

Manuscript Details

Manuscript number	JAG_2018_290_R1
Title	Locating emergent trees in a tropical rainforest using data from an Unmanned Aerial Vehicle (UAV)
Article type	Short Communication

Abstract

Emergent trees, which are taller than surrounding trees with exposed crowns, provide crucial services to several rainforest species especially to endangered primates such as gibbons and siamangs (Hylobatidae). Hylobatids show a preference for emergent trees as sleeping sites and for vocal displays, however, they are under threat from both habitat modifications and the impacts of climate change. Traditional plot-based ground surveys have limitations in detecting and mapping emergent trees across a landscape, especially in dense tropical forests. In this study, a method is developed to detect emergent trees in a tropical rainforest in Sumatra, Indonesia, using a photogrammetric point cloud derived from RGB images collected using an Unmanned Aerial Vehicle (UAV). If a treetop, identified as a local maximum in a Digital Surface Model generated from the point cloud, was higher than the surrounding treetops (Trees_EM), and its crown was exposed above its neighbours (Trees_SL; assessed using slope and circularity measures), it was identified as an emergent tree, which might therefore be selected preferentially as a sleeping tree by hylobatids. A total of 54 out of 63 trees were classified as emergent by the developed algorithm and in the field. The algorithm is based on relative height rather than canopy height (due to a lack of terrain data in photogrammetric point clouds in a rainforest environment), which makes it equally applicable to photogrammetric and airborne laser scanning point cloud data.

Keywords	Habitat mapping; Drones; Point cloud; Sleeping trees; Conservation; Rainforest; Sumatra
Taxonomy	Environmental Science, Mapping
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Suggested reviewers	Andrew Skidmore, Frieke Van Coillie, Martin Rutzinger, Arko Lucieer

Submission Files Included in this PDF

File Name [File Type]

EmergentTrees_CoverLetter_20180529.docx [Cover Letter]

EmergentTrees_Responses_20180529.docx [Response to Reviewers]

EmergentTrees_Highlights_20180529.docx [Highlights]

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Dr. F. van der Meer
Editor-in- Chief
International Journal of Applied Earth Observation and Geoinformation

29.05.2018

Dear Dr van der Meer,

Please find attached our revised manuscript entitled 'Locating emergent trees in a tropical rainforest using data from an Unmanned Aerial Vehicle (UAV)', for your kind consideration. We have addressed all the comments/suggestions of the reviewers, and provided a list of changes.

The word count of the manuscript, including tables and figures, is 2962. Two researchers (Emma Hankinson and Nathan Harrison), who collected field data for validation, have been added as co-authors. We hope that you will find this manuscript suitable for publication in the *International Journal of Applied Earth Observation and Geoinformation* as a Short Communication paper.

Thank you.

Yours sincerely,

Cici Alexander

(On behalf of myself, Amanda Korstjens, Emma Hankinson, Graham Usher, Nathan Harrison, Matthew Nowak, Abdullah Abdullah, Serge Wich and Ross Hill)

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Cici Alexander, Amanda H. Korstjens, Emma Hankinson, Graham Usher, Nathan Harrison, Matthew G. Nowak, Abdullah Abdullah, Serge A. Wich, Ross A. Hill

Line/Figure #	Reviewers' comments	Responses	Modifications
	Reviewer #1		
	General comments		
	In the highlights the last point is irrelevant as LiDAR data is not used in this study. Please remove it.	Removed	
	The authors use the terms "emergent trees" and "sleeping trees" interchangeably. For sake of clarity they should use only one definition and use this consistently throughout the manuscript.	References to "sleeping trees" have been deleted wherever they are not necessary.	
	The description of the methods is somewhat confusing and in some parts should be rephrased for sake of clarity.	References to Figure 2 have been added, to better describe the method.	
	Specific comments		
59	What do the authors mean by landscape level? Please specify	The sentence has been modified, based on the reviewer's next suggestion. It was just to mention that only small areas are covered in ground-based surveys, while data from large areas can be collected through remote sensing.	Lines 62-64: '...by providing a continuous representation of the forest canopy; a limitation of ground based surveys is that data are collected only for small sample areas or plots.'
60-62	Another limitation of ground based surveys is that they are only performed for small sample areas (sample plots), whereas remotely sensed data allow to provide a continuous representation of the forest canopy. I suggest that the author include this.	Thank you for the suggestion. The previous sentence has been modified since the meaning was not clear.	Same as above.

64-65	The authors should specifically mention what the advantages are for ALS.	Modified.	Lines 68-70: 'ALS has distinct advantages over other remote sensing techniques in describing the three-dimensional structure of forests throughout their vertical profile, and capturing underlying terrain information.'
65-67	I am not sure these statements are fully true. In particular: - Is true that ALS data are expensive but not because of the processing. Thus I would suggest to remove that part of the sentence.	Modified.	Lines 70-71: 'However, these data are still expensive to acquire, especially for small areas, for example for mapping the territories of groups of primates.'
65-67	For how it is stated it seems that UAVs are cost-effective compared to airborne data, but this is not true when looking at the price per hectare. In this case UAVs are more expensive. UAVs may be more cost effective than manned airborne data when the area of interest is small and the required level of detail is high, unless applied in a sampling context as in: o Puliti et al. 2017. Use of partial-coverage UAV data in sampling for large scale forest inventories. Remote Sensing of Environment. I suggest that the authors read this paper and as it is one of the few providing some cost figures to actually evaluate the cost-effectiveness of UAVs over ALS data.	Added reference, and modified the sentence.	Lines 72-73: 'Unmanned Aerial Vehicles (UAVs) are a low-cost alternative to manned aircraft for collecting data from small areas (Puliti et al. 2017), and ...'
70-74	Please provide further references (in addition to Tuominen et al.) on previous studies that used UAV	Added references.	Lines 80-81: '...for deriving canopy height (Dandois and Ellis 2013; Lisein et al. 2013; Puliti et al. 2015; Tuominen et al. 2015).'

	<p>photogrammetry for modelling forest canopy structure. See for example:</p> <ul style="list-style-type: none"> - Dandois and Ellis 2013. High spatial resolution three-dimensional mapping of vegetation spectral dynamics using computer vision. <i>Remote Sens. Environ.</i> 136, 259-276. - Lisein, J.; Pierrot-Deseilligny, M.; Bonnet, S.; Lejeune, P. 2013. A photogrammetric workflow for the creation of a forest canopy height model from small unmanned aerial system imagery. <i>Forests</i>, 4, 922-944. - Puliti, S.; Ørka, H.; Gobakken, T.; Næsset, E. 2015. Inventory of small forest areas using an unmanned aerial system. <i>Remote Sensing</i>, 7, 9632-9654. 		
83	<p>In section 2 there are several parameters related to the UAV flight that are missing but they are relevant for reproducing such experiment. The authors should at least include information on the number of flights and total time (hours and/or days) required to perform the acquisition, image acquisition overlap (forward and lateral overlap), and acquisition of ground control points (if acquired at all).</p>	<p>Additional information about the flights have been added. Ground Control Points were not acquired for this study.</p>	<p>Line 94: 'Airborne data from three flights...' Lines 97-98: 'The average flying altitude was 198 m above the launch location, covering an area of approximately 11.2 sq km, and generated 5400 images.'</p>
95-96	<p>The structure from motion part in Photoscan is only a part of the processing, which actually is related to the estimation of the camera exterior and interior parameters and not related to the 3D reconstruction. The</p>	<p>Modified.</p>	<p>Lines 105-106: '... using Structure from Motion (SfM) and photogrammetric algorithms implemented in Agisoft PhotoScan v1.3.0.'</p>

	3D reconstruction is performed according to photogrammetric algorithms. The authors should rephrase this sentence.		
103	I believe that the authors should provide some reference on the definition of emergent trees. Here you define emergent trees as those that are at least 5 m above the rest of the canopy.	This is based on field observations.	
107	The entire section 3.2 is somewhat confusing and hard to follow. I suggest that the authors rephrase the entire paragraph to ensure a clear explanation of the different processing steps adopted.	References to Figure 2 have been added, to better describe the method.	Lines 120-122
147	The legends in figure 2 are not readable. Please enlarge these.	Done.	Figure 2
154-157	I do not understand why the authors at the end of the discussion introduce a new analysis with new results. First of all this should have been introduced in the methods. Secondly what does this exploratory algorithm consists in? It is very obscure to the reader how you found these results. If this is to be included in the paper please describe it in the methods and report the results more thoroughly.	The reference to the exploratory algorithm has been removed, and the section has been modified.	
157-159	How can the authors say that this will be done in the future? If, as suggested here by the authors there are plans to acquire field reference data, I believe it should be used to validate the	The results were validated using a sample of 63 trees, and the results have been included.	Lines 135-136: 'A sample of 63 emergent trees were located in the field using the same criteria applied to classify Trees_EM.' Lines 143-146: 'From the field data, ... were classified as Trees_SL (of which two

	results of this study and not of future studies.		were verified in the field as actual sleeping trees used by siamang).'
172-173	How can the authors quantify the quality of their method in "...high likelihood of being selected as sleeping trees ..." when they did not provide any validation data to support this statement? Please rephrase this sentence.	Modified.	Line 177-178

1 **Locating emergent trees in a tropical rainforest using data**

2 **from an Unmanned Aerial Vehicle (UAV)**

3 **Highlights**

- 4 ▪ Emergent trees are used as 'sleeping' trees by endangered primates such as gibbons
- 5 ▪ A method is developed to detect emergent trees in a rainforest using data from UAVs
- 6 ▪ Relative heights are used instead of canopy heights to identify emergent trees

1 Locating emergent trees in a tropical rainforest using data 2 from an Unmanned Aerial Vehicle (UAV)

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Locating emergent trees in a tropical rainforest using data from an Unmanned Aerial Vehicle (UAV)

Abstract

32 Emergent trees, which are taller than surrounding trees with exposed crowns, provide crucial
33 services to several rainforest species especially to endangered primates such as gibbons and
34 siamangs (Hylobatidae). Hylobatids show a preference for emergent trees as sleeping sites and for
35 vocal displays, however, they are under threat from both habitat modifications and the impacts of
36 climate change. Traditional plot-based ground surveys have limitations in detecting and mapping
37 emergent trees across a landscape, especially in dense tropical forests. In this study, a method is
38 developed to detect emergent trees in a tropical rainforest in Sumatra, Indonesia, using a
39 photogrammetric point cloud derived from RGB images collected using an Unmanned Aerial Vehicle
40 (UAV). If a treetop, identified as a local maximum in a Digital Surface Model generated from the
41 point cloud, was higher than the surrounding treetops (Trees_EM), and its crown was exposed above
42 its neighbours (Trees_SL; assessed using slope and circularity measures), it was identified as an
43 emergent tree, which might therefore be selected preferentially as a sleeping tree by hylobatids. A
44 total of 54 out of 63 trees were classified as emergent by the developed algorithm and in the field.
45 The algorithm is based on relative height rather than canopy height (due to a lack of terrain data in
46 photogrammetric point clouds in a rainforest environment), which makes it equally applicable to
47 photogrammetric and airborne laser scanning point cloud data.

48

49 **Keywords:** Habitat mapping, Drones, Point cloud, Sleeping trees, Conservation, Rainforest, Sumatra

50 **1. Introduction**

51 Non-human primates are an essential component of tropical biodiversity and they play important
52 roles in forest regeneration and ecosystem health (Chapman et al. 2013). Arboreal primates spend a
53 significant part of their days moving through the canopy, and about half of their life at sleeping sites,
54 with most species rarely climbing down to the ground in suitable habitats with tall well-connected
55 trees. Unlike larger apes such as orang-utans (*Pongo* spp.), smaller apes such as hylobatids do not
56 build nests. Instead, hylobatids prefer to sleep in liana-free emergent trees with exposed crowns
57 that have limited accessibility from surrounding trees, to avoid predators and provide a high vantage
58 point (Anderson 1998). Abundance of secure and stable sleeping sites, along with other factors, may
59 be crucial for the survival of hylobatids, under the threats of increased deforestation and climate
60 change (Cheyne et al. 2012; Reichard 1998).

61 Remote sensing has improved our understanding of the habitat preferences of birds and mammals
62 (Goetz et al. 2007; Palminteri et al. 2012) by providing a continuous representation of the forest
63 canopy. A limitation of ground based surveys is that data are collected only for small sample areas or
64 plots. Furthermore, ground-based surveys in dense tropical forests are time-consuming, with
65 complex multi-layered canopies and sometimes difficult terrain limiting visibility and access.
66 Airborne Laser Scanner (ALS) data have been used to relate the presence and movement patterns of
67 primates to forest structure, based on canopy height, closure and connectivity (Davies et al. 2017;
68 McLean et al. 2016). ALS has distinct advantages over other remote sensing techniques in describing
69 the three-dimensional structure of forests throughout their vertical profile, and capturing underlying
70 terrain information. However, these data are still expensive to acquire, especially for small areas,
71 such as mapping the territories of groups of primates.

72 Unmanned Aerial Vehicles (UAVs) are a low-cost alternative to manned aircraft for collecting data
73 from small areas (Puliti et al. 2017), and UAV data have been used for rapid and efficient location of
74 nests of chimpanzees (*Pan* spp.) and orang-utans (*Pongo* spp.) (van Andel et al. 2015; Wich et al.
75 2015). Photogrammetric point clouds on a forest canopy surface can be generated from an RGB
76 camera mounted on a UAV. One of the main differences between photogrammetric and ALS point
77 clouds, is the absence of points below dense forest canopy in the former. Unlike ALS,
78 photogrammetric UAV point clouds are generated through image matching only on surfaces
79 captured by the camera. This makes it very difficult to generate a reliable terrain model in dense
80 forests from UAV data, which is essential for deriving canopy height (Dandois and Ellis 2013; Lisein et
81 al. 2013; Puliti et al. 2015; Tuominen et al. 2015).

82 Emergent trees are identified in the field based on their relative height from neighbouring trees,
83 which could be estimated using UAV data, even in the absence of a terrain model. Although
84 emergent trees provide essential services to a range of species such as langurs (Presbytinae), fruit
85 bats (Megachiroptera) and eagles (*Nisaetus* spp.) in addition to hylobatids, and have been shown to
86 be a major contributor to rainfall recycling (Holzman 2009; Kunert et al. 2017), their detection,
87 mapping and monitoring have been largely overlooked in earlier studies. The main aim of this study
88 was therefore to assess the suitability of UAV point cloud data for locating emergent trees (and
89 therefore potential sleeping trees for hylobatids) in a tropical rainforest in Northern Sumatra,
90 Indonesia.

91 **2. Study Area and Datasets**

92 The study site is in Sikundur in the Leuser Ecosystem in Northern Sumatra, the only known place
93 where three ape species, orang-utans (*Pongo abelii*), white-handed gibbons (*Hylobates lar*) and
94 siamangs (*Symphalangus syndactylus*), still co-exist (Palombit 1996). Airborne data from three flights
95 were collected using a UAV system comprising a Skywalker UAV (1.7m wingspan), fitted with an APM
96 2.6 autopilot module, RfD900 long-range telemetry and a GoPro Hero3 Black Edition camera,
97 between 22nd and 25th January 2015. The average flying altitude was 198 m above the launch

98 location, covering an area of approximately 11.2 sq km, and generated 5400 images. An area of 6.5
99 sq km (centre: 98.07° E; 3.96° N) along the Besitang River, with known presence of gibbons and
100 siamangs, was used as the study area.

101 **3. Methods**

102 **3.1 Initial selection of treetops**

103 An ortho-photo mosaic with a pixel size of 25 cm, a Digital Surface Model (DSM) with a grid size of 50
104 cm and a point cloud with an average density of 16.59 points m⁻², were generated from the UAV
105 data using Structure from Motion (SfM) and photogrammetric algorithms implemented in Agisoft
106 PhotoScan v1.3.0. The DSM was clipped to the study area and a slope raster was generated in
107 ArcMap™ 10.1. Locations of tree tops were initially identified as grid cells in the DSM which were
108 local maxima within a circular neighbourhood of 5-m radius (Trees_LM); a circular neighbourhood of
109 5 m identified most of the prominent canopy trees based on visual analysis.

110 **3.2 Locations of emergent trees**

111 Trees were selected as emergent trees if their treetops were the local maxima within a circular
112 neighbourhood of 25-m radius and were at least 5 m taller than the surrounding treetops
113 (Trees_EM). Since this forest has been selectively logged in the past, and very few trees in a similar
114 study site in the region were found to have a crown radius larger than 12.5 m (Alexander et al.
115 2017), a neighbourhood radius of 25 m was considered to be adequate. Trees_EM was thus a subset
116 of Trees_LM.

117 Sleeping trees of hylobatids have been observed to often have exposed crowns, with the trunk
118 visible above the canopies of surrounding trees. The slope of the DSM represents the height
119 difference between adjacent grid cells; a slope of 85° would correspond to an elevation difference of
120 5.72 m for a cell size of 50 cm. High slopes would also indicate less connectivity to the surrounding
121 trees. The slope raster (Figure 2B) was classified into six separate binary layers with cut-offs at 65°,
122 70°, 75°, 80° and 85° respectively (Figure 2C), and the layers were converted into polygons.
123 Circularity of a polygon was estimated as the ratio of the area calculated from the perimeter
124 assuming a circle and the actual area of the polygon. Circularity would be 1 for a circle while higher
125 values would indicate linear or elongated features.

126 Polygons with circularity less than 5, and surface areas between 10 m² and 500 m² were selected. A
127 circularity of 5 was chosen based on visual analysis, since pixelated boundaries from the grid cells
128 increased the circularity scores. Surface areas beyond the selected thresholds had a greater
129 probability of belonging to parts of trees, groups of trees or gaps between trees. Polygons belonging
130 to the six slope classes for each tree (or gap) were merged together. This was a simple step to
131 ensure that the largest slope class for each tree was selected to generate the tree polygon. If a tree
132 belonged to slope class > 85°, it would belong to all other classes, but the area of the crown polygon
133 would be the largest for slope class > 85° since it would be the closest to the edge of the tree crown.
134 Trees initially selected from Trees_EM and within these selected tree polygons were classified as
135 locations of potential sleeping trees (Trees_SL). A sample of 63 emergent trees were located in the
136 field using the same criteria applied to classify Trees_EM.

137 **4. Results and Discussion**

138 **4.1 Emergent trees**

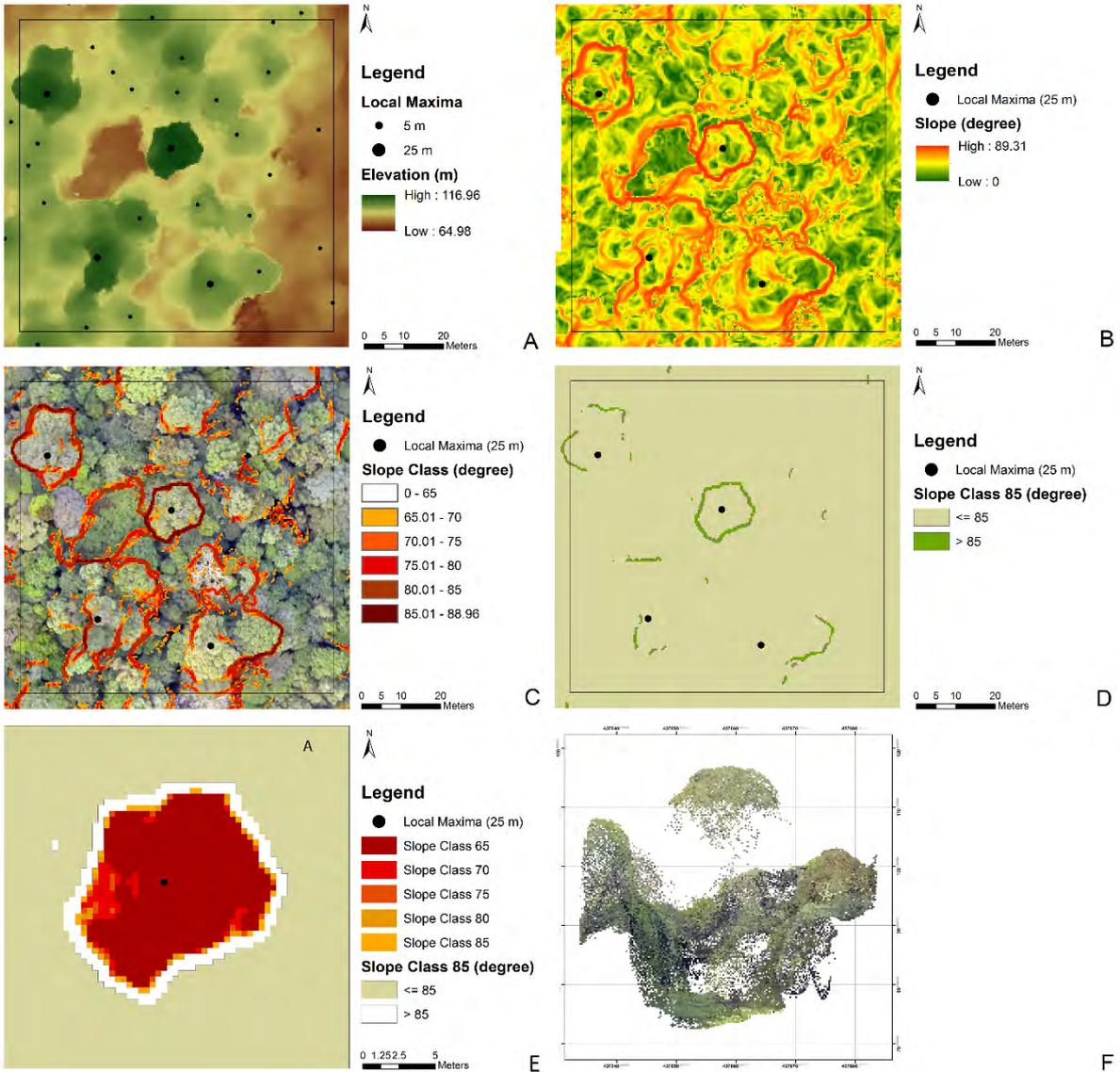
139 The developed method identified 19,478 points as treetops or local maxima within circular
140 neighbourhoods of 5-m radius. This provided an estimated density of 29.97 canopy trees ha⁻¹, out of
141 which 1537 (7.89%) points were also the local maxima within a radius of 25 m. There were 405 trees,
142 with treetops at least 5 m above the highest treetop within a 25-m radius (Trees_EM), and among
143 these, 152 trees were considered to be potential sleeping trees (Trees_SL; Figure 1). From the field

144 data, of the 63 field assessed emergent trees (matching the criteria used to determine Trees_EM),
145 54 were selected in Trees_EM and 33 of these were classified as Trees_SL (of which two were
146 verified in the field as actual sleeping trees used by siamang).



147
148 Figure 1: Estimated locations of potential sleeping trees (Trees_SL) overlaid on an ortho-photo mosaic of the study area; the area within
149 the red square is shown in Figure 2. Inset: Location of the study site (in red) in Sumatra.

150 The developed method (Figure 2) for detecting potential sleeping trees (Trees_SL) was based on
151 observed preferences of hylobatids in other study sites, from published literature. Field observations
152 can be difficult to translate into values required for developing algorithms since variables such as
153 mean canopy height are difficult to measure in the field and are scale-dependent for
154 implementation. It would also be difficult to determine the preferred height above neighbouring
155 tree crowns from ground surveys, due to issues with visibility of emergent tree crown tops from the
156 ground. The radius and height difference for detecting potential sleeping trees could therefore be
157 refined in future studies when the primates in the study area are habituated and more field data
158 become available.



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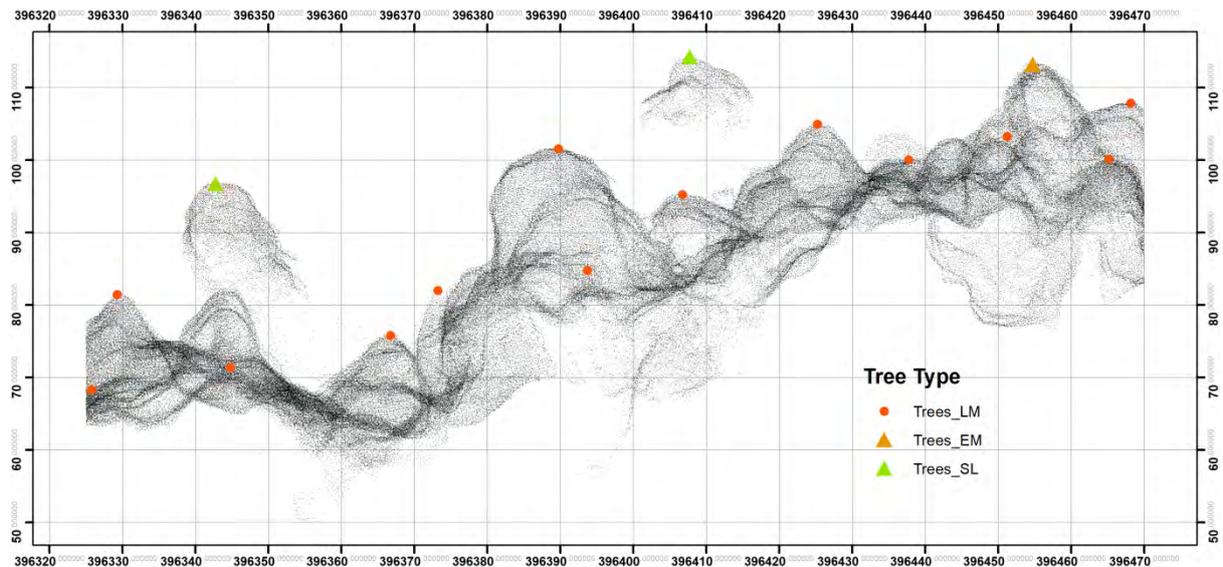
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Figure 2: All the detected treetops—local maxima within circular neighbourhoods of 5 m—overlaid on the Digital Surface Model (A); Local maxima within 25-m radius overlaid on the slope raster (B); Polygons representing slope classes greater than 65° overlaid on the ortho-mosaic (C); Binary classification of polygons generated from a DSM with 85° as the cut-off (D); Tree polygons enclosed by slope classes 65° to 85° (E); and an RGB image generated in ArcMap™ 10.1 from the UAV point cloud within 25-m radius of the located treetop, with Northing on the X-axis and Elevation on the Y-axis (F)



166
 167 Figure 3: UAV point cloud with Easting on the X-axis and Elevation on the Y-axis of an area (145 m × 45 m in plan) showing detected
 168 treetops/local maxima within a radius of 5 m (Trees_LM) and emergent trees (Trees_EM and Trees_SL)

169 **Conclusion**

170 Emergent trees play an important role in tropical rainforests by providing sleeping, nesting and
 171 vocalisation sites for several species, and contributing to rainfall recycling. However, the presence of
 172 emergent trees has been largely overlooked as a variable in habitat studies (Hamard et al. 2010).
 173 This is probably due to their low densities and the difficulty in detecting them from the ground in
 174 field surveys. It is important to map and monitor these trees since they are under threat from both
 175 habitat modifications through selective logging and increased frequency of storms and other impacts
 176 of climate change.

177 A method was developed in this study to locate emergent trees in a tropical forest using UAV data,
 178 although the method is equally applicable to ALS data. The ability to generate a terrain model in
 179 forested areas is a distinct advantage of ALS data, and a limitation of UAV data. However, emergent
 180 trees are recognised based on their relative height from neighbouring trees, which can be derived
 181 from UAV data, without the requirement for a terrain model or absolute heights. Extracting
 182 information from UAV data still relies largely on algorithms developed for ALS data. It will be useful
 183 to develop algorithms for extracting information from UAV data, taking advantage of the ability to
 184 provide spectral and structural information at a cost much lower than manned aircraft.

185 **Acknowledgements**

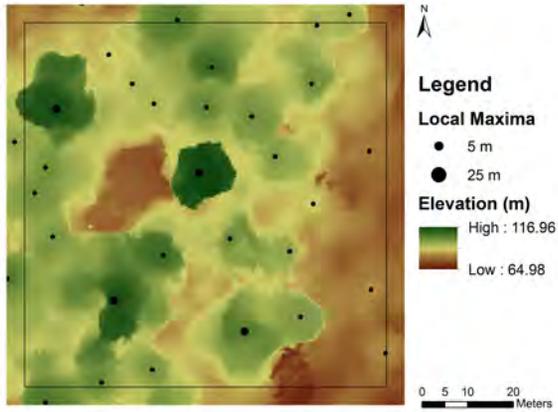
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 190 supporting our work: Indonesian State Ministry for Research and Technology, Ministry of
 191 Environment and Forestry of the Republic of Indonesia, and Gunung Leuser National Park.

192 **References**

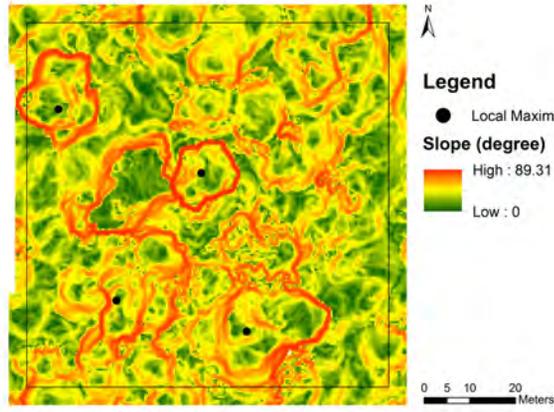
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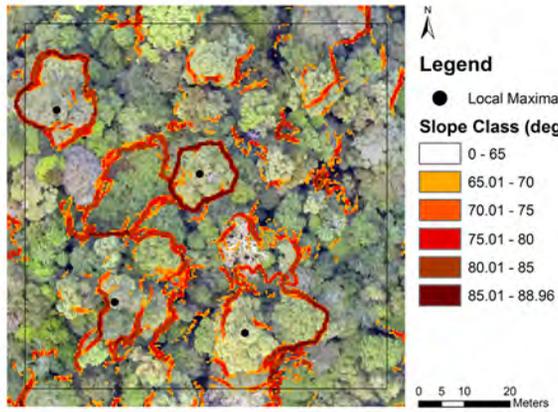




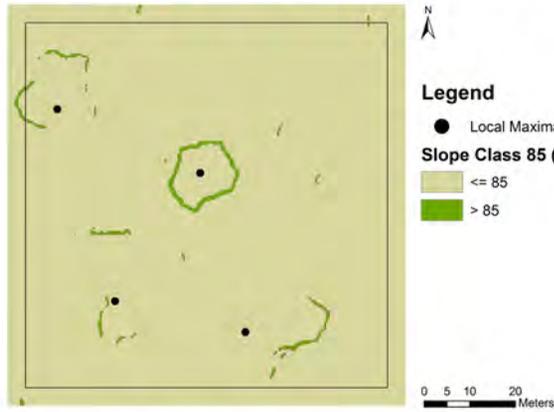
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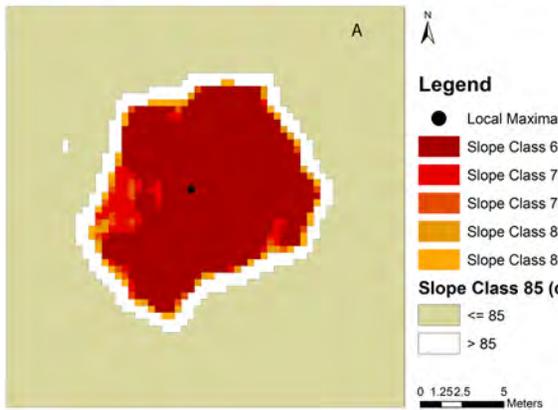
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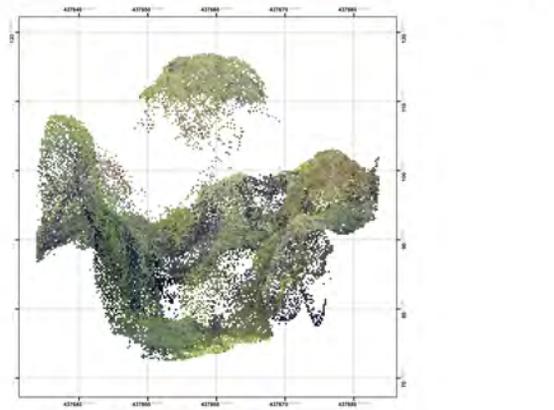
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