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

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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.

1. Introduction

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

Remote sensing has improved our understanding of the habitat preferences of birds and mammals (Goetz et al., 2007; Palminteri et al., 2012) 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. Furthermore, ground-based surveys in dense tropical forests are time-consuming, with complex multi-layered canopies and sometimes difficult terrain limiting visibility and access. Airborne Laser Scanner (ALS) data have been used to relate the presence and movement patterns of primates to forest structure, based on canopy height, closure and connectivity (Davies et al., 2017; McLean et al., 2016). 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. However, these data are still expensive to acquire, especially

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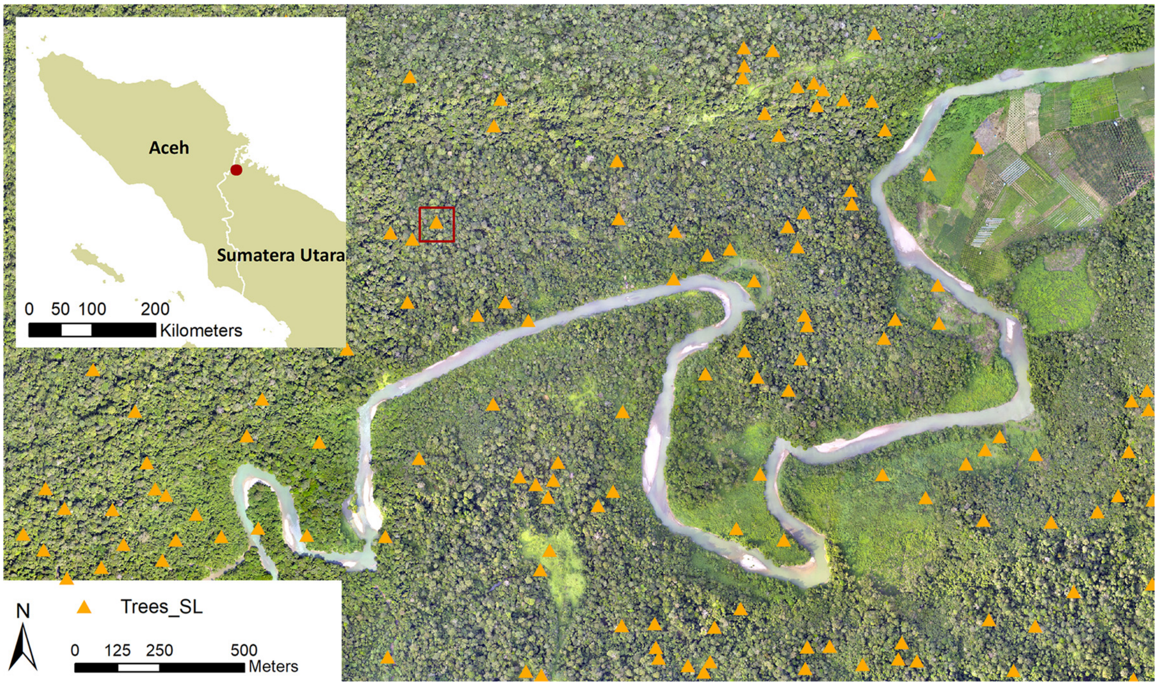

Fig. 1. Estimated locations of potential sleeping trees (Trees_SL) overlayed on an ortho-photo mosaic of the study area; the area within the red square is shown in Fig. 2. Inset: Location of the study site (in red) in Sumatra (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

for small areas, such as mapping the territories of groups of primates.

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

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

2. Study Area and Datasets

The study site is in Sikundur in the Leuser Ecosystem in Northern Sumatra, the only known place where three ape species, orang-utans (*Pongo abelii*), white-handed gibbons (*Hylobates lar*) and siamangs (*Symphalangus syndactylus*), still co-exist (Palombit, 1996). Airborne data from three flights were collected using a UAV system comprising a Skywalker UAV (1.7 m wingspan), fitted with an APM 2.6 autopilot module, RfD900 long-range telemetry and a GoPro Hero3 Black Edition camera, between 22nd and 25th January 2015. The average flying altitude was 198 m above the launch location, covering an area of approximately 11.2 sq km, and generated 5400 images. An area of 6.5 sq km (centre: 98.07 °E; 3.96 °N) along the Besitang River, with known presence of gibbons and siamangs, was used as the study area.

3. Methods

3.1. Initial selection of treetops

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

3.2. Locations of emergent trees

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

Sleeping trees of hylobatids have been observed to often have exposed crowns, with the trunk visible above the canopies of surrounding trees. The slope of the DSM represents the height difference between adjacent grid cells; a slope of 85° would correspond to an elevation difference of 5.72 m for a cell size of 50 cm. High slopes would also indicate less connectivity to the surrounding trees. The slope raster

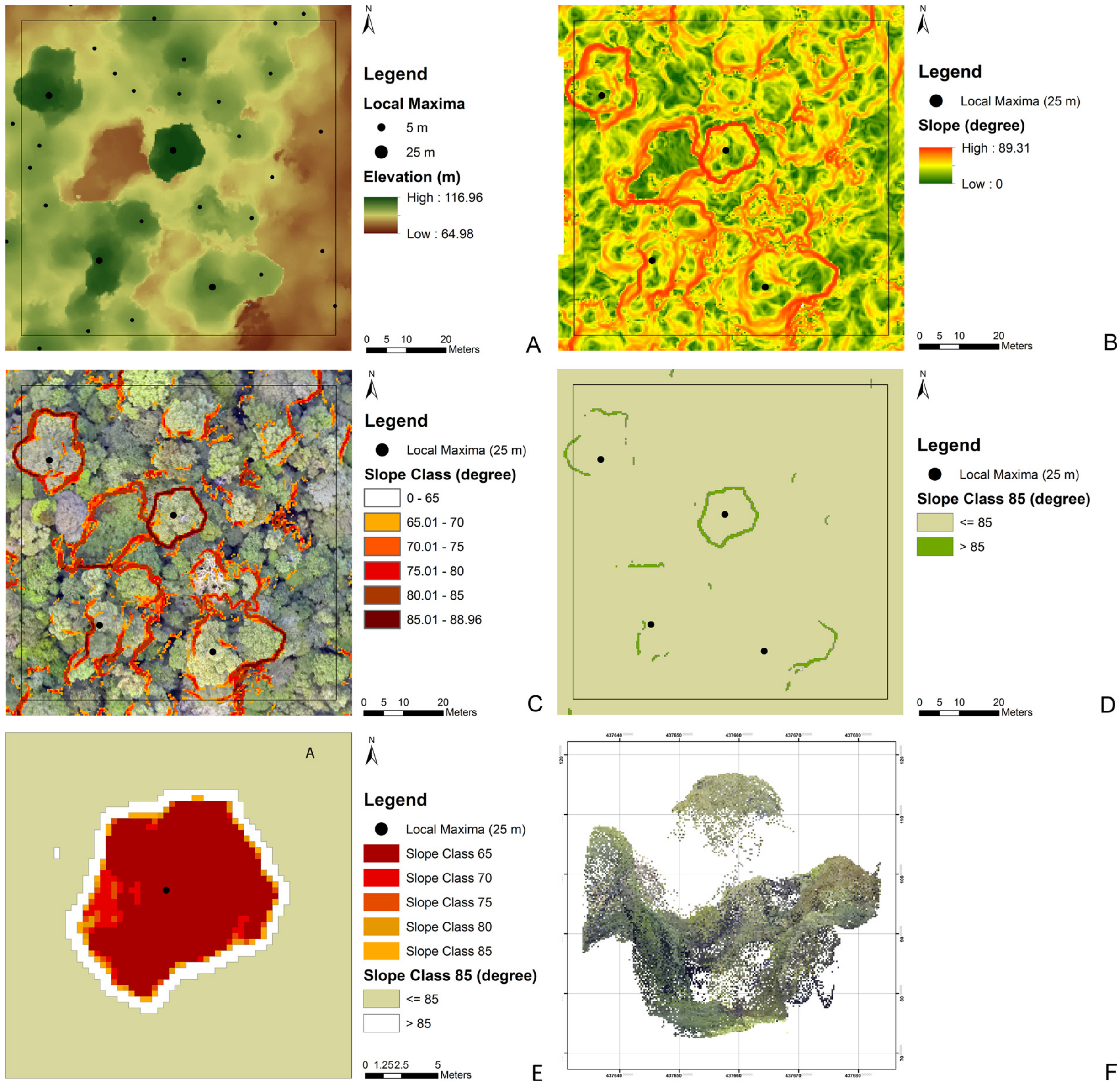

Fig. 2. All the detected treetops—local maxima within circular neighbourhoods of 5 m—overlayed on the Digital Surface Model (A); Local maxima within 25-m radius overlayed on the slope raster (B); Polygons representing slope classes greater than 65° overlayed on the ortho-mosaic (C); Binary classification of polygons generated from a DSM with 85° as the cut-off (D); Tree polygons enclosed by slope classes 65°–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).

(Fig. 2B) was classified into six separate binary layers with cut-offs at 65°, 70°, 75°, 80° and 85° respectively (Fig. 2C), and the layers were converted into polygons. Circularity of a polygon was estimated as the ratio of the area calculated from the perimeter assuming a circle and the actual area of the polygon. Circularity would be 1 for a circle while higher values would indicate linear or elongated features.

Polygons with circularity less than 5, and surface areas between 10 m^2 and 500 m^2 were selected. A circularity of 5 was chosen based on visual analysis, since pixelated boundaries from the grid cells increased the circularity scores. Surface areas beyond the selected thresholds had a greater probability of belonging to parts of trees, groups of trees or gaps between trees. Polygons belonging to the six slope classes for each tree (or gap) were merged together. This was a simple step to ensure that the largest slope class for each tree was selected to generate the tree polygon. If a tree belonged to slope class > 85°, it would belong to all other classes, but the area of the crown polygon would be the largest for slope class > 85° since it would be the closest to the edge of the tree crown. Trees initially selected from Trees_EM and within these selected tree polygons were classified as locations of potential sleeping trees (Trees_SL). A sample of 63 emergent trees were located in the field using the same criteria applied to classify Trees_EM.

4. Results and Discussion

The developed method identified 19,478 points as treetops or local maxima within circular neighbourhoods of 5-m radius. This provided an estimated density of 29.97 canopy trees ha^{-1}, out of which 1537 (7.89%) points were also the local maxima within a radius of 25 m. There were 405 trees, with treetops at least 5 m above the highest treetop within a 25-m radius (Trees_EM), and among these, 152 trees were considered to be potential sleeping trees (Trees_SL; Fig. 1). From the field data, of the 63 field assessed emergent trees (matching the criteria used to determine Trees_EM), 54 were selected in Trees_EM and 33 of these were classified as Trees_SL (of which two were verified in the field as actual sleeping trees used by siamang).

The developed method (Fig. 2) for detecting potential sleeping trees

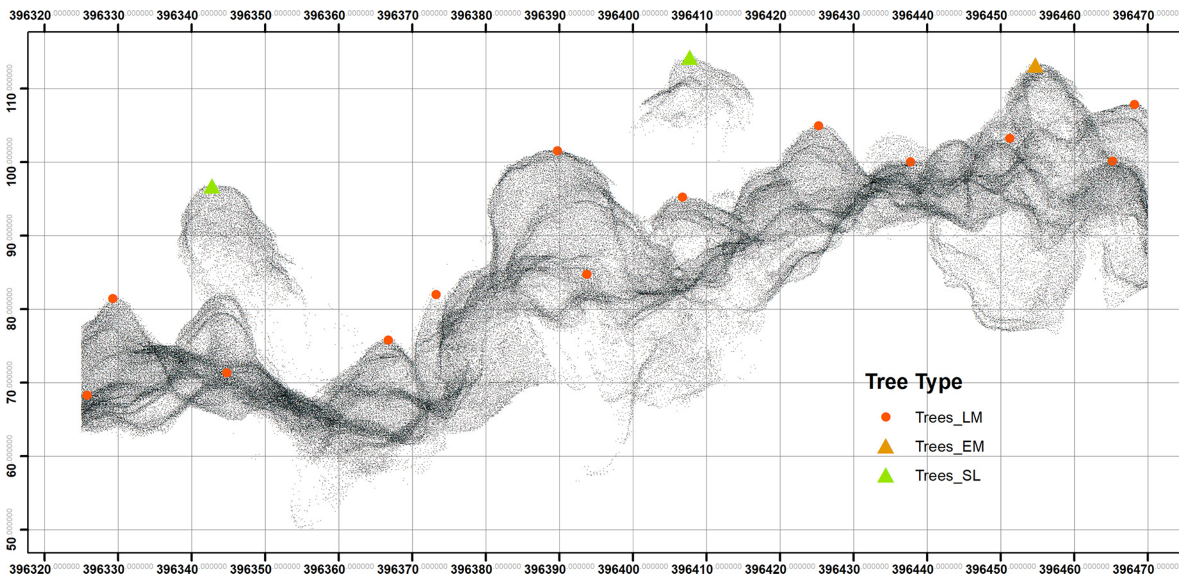

Fig. 3. UAV point cloud with Easting on the X-axis and Elevation on the Y-axis of an area (145 m × 45 m in plan) showing detected treetops/local maxima within a radius of 5 m (Trees_LM) and emergent trees (Trees_EM and Trees_SL).

(Trees_SL) was based on observed preferences of hylobatids in other study sites, from published literature. Field observations can be difficult to translate into values required for developing algorithms since variables such as mean canopy height are difficult to measure in the field and are scale-dependent for implementation. It would also be difficult to determine the preferred height above neighbouring tree crowns from ground surveys, due to issues with visibility of emergent tree crown tops from the ground. The radius and height difference for detecting potential sleeping trees could therefore be refined in future studies when the primates in the study area are habituated and more field data become available (Fig. 3).

5. Conclusion

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

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

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