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### Abstract

Conservationists increasingly employ drones to reduce poaching of animals. However, there are no published studies on the detection probability of poachers and the factors influencing detection. In an experimental setting with voluntary subjects, we evaluated the influence of various factors on poacher detection probability: camera (visual spectrum: RGB and thermal infrared: TIR), density of canopy cover, subject distance from the image centreline, subject contrast against the background, altitude of the drone and image analyst. We manually analysed the footage and marked all recorded subject detections. A multilevel model statistical approach was used to analyse the TIR image data and a general linear model approach was used for the RGB image data. We found that the TIR camera had a higher detection probability than the RGB camera. Detection probability in TIR images was significantly influenced by canopy density, subject distance from the centreline and the analyst. Detection probability in RGB images was significantly influenced by canopy density, subject contrast against the background, altitude and the analyst. Overall, our findings indicate that TIR cameras improve human detection, particularly at cooler times of the day, but this is significantly hampered by thick vegetation cover. The effects of diminished detection with increased distance from the image centreline can be improved by increasing the overlap between images although this requires more flights over a specific area. Analyst experience also contributed to detection probability, but this might cease to become a problem following the development of automated detection using machine learning.

<b>Keywords</b>	uav; poaching, thermal; comparison; distance; contrast
<b>Taxonomy</b>	Wildlife Conservation, Environmental Protection, Environmental Monitoring, Environmental Technology, Environmental Issues of Natural Resources
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**Detecting ‘poachers’ with drones: Factors influencing the probability of detection with TIR and RGB imaging in miombo woodlands, Tanzania**

by

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## **Authors statements**

We the undersigned declare that this manuscript is **original**, has not been published before and is not currently being considered for publication elsewhere.

We wish to confirm that there are **no known conflicts of interest** associated with this publication and there has been no significant financial support for this work that could have influenced its outcome.

We confirm that the manuscript has been read and **approved by all named authors** and that there are no other persons who satisfied the criteria for authorship but are not listed. We further confirm that the order of authors listed in the manuscript has been approved by all of us.

We confirm that we have given due consideration to the **protection of intellectual property** associated with this work and that there are no impediments to publication, including the timing of publication, with respect to intellectual property. In so doing we confirm that we have followed the regulations of our institutions concerning intellectual property.

We further confirm that any aspect of the work covered in this manuscript that has involved either experimental animals or human patients has been conducted with the **ethical approval** of all relevant bodies and that such approvals are acknowledged within the manuscript.

We understand that the **Corresponding Author** is the sole contact for the Editorial process (including Editorial Manager and direct communications with the office). He/she is responsible for communicating with the other authors about progress, submissions of revisions and final approval of proofs. We confirm that we have provided a current, correct email address which is accessible by the Corresponding Author.

We confirm that this paper in any form has **not been previously been submitted** in Biological Conservation Journal.

This research was conducted as dissertation by Leonard Hambrecht for the course “M.Sc. Wildlife Conservation & UAV Technology” 2016/2017 at the Liverpool John Moores University.

## **Main Findings**

The study focused on the comparison between TIR (thermal infrared) cameras and RGB (visual spectrum) cameras attached to a drone for detecting poachers in miombo woodlands in Tanzania. We found that TIR cameras improve detection of poachers over RGB cameras particular in cooler times of the day. However, detection is significantly hampered by thick vegetation cover. The effects of diminished detection with increased distance from the image centreline can be improved by increasing the overlap between images although this requires more flights over a specific area. Analysts experience can furthermore improve the probability of detection. These finding can help drone operators to evaluate the limitations of drones for detecting poachers and to ultimately increase the drone defectiveness.

**Authors Signatures**

26/10/2018

Date, Leonard Hambrecht



28/10/18

Date, Richard P. Brown



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26/10/2018

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# **Detecting ‘poachers’ with drones: Factors influencing the probability of detection with TIR and RGB imaging in miombo woodlands, Tanzania**

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## **Acknowledgements**

The use of human test subjects for this research was approved by the “University Research Ethics Committee” (UREC) of LJMU, with an approval reference of 17/NSP/008. Flights were performed according to the “LJMU Operations Manual for UAV’s” as well as the “Aeronautical Information Circular” (AIC) number 5/17 (Pink 62) of 1 January 2017 and according to the “Tanzania Civil Aviation Regulations” (TCARs).

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## **Declaration of Interest**

We wish to confirm that there are no known conflicts of interest associated with this publication and there has been no significant financial support for this work that could have influenced its outcome.

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3  
4 **Abstract**

5 Conservationist increasingly employ drones to reduce poaching of animals. However, there are no  
6 published studies on the detection probability of poachers and the factors influencing detection. In  
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8 poacher detection probability: camera (visual spectrum: RGB and thermal infrared: TIR), density of  
9 canopy cover, subject distance from the image centreline, subject contrast against the background,  
10 altitude of the drone and image analyst. We manually analysed the footage and marked all recorded  
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15 analyst. Detection probability in RGB images was significantly influenced by canopy density,  
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22 automated detection using machine learning.

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36 **Keywords:**

37 UAV, drone, thermal, TIR, RGB, comparison, contrast, distance, centerline, poachers, people, time  
38 of day, poaching, conservation, canopy, density

# 39 **1 Introduction**

40 Poaching, the unlawful harvest of wildlife products, supports illegal global wildlife trade and is a  
41 major conservation issue due to its impact on species extinctions. The demand for illegal wildlife  
42 products has risen in the few last years with 7000 species recorded as having been trafficked  
43 (Lawson and Vines, 2014; United Nations Office on Drugs and Crime, 2016). This results in the  
44 decline of threatened species, as well as rise in international security threats and economic losses  
45 (Balazs, 2016; Becker et al., 2013; Chapron et al., 2008; Liberg et al., 2012; Naidoo et al., 2016;  
46 United Nations Office on Drugs and Crime, 2016). Wildlife enforcement officers and  
47 conservationists try to fight poaching using a variety of methods, such as reducing demand in key  
48 areas such as Asia, implementing community conservation areas, deploying ranger patrols in  
49 protected areas, strengthening wildlife laws, dehorning rhinos and implementing new technologies  
50 such as DNA mapping, mobile biological sensors and drones (Dinerstein et al., 2017; Lunstrum,  
51 2014; Mukwazvure and Magadza, 2014). Drones are a cost-effective and flexible tool that can be  
52 used in the field to monitor protected habitat and gather intelligence on wildlife crime activities  
53 (Koh and Wich, 2012; Linchant et al., 2015; World Bank, 2018). This intelligence includes the  
54 detection of poachers in the field (Air Shepherd, 2017; Mulero-Pázmány et al., 2014; Smart parks,  
55 2018).

56 There are several key safety, technical and practical differences between the use of drones for  
57 detecting poachers and the more traditional use of manned aircrafts. Most importantly, the latter  
58 pose a higher risk to the operator as poachers can deploy powerful weapons. In contrast, drones  
59 allow detection while simultaneously minimizing confrontations with poachers (Baggaley, 2017;  
60 Parveen, 2016). Secondly, manned aircraft require an on-board observer, while drones can use a  
61 variety of sensors to record still and moving images that either need to be viewed as a live stream or  
62 analysed after the flight. Additional advantages of using drones include their cost-effectiveness, the  
63 fact that they do not require a runway and that they can be programmed to follow precisely a  
64 predefined path (Kakaes et al., 2015). Furthermore, drones have been found to be able deliver more  
65 accurate animal count data than traditional ground-based surveys (Hodgson et al., 2018).

66 Although their deployments in anti-poaching efforts are promising, there are no studies that have  
67 explicitly investigated the factors that determine detection probability in this specific context.  
68 However, it is important to do so for several reasons, including the optimization of flight patterns to  
69 improve detection and identify the environmental conditions under which poachers are likely to be  
70 missed during drone missions. Fixed wing drones are the preferred tool for anti-poaching operations  
71 because of their long flight duration and extended range (Mulero-Pázmány et al., 2014; Olivares-  
72 Mendez et al., 2015).

73 There are various factors that affect the probability of detecting animals – and potentially humans –  
74 including body size, position of the sun, distance from the transect, group density, target contrast,  
75 terrain ruggedness, animal activity, vegetation type and camera type (Caughley et al., 1976;  
76 Chrétien et al., 2015; Chrétien et al., 2016; Patterson et al., 2015; Ransom, 2012; Schlossberg et al.,  
77 2016; Zabransky et al., 2016). Two types of camera are most typically used: those that use the Red  
78 Green Blue colour model (RGB) and thermal infrared (TIR) devices. RGB cameras acquire images  
79 in the light spectrum visible to humans and can be found on most consumer drones. They are often  
80 more affordable and may have a higher resolution than TIR cameras (Wich and Koh, 2018). TIR  
81 cameras capture infrared radiation which is emitted as heat from different sources of energy as well  
82 as endothermic organisms (Vollmer and Möllmann, 2010). This makes them useful for detecting  
83 poachers who generally operate at night to reduce the risk of detection (Mulero-Pázmány et al.,  
84 2014). TIR cameras have been used for decades to remotely sense wildlife and, with drones, the  
85 focus has been to survey large terrestrial as well as marine mammals (Chrétien et al., 2016, 2015;  
86 Christiansen et al., 2014; Seymour et al., 2017; Wride and Baker, 1977). In recent years, algorithms  
87 have been developed to improve the detection of animals in TIR camera footage and made  
88 automatic detection possible (Burke et al., 2018a, 2018b; Christiansen et al., 2014; Longmore et al.,  
89 2017; Seymour et al., 2017). There are no studies that have examined the detection probabilities of  
90 poachers by RGB and TIR imaging cameras.

91 In this study we investigate the factors that determine the detection probability of people (subjects)  
92 in a Miombo woodland in Tanzania. We conducted an experiment in which a drone with RGB and  
93 TIR imaging cameras was flown over a group of test subjects to determine which of the following  
94 variables influenced detection probability: camera type (RGB or TIR), canopy cover, subjects  
95 distance from image centreline, contrast between subject and background and the altitude of the  
96 drone. Contrasts between subjects and the background was controlled through use of differently  
97 coloured t-shirts. We hypothesized that the probability of detection is negatively affected by a dense  
98 canopy cover, a larger distance from the image centreline and higher altitude for both RGB and TIR  
99 cameras. In addition, we hypothesized that a larger contrast between the subject and background  
100 increases the probability of detection for RGB cameras and that detection will be better with the  
101 TIR camera during low light conditions.

## 102 **2 Methods**

103

### 104 **2.1. Study Area**

105 The study was conducted at the Issa study site (-5.50, 30.56) in the western part of Tanzania. This  
106 location lies at 1500 meters (m) above sea level and the dominant vegetation type is miombo  
107 woodland (dominated by the genera: *Brachystegia* and *Julbernardia*) (Piel et al., 2015). The data  
108 were collected in March 2017, which coincides with the end of the rainy season, when the  
109 vegetation is green and dense across the region.

110

### 111 **2.2. Drone and Cameras**

112 We used a multicopter consisting of a DJI F550 frame with a Pixhawk flight controller. The drone  
113 carried two cameras: 1) a 16 MP RGB Survey 2 camera (Mapir, 2016a) with a field of view (FOV)  
114 of 82° which was triggered by the flight controller to take an image at 10m intervals, 2) a  
115 ThermalCapture v1.0 TIR camera with a TAU 640 core with a FOV of 45° (TeAx Technology,  
116 2018). The RGB camera was set at ISO 100 and a shutter speed of 1/250. The TIR camera  
117 continuously recorded video with automatic settings. All flights were conducted by one of the  
118 authors (SW). The two cameras used were: 1) a 16 MP RGB Survey 2 camera (Mapir, 2016a) with  
119 a field of view (FOV) of 82° which was triggered by the flight controller to take an image at an  
120 interval of every 10 m, 2) a ThermalCapture v1.0 TIR camera with a TAU 640 core with a FOV of  
121 45° (TeAx Technology, 2018). The RGB camera was set at ISO 100 and a shutter speed of 1/250.  
122 The TIR camera continuously recorded video with automatic settings.

123

### 124 **2.3. Flight Path**

125 Drone flight paths (Appendix A.1) were created using Mission Planner software (ArduPilot Dev  
126 Team, 2017) and uploaded to the Pixhawk flight controller. Take-offs and landings were conducted  
127 in loiter mode whereas auto mode was used for the flight pattern. The flight pattern consists of three  
128 parallel rows with a length of 70 m each and a connection section of 30 m in length between each  
129 row. The descent (dotted line) leads the drone back to its take-off location (Appendix A, Black  
130 Square). The flight pattern was performed twice at two different altitudes (70 m and 100 m),  
131 providing six rows per flight. The upper altitude of 100 m was chosen as it was close to the usual  
132 operation altitude of fixed wing drones while still staying within the legal boundaries of 122 m (400  
133 ft.) (Tanzania Civil Aviation Authority, 2017). The lower altitude of 70 m was chosen as the lowest  
134 recommended altitude for safe operation of fixed wing drones and the 70 – 100 m range was  
135 considered suitable for this type of drone. The average flight duration during the data collection was

136 approximately six minutes at a ground speed of 4 – 5 m/s. Two flight areas were set up at different  
137 locations with the same flight pattern as can be seen in Appendix A. A total of seven flights were  
138 conducted: four in flight area 1 and three in flight area 2. A dawn flight (7:30 am) was conducted in  
139 each area, followed by a second flight at dusk on the same day (7:00 pm). These times were chosen  
140 to improve the image quality of the TIR images, as lower environmental temperatures create a  
141 greater contrast between a person and their surroundings. However, low light levels during several  
142 of these flights meant that the RGB camera was unable to produce sufficiently exposed images.

143

#### 144 **2.4. Location**

145 We selected 24 locations within each flight area and then randomly assigned each test subject to one  
146 of them. The locations were chosen on-site to create an equal spatial distribution of locations in the  
147 area and with equal frequencies of dense and less dense canopy covers. GPS coordinates of the  
148 locations were recorded with the MobileMapper 20 (MM20) model by Spectra Precision. The  
149 MM20 has an accuracy of <2 m in real-time (Trimb et al., 2013).

150

#### 151 **2.5. Test Subjects and T-shirt Colours**

152 A group of 10 - 20 voluntary subjects (varying per flight) were positioned within the flight area for  
153 each of the flights. Each subject wore a standard red, green or blue t-shirt to create a controlled  
154 contrast with the background. Each subject wore the same t-shirt and was positioned at the same  
155 location for each flight. The test subjects were required to stay at their assigned locations during the  
156 flights, with a single subject assigned to each location.

157

#### 158 **2.6. Canopy Cover**

159 The canopy densities of the locations were measured by photographing the canopy and calculating  
160 the canopy density in the software CanopyDigi (Goodenough and Goodenough, 2016). CanopyDigi  
161 gives a calculated value between 0 (open sky) and 1 (completely covered) for each image. Photos  
162 were taken with a 24-mm fixed focal length lens mounted on an APS-C camera body with a 1.6  
163 crop sensor resulting in a FOV of 59°. The camera was set up on a tripod at a height of 1.5 m and  
164 aligned horizontally using a level. Goodenough and Goodenough (2012) recommend a cloudy sky  
165 for best results when photographing the canopy cover. However, this was not always possible and  
166 most images were taken with a clear sky and the sun in the frame. This resulted in brighter images  
167 which were compensated by adjusting the auto exposure of the camera by -1 stop. This adjustment  
168 darkened the images to compensate for the bright sky. The camera was manually focused on the

169 closest branch to ensure sharp images and an aperture of f/16 was used for a sufficient depth of  
170 field. ReaConverter Light (ReaSoft Development, 2017) was used to convert the images into the file  
171 format required by CanopyDigi (Goodenough and Goodenough, 2012). The threshold values in  
172 CanopyDigi were adjusted to deal with images in which the sun was visible in the frame. The  
173 thresholds used a range from 45 to 125.

174

## 175 **2.7. Image Processing and analyses**

176 Footage from the two cameras were checked for quality. Any footage taken during take-off, landing  
177 or from the connection and transition piece was discarded. We reviewed the footage from the TIR  
178 camera in the proprietary ThermoViewer 2.1.2 software (TeAx Technology, 2017). The Non  
179 Uniformity Correction (NUC) option was turned on in ThermoViewer, as recommended by the  
180 manufacturers. Video footage was converted into 3 to 4 JPG images per row. We converted the  
181 RGB camera footage from raw into JPG images using the MAPIR plugin (Mapir, 2016b) for the  
182 Fiji software (Schindelin et al., 2012). RGB images were then downscaled to the same resolution as  
183 the TIR images (701x512) with the Exiftool software (Harvey, 2017). This allows for a universal  
184 comparison of the two image types, independent of resolution quality.

185 Images were analysed separately by three independent analysts, none of whom had previous  
186 experience in detecting human subjects in aerial images. Images were provided to the analysts in a  
187 random order. In avoiding the sequential showing of all images from one row, analysts could not  
188 apply their knowledge of locations from previous images to detect the subjects. The plugin in Cell  
189 Count (De Vos, 2010) for the ImageJ .1.8.0 software (Rueden et al., 2017) was used to annotate  
190 detected subjects in the images.

191 The images were not georeferenced and the subjects are identified by their relative location to each  
192 other and to landmarks, and the colour of their t-shirts (Appendix B). The results of images from the  
193 same row were summarized, thereby simulating a tracking motion in moving images. The multiple  
194 angles simulate a tracking motion of a subject in the frame. The tracking enhances the probability of  
195 detection because of the multiple camera angles (Gonzalez et al., 2016).

196

## 197 **2.8. Calculating the Distance to the Centreline of the Image**

198 We calculated the distance from each subject to the centreline using QGIS 2.18 (Quantum GIS  
199 Development Team, 2017). The calculation of the distances used the GPX track as centreline and  
200 the shortest distance to each location was calculated with the distance matrix tool.

201

## 202 2.9. Statistical Analysis

203 All analyses were carried out using the lme4, glm2 and MuMIn packages in R v3.4.1 (Bates et al.,  
 204 2017; R Core Team, 2017). We chose a multilevel model approach to accomodate random effects,  
 205 repeated measurements and crossed data (Field et al., 2012; Grueber et al., 2011; Qian et al., 2010).  
 206 Following the approach suggested by Grueber et al. (2011), entries with missing data were excluded  
 207 from the analysis. We used a general linear model for the data from the RGB camera as described  
 208 below. All responses were binary (detection (1)/no-detection (0)) and thus a logit link function was  
 209 used for all analyses. The variables used in the code for the global data models can be seen in Table  
 210 1.

211 *Table 1 Overview of the tested variables with description.*

No	Variable type		Variable	Definition
<u>Response variable</u>				
0	Binomial		Detected	Detected = 1; undetected = 0
<u>Predictor variable</u>				
1	Continuous	Fixed	<i>Canopy density</i>	Canopy density between 0 and 1
2	Continuous	Fixed	<i>Distance</i>	Distance from centreline (m)
3	Binomial	Fixed	<i>Altitude</i>	70 m = 0; 100 m = 1
4	Nominal	Fixed	<i>Colour</i>	White/ TIR = 0; red = 1; blue = 2; green = 3
5	Binomial	Fixed	<i>Time of day</i>	Dusk = 0; dawn = 1
6	Nominal	Fixed	<i>Analyst</i>	Analyst 1, 2, 3
<u>Hierarchical variable</u>				
7	Nominal	Random	Flight Number	Identification number of flight

212  
 213 Continuous variables were group-centred. Two separate base data models were created for the TIR  
 214 images and RGB images. In the TIR base data model, the variable colour was not included since the  
 215 TIR images only display in black and white. The inclusion of Flight Number as a random intercept  
 216 significantly improved the TIR data model. However, random effects did not improve the RGB base  
 217 data model and so a general linear model was used (using the “glm” function in the “glm2”  
 218 package: Marschner, 2018). Maximum likelihood was used to perform the model estimation for  
 219 both data models. Data sub-models were created from the base data models, using the function  
 220 “dredge” from the “MuMIn” (Bartón, 2017) packages as described by Grueber et al. (2011). This  
 221 resulted in a total of 64 data sub-models for the RGB images and 32 data sub-models for the TIR  
 222 images. The Akaike Information Criterion corrected for small sample sizes (AICc) was used to

223 assess the data (sub) models (Akaike, 1998; Grueber et al., 2011). Data models with cut-off values  
224 of 2AICc were selected using the “get.model” function from the “MuMIn” packages as shown by  
225 (Bartón, 2016; Grueber et al., 2011). The final data models above this cut-off point were averaged  
226 using the zero method to compare between them and identify the one with the best fit (Nakagawa  
227 and Freckleton, 2011). These data models have been ranked by their AICc values and their Akaike  
228 weight (lower AICc indicates a better model fit and a higher Akaike weight shows a more  
229 parsimonious fit overall) (Patterson et al., 2016). The last step was to conduct a Tukey’s honestly  
230 significant difference (HSD) analysis with the “glht” function from the “multcomp” package  
231 (Hothorn et al., 2008; Piepho, 2004) to analyse the differences between individual colours and their  
232 effect on the probability of detection.

233

234 **3 Results**

235 To determine which factors influenced detection probability we fitted models to the TIR and RGB  
 236 data. The analyses are first presented individually and then compared.

237

238 **3.1. TIR data model**

239 For the TIR data model, three models were selected under the described AICc criterion (Table 2).

240 *Canopy density, Distance and Analyst* were included in the best data model.

241 *Table 2: A summary of the three selected data models under the AICc criterion (from 32 data sub*  
 242 *models) for the detection of subjects using a TIR imaging camera. The best data model includes*  
 243 *Canopy density, Distance and Analyst.*

<b>Data model name</b>	<b>Df</b>	<b>LogLik</b>	<b>AICc</b>	<b>Delta</b>	<b>weight</b>
Canopy density + Distance + Analyst	5	-1117.35	2244.72	0.00	0.50
Canopy density + Distance + Time of Day + Analyst	6	-1116.84	2245.72	1.00	0.31
Canopy density + Time of Day + Altitude + Analyst	6	-1117.31	2246.66	1.94	0.19

244

245 For the TIR data model, three data models were selected under the described criterion (Table 2).

246 The best data model contained the variables *Canopy density, Distance and Analyst*. The best fitting  
 247 data model is described in Table 3 in more detail.

248 *Table 3: The data model with the best fit for the TIR images include the variables Canopy density*  
 249 *( $p < 0.001$ ), Distance ( $p < 0.001$ ) and Analyst ( $p = 0.005$ ).*

<b>Variable</b>	<b>Estimate</b>	<b>95% Confident</b>	<b>Standard Error</b>	<b>p</b>
(Intercept)	0.082202	-0.57588189, 0.74028561	0.335592	0.807
Canopy density	-2.512167	-2.93676277, -2.08757128	0.216496	<0.001
Distance	-0.040112	-0.04966423, -0.03056052	0.004870	<0.001
Analyst	-0.178310	-0.30211515, -0.05450457	0.063127	0.005

250

251 The variables *Canopy density* and *Distance* had negative coefficients, which indicates a decrease in  
 252 the probability of detection with an increase in vegetation density and/or increase in distance from  
 253 the centreline. The negative coefficient for *Analyst* is irrelevant since analysts were ranked in a  
 254 random order.

255

256 **3.2. RGB data model**

257 The best data model for the RGB data included *Canopy density*, *Altitude*, *Colour*, and *Analyst* as  
 258 variables (Table 4). All of these variables were significant (Table 5). The variables *Canopy density*  
 259 and *Altitude* had negative coefficients, which indicates that an increase in the vegetation density and  
 260 altitude negatively influences the probability of detection. The variable *Colour* also had a  
 261 significant effect on the probability of detection while the variable *Distance* was not included in the  
 262 best data model, which indicates it does not affect the probability of detection. As in the TIR model,  
 263 the negative coefficient for *Analyst* was meaningless.

265 *Table 4: A summary of the top three data models that were selected under the 2AICc criteria (from*  
 266 *64 data sub-models) for the RGB camera. Canopy density, Altitude, Colour and Analyst are*  
 267 *included in the best data model.*

<b>Data model name</b>	<b>Df</b>	<b>LogLik</b>	<b>AICc</b>	<b>Delta</b>	<b>weight</b>
Canopy density + Altitude + Colour + Analyst	5	-352.23	714.53	0.00	0.54
Canopy density + Altitude + Colour + Time of Day + Analyst	6	-352.02	716.15	1.62	0.24
Canopy density + Distance + Altitude + Colour + Analyst	6	-352.10	716.31	1.78	0.22

268

269 *Table 5: The best fitting RGB data model includes Canopy density ( $p < 0.001$ ), Altitude ( $p < 0.001$ ),*  
 270 *Colour ( $p = 0.012$ ) and Analyst ( $p = 0.013$ ).*

<b>Variable</b>	<b>Estimate</b>	<b>95% Confident</b>	<b>Standard Error</b>	<b>p</b>
(Intercept)	0.0697321	-0.60499062, 0.74445474	0.3437274	0.840
Canopy density	-4.4783526	-5.33703130, -3.61967387	0.4374412	<0.001
Altitude	-0.9168489	-1.29410419, -0.53959361	0.1921870	<0.001
Colour	-0.3111846	-0.55472733, -0.06764184	0.1240692	0.012
Analyst	-0.2884761	-0.51514749, -0.06180480	0.1154742	0.013

271

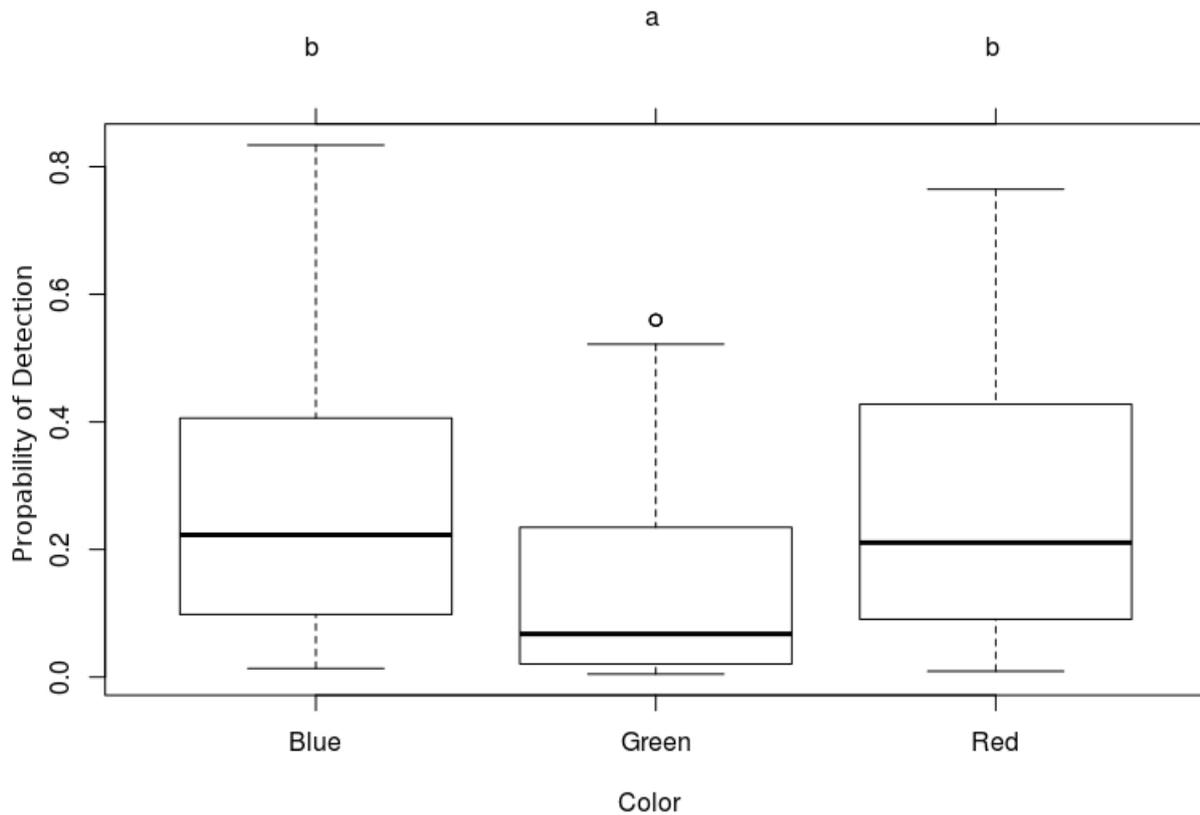


Figure 1. Box-and-whisker plots that summarize detection probabilities for the three t-shirt colours worn by subjects.

272 All variables included in the best fitting RGB data model have a negative coefficient indicating that  
 273 an increase in *Canopy density* and *Altitude* have a negative effect on the probability of detection.  
 274 The *Colour* variable was further analysed with a Tukey’s HSD post-hoc test to assess which colours  
 275 were significantly different (Figure 1). The Tukey’s HSD analysis showed that the probability of  
 276 detection of a green subject (a) was significantly lower than the probability of detection of either a  
 277 blue or red t-shirt (b) (Figure 1).

278

### 279 3.3. Comparison

280 The overall detection probability was higher  
 281 for TIR images than for RGB images (Figure  
 282 2). A two sample t-test showed a significant  
 283 ( $p < 0.005$ ) difference in mean detection  
 284 probabilities between RGB and TIR images.  
 285 The best fitting models were compared for  
 286 TIR and RGB images. Only *Canopy density*

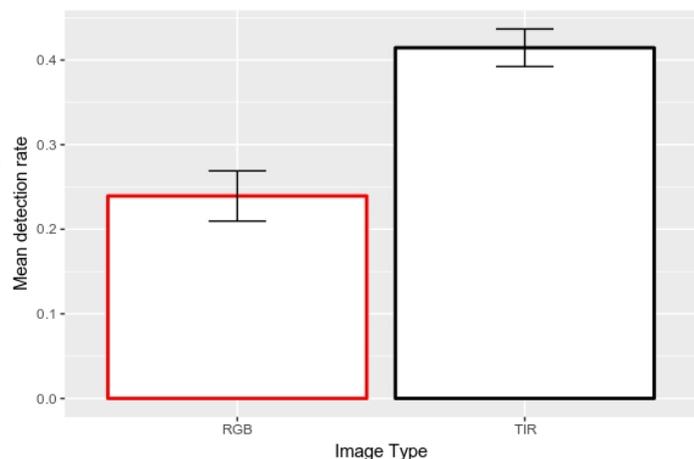


Figure 2. Bar charts that summarize mean subject detection probability with standard error.

287 (negative coefficient) and *Analyst* were included in both data models. *Distance* was only included in  
288 the TIR data model, whereas *Altitude* and *Colour* were included in the RGB data model. As  
289 previously stated, *Colour* was not included in the TIR base data model.  
290 It is important to note that *Time of Day* was not significant in either data model.

## 291 **4 Discussion**

292 We aimed to identify factors that have a significant effect on the probability of detection of  
293 poachers by drones using two camera types (RGB and TIR). Factors that had a significant effect on  
294 the probability of detection by TIR images were canopy density, subject distance from the image  
295 centreline and the image analyst, while the RGB camera was significantly affected by canopy density,  
296 altitude of the drone, the subjects' contrast against the background and the image analyst.

297 Canopy density had a significant negative influence on detection probability for both cameras. This  
298 is in accordance with studies on aerial surveying of animals that have found that vegetation density  
299 or habitat type has a significant negative impact on probability of detection (Chrétien et al., 2015;  
300 Ransom, 2012; Schlossberg et al., 2016; Zabransky et al., 2016). Our results are also consistent with  
301 a study that found that habitat type had a significant impact on detection of caribou (Patterson et al.  
302 2016).

303 Our study also showed a decrease in detection probability with increasing distance from the image  
304 centreline, for TIR images. In contrast, no equivalent effect was found in our RGB analysis or by a  
305 previous caribou study (Patterson et al., 2016). The latter used a 50-mm lens on a full-frame camera  
306 attached to the drone resulting in a FOV of 40°. On this system, distortion and other effects towards  
307 the edges of the frame are minimal and it could thus be expected that no effect would be observed.  
308 Our RGB camera had a wide-angle lens with a FOV of 82° and therefore has a greater distortion  
309 than a normal lens (Brauer-Burchardt and Voss, 2001). In contrast, the TIR camera we deployed in  
310 our study had a narrow FOV of 45°. This runs counter to the suggestion that greater distortion from  
311 a wider FOV could explain the significant effect for the TIR but not the RGB camera. We were  
312 unable to find any similar reports in literature, however, the impact of the distance from the  
313 centreline on the probability of detection is well-known in line-transect surveys (Ridgway, 2010).  
314 Other studies have hypothesized that subjects' distance from the centreline is affected by the height  
315 of the canopy (Israel, 2011).

316 The RGB images revealed that detection was strongly influenced by the subjects' colour against the  
317 background. A similar effect was found by Patterson et al. (2016) who found that targets with  
318 greater contrast against the landscape were more easily detected. Detection is also impeded by  
319 greater contrast variation in the image background, as this results in variable contrast of the subject  
320 against the background (Abd-Elrahman et al., 2005). Chrétien et al. (2015) found animals with  
321 cryptic fur have a lower probability of detection because they blend into their environment. Hence,  
322 our findings add to previous studies that have shown that aspects of colour, such as contrast, affect  
323 the probability detection using RGB images.

324 Higher flight altitudes also showed lower detection probabilities for RGB images. One way around  
325 this might be to use the full resolution original images. Patterson et al. (2016) flew at a constant  
326 altitude of around 690 m with no significant variation in elevation in the study area; and therefore  
327 was not able to test for the effect of altitude on the probability of detection. However, our results do  
328 suggest that the TIR imaging camera is superior at higher flight elevations for the same number of  
329 pixels. This could be important in cases where drones must be flown low or where drone height  
330 above ground will vary considerably over an area being investigated.

331 Another significant effect in the data models was the variation in detection probabilities between  
332 observers. Patterson et al. (2016) did not find an analyst effect in their study. A possible explanation  
333 might be that Patterson et al. (2016) used a controlled procedure for the analysts who were  
334 instructed to work through a fixed number of images per day, while the analysts themselves had no  
335 previous experience. In our study the analyst effect might be due to the use of three different  
336 analysts, with different experience levels.

337 Time of day was included as factors in the present study for RGB and TIR images, however no  
338 significant difference was found. In contrast, Patterson et al. (2016) found a significant time of day  
339 effect. Nonetheless, their flights were performed in a larger time window (7:00 – 9:30 am and 2:00  
340 – 3:00 pm), with more targets being detected in the afternoon. Also, their study site was in  
341 Labrador, Canada with potentially very different changes in light level between the two flight  
342 periods, relative to Tanzania.

343 An increasing number of research projects are examining the use of drones for ecological  
344 conservation and anti-poaching efforts (Chrétien et al., 2015; Christiansen et al., 2014; Christie et  
345 al., 2016; Linchant et al., 2015; Martin et al., 2012; Mukwazvure and Magadza, 2014; Mulero-  
346 Pázmány et al., 2014; Olivares-Mendez et al., 2015; Patterson et al., 2015; Vermeulen et al., 2013).  
347 This is the first study to focus on poacher-detection and the first to explore the factors affecting  
348 detection probabilities for TIR imaging. Most other studies that have examined TIR imaging with  
349 drones have focused on the automated detection of animals and humans, which is essential to  
350 reduce the researcher-hours spent on analysing images and can facilitate near-real time detection of  
351 animals/humans in the field (Christiansen et al., 2014; Gonzalez et al., 2016; Longmore et al., 2017;  
352 McMillen, 2016; Olivares-Mendez et al., 2015; Seymour et al., 2017). Burke et al. (2018b) applied  
353 automatic detection software to the TIR images used in our study. Promising methods for increased  
354 detection probabilities lie in the integration of data from multiple sensors such as RGB and TIR  
355 cameras (Chrétien et al., 2015; Christiansen et al., 2014).

356 In conclusion, the TIR images allowed for higher detection probability of our experimental  
357 poachers than RGB images. This provides a clear advantage against poachers are trying to hide

358 under vegetation, wear low-contrast clothing, or operate at night. However, during the daytime,  
359 when temperatures are higher, the RGB performs better than the TIR camera. As expected,  
360 poachers hiding under thick vegetation remain undetected with both systems. Distance from the  
361 flight midline also influenced detection and should be considered when conducting anti-poaching  
362 missions. Potential improvements to detect poachers under trees might be achieved by use of a  
363 camera placed at an oblique angle as well as use of machine learning for detection instead of human  
364 image analysts.

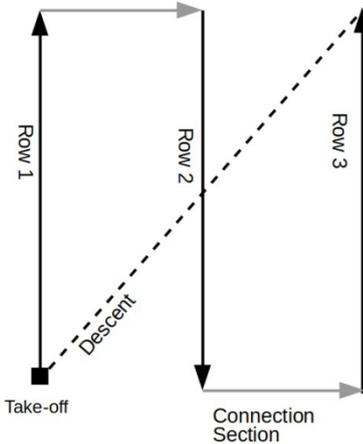
365

366 **5 Glossary**

- 367 **Altitude:** The altitude of the drone measured from the take-off point.  
368 **Analyst:** Person who reviewed each image from the drone and marks every person detected in the  
369 images.  
370 **Canopy Cover:** Percentage of canopy covering the location compared to open sky.  
371 **Colour:** Test subject have been wearing uniform red, green or blue coloured t-shirt to create a  
372 controlled contrast against the green vegetation in the background.  
373 **Distance:** The distance of a test subject to the centreline of an image in meters.  
374 **Field of View (FOV):** A measurement of a lens in degrees of the area in front of the lens which is  
375 been captured.  
376 **Probability of Detection:** The likelihood that an object is been detecting.  
377 **Red Green Blue (RGB):** Colour model used by most common cameras today.  
378 **Time of Day:** Variable to compare the influence of dawn and dusk on the probability of detection.  
379 **Thermal Infrared (TIR):** A wave spectrum which is radiated by warm objects.

380 **6 Appendix**

381 **A. Flight pattern**



*Appendix A: Flight pattern of the drone. Each row is 70 m in length and the Connection Sections are 30 m long. The Decent leads the drone back to the Take-off area.*

382

383

384 **B. Comparison between RGB and TIR images.**



*Appendix B: Comparison between RGB images on the left and TIR on right. Both images show the same area, at the same resolution with two people visible.*

385  
386

387 Appendix B to be printed in colour

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