transect from GIS software into the mission planner app so we can locate the target survey areas and use the polygons/ROIs to help to create the mission shape for each transect.

Most mission planning apps require special attention including camera angle, altitude, image overlap, drone speed, and battery life.

- *Camera angle*. The goal is to set the camera to a nadir or orthogonal view (perpendicular) to the ground. Mission planner apps usually have a setting to set the camera angle for the drone system with a built-in camera. Drones with built-in cameras, such as the DJI Phantom series, use a gimbal mechanism that maintains a nadir camera angle regardless of the tilt of the drone. If using an externally integrated camera, there is an additional consideration. During the flight, the drone will tilt forward in the flight direction. One should manually adjust the camera angle to mitigate this tilt.

- *Flight altitude*. The flight altitude of each mission/transect will vary between 40 – 80 meters, depending on the vegetation cover and topography/terrain of the transect. Set the flight altitude higher when the transect is topographically variable. Always set the altitude based on the highest terrain or the highest tree canopies, or use a terrain following if the feature is applicable.
- *Image overlap*. We can set the front and side overlap to 80% as a safe setting for image overlap. The overlap of the images during the flight can change because of varying terrain or wind. Having too little overlap can impact image point matching, 3D model reconstruction and therefore decrease model accuracy or even cause model reconstruction to fail.
- *Flight speed*. Most mission planner apps have at least three speed levels: slow, normal, and fast. Some tradeoffs will occur when choosing different speeds. Drone flight at a slow speed will require a longer flight time and need more battery power. Flights flown at the fastest speed level will give the shortest flight time and require less battery power, but the images can be blurry because of the increased motion of the drone. It is recommended to test the flight mission before conducting the actual survey to better understand which setup will provide the best tradeoff between image quality and flight time/battery power.
- *Battery life*. Battery life for UAV flights is maximized when flights are well-planned, conducted in the shortest amount of time with minimal payload, and in optimal wind conditions. UAV batteries typically require about 40 – 60 minutes for charging and may be a limitation to UAV surveys in some localities. Thus, the ready availability of sufficient

battery life, spare batteries, and/or a plan for charging batteries is recommended, especially for remote locations. As a general rule, we have noted that the surveys conducted with a standard Phantom 4 Pro quadcopter at 60m above canopy height allowed for a survey time of about 18 minutes, which was sufficient to image a ground-based survey area of 80 m by 540 m with 80% front and side overlaps

Image quality

Acquiring high-quality drone images is crucial since imagery will be the main dataset acquired for nest surveys. With built-in or externally mounted cameras, some changes need to be made to default settings to ensure the camera is able to capture quality aerial imagery. Drone systems from DJI have a native app called ‘DJI GO’ that can be used to adjust some settings of the built-in camera system, such as ISO, shutter speed, white balance, image format, etc.

Two key concepts should be prioritized on camera system configuration: proper exposure and focus (Mosbrucker et al., 2017). Low light conditions should be avoided when conducting surveys and ensure the drone camera is set to a fixed aperture, fast shutter speed, low ISO, and a fixed focus, to prevent auto adjustment when capturing images. The white balance should be set manually to get a consistent color balance on the images during the surveys. It is recommended to always examine images for motion blur or exposure issues immediately after the flight and repeat the survey as needed.

RAW + JPG or TIFF format should be used when possible to get uncompressed and higher quality images, and a plan should be made to compensate data storage for the larger file sizes associated with these formats. The benefit of capturing uncompressed images is the possibility to perform image correction (i.e. exposure correction) using photo editing software (e.g. Adobe Lightroom CC) without losing metadata or image quality (Verma & Brouke, 2019). In image processing, better tie-point matching and overall model accuracy also can be achieved with the use of uncompressed files as these files offer less pixel noise and a higher dynamic range (Mosbrucker et al., 2017). We suggest setting the image format to a JPG file format if the RAW image format is not available and/or if there is a limitation on local storage or processing power.

Lastly, users should remember to check that geotagging is enabled and the camera date/time are accurate. These records will help in image processing especially when aligning the images since ground control points (or GCPs) are typically not used for nest surveys or other applications in densely forested landscapes.

3.5. Metadata and Data Management

It is very important to always record the mission and flight information for each survey. The flight log sheet can be very basic since most nest surveys typically use visible RGB (red, green, and blue) sensors. At the very least, flight logs should record information on survey location, flight date/time, weather, the drone system, and the flight settings. An example of the flight log detail that we have established for drone-based nest surveys is shown in Figure 2.3 below.

Flight Log Sheet: Orangutan Nest Survey

Flight ID	:	Date (yyyy/mm/dd)	: _________/_________/_________
Location	:	Site/Block ID	:
GPS Coord.	: __________________________________, __________________________________		
Landscape Type	:	Landcover Type	:
Pilot/People Present	: /		
Sky Conditions	: clear / cloudy / very cloudy / haze	Windspeed (m/s)	: breezy / windy / extremely windy / ______km/h
Aircraft Type	: multicopter / fixed-wing	Aircraft ID	:
Sensor Type	:		
Take off (hh:mm)	: ____________PM / AM	Landing (hh:mm)	: ____________PM / AM
Flight Altitude	: ____________m	Camera Angle	: nadir / oblique / ___________°
Flight Dimensions	: ____________ x ____________m	Flight Type	: grid pattern /
Frontlap/Sidelap	: ____________% / ____________%	Estimated GSD	: ______________cm/pixel
Speed	: slow / medium / fast / ________km/h	Total Path	: ______________m
Flight Duration	: ___________minutes	Total Images	:
GCP set out?	:		

Comments:

Figure 3.3: Example of a flight log sheet for aerial-based nest surveys.

Field logs can be maintained in a field book so all the written flight records are kept in one place or can be printed. In all cases, we recommend the use of waterproof paper. Following a given survey, we strongly recommend digitization of detailed flight metadata for each flight in a word file that is appropriately named and saved with the survey name, date, and the flight ID. Files should be saved within an appropriately named folder structure that separates raw data files from processed data files and permits tracing of data processing workflows.

In the field, it is recommended to always make a copy of the drone images after the flight mission is completed. The folder of each set of drone data should be named with the flight ID so the dataset is well-organized in the drone images folder. It is also recommended to have extra SD cards when conducting the drone nest survey to ensure there is always sufficient storage capacity while in the field. Back up all drone data on at least two separate hard drives and store these in separate bags/ vehicles to ensure data safety and redundancy.

3.6. Post-processing

There are many software options for image processing, and each software has a different approach to generating products such as orthomosaics. The two industry-standard and most used software environments available for SfM photogrammetry image processing are Agisoft Metashape (new version of Agisoft Photoscan, https://www.agisoft.com/) and Pix4D (https://www.pix4d.com/). ArcGIS Pro (https://www.esri.com/en-us/arcgis/products/arcgis-pro/overview) can also perform ortho mapping workflows, but the 'advanced' license is needed to have access to this capability. DroneDeploy (https://www.dronedeploy.com/) uses a different approach to generate the orthomosaics by uploading the drone images to the provider's server where their "Map Engine" will perform the rest of the image processing. Once the data is processed, one would be able to export the ortho product from the server. MicMac (https://micmac.ensg.eu/) is a free open-source photogrammetry software that can be used to create ortho-imagery and orthomosaics. The model building workflow and the user interface is not as 'user-friendly' as commercial software, but it could be a good option for researchers and students to generate orthomosaics of drone nest surveys with no license or subscription fee.

Besides photogrammetry software for generating orthomosaics, GIS software is also needed for further data analysis. With Agisoft Metashape, we can identify and mark the orangutan nests directly from the drone images or orthomosaics, but we still need a GIS program to measure the distance of nests to the transect line in order to estimate nest density. A GIS program will also be used for more advanced spatial analyses such as population distribution mapping, habitat assessment, conservation planning, and land management, as well as data visualization and map production. ArcMap from ESRI (https://desktop.arcgis.com/en/arcmap/) is the most popular commercial GIS software with a lot of spatial analysis toolsets and mapping capabilities. Another option for GIS software is QGIS (https://qgis.org/), free open-source software that has been used by many people for research and commercial purposes. The capability to run in Windows, macOS, and Linux, is another advantage of QGIS which gives more flexibility for users to do GIS analysis with any operating system they may have.

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Vita

Muhammad Sugihono Hanggito completed his bachelor's degree in Forestry Sciences at the Universitas Mulawarman in 2014. He joined the Biodiversity and Conservation Laboratory in the Tropical Rain Forests Research Center at the Universitas Mulawarman in 2011 and participated in several collaborative research opportunities with universities from the United States such as the University of Wisconsin-Oshkosh and The University of Texas at El Paso. After graduating from college, he worked at the Ecology and Conservation Center for Tropical Studies (ECOSITROP) and continued his passion on research in the tropical rainforest ecosystem in Kalimantan, Indonesia. During his work in ECOSITROP, he was also involved with many conservation efforts; from assisting oil palm plantation, timber plantation, and coal mining concession owners in implementing land and forest management best practices, to training and developing standard operating procedures for orangutan rescue and translocation, until he got an invitation from Dr. Craig Tweedie to be a graduate student in Environmental Sciences Master's Program at UTEP in 2017.

During his master's study, he worked as a research assistant in the System Ecology Laboratory (SEL) at UTEP where he actively participated in research focused on the phenology desert vegetation and vegetation mapping at the USDA Jornada Experimental Range in the northern Chihuahuan Desert, while working on his thesis project in East Kalimantan, Indonesia. In his thesis entitled, "Development of an unmanned aerial vehicle-based orangutan population assessment in the multifunctional landscape of East Kalimantan", he examined the use of UAVs, or drones, on orangutan nest surveys and developed a new approach for rapidly surveying critical orangutan habitats and quantifying orangutan population metrics. Mr. Hanggito's research interests focus on the application of remote sensing technology for wildlife conservation and habitat management especially in non-protected areas where conservation needs are most urgent.