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A view from above: Unmanned aerial vehicles (UAVs) provide a new tool for assessing liana infestation in tropical forest canopies

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Abstract

1. Tropical forests store and sequester large quantities of carbon, mitigating climate change. Lianas (woody vines) are important tropical forest components, most conspicuous in the canopy. Lianas reduce forest carbon uptake and their recent increase may, therefore, limit forest carbon storage with global consequences for climate change. Liana infestation of tree crowns is traditionally assessed from the ground, which is labour intensive and difficult, particularly for upper canopy layers.
2. We used a lightweight unmanned aerial vehicle (UAV) to assess liana infestation of tree canopies from above. It was a commercially available quadcopter UAV with an integrated, standard three-waveband camera to collect aerial image data for 150 ha of tropical forest canopy. By visually interpreting the images, we assessed the degree of liana infestation for 14.15 ha of forest for which ground-based estimates were collected simultaneously. We compared the UAV liana infestation estimates with those from the ground to determine the validity, strengths, and weaknesses of using UAVs as a new method for assessing liana infestation of tree canopies.
3. Estimates of liana infestation from the UAV correlated strongly with ground-based surveys at individual tree and plot level, and across multiple forest types and spatial resolutions, improving liana infestation assessment for upper canopy layers. Importantly, UAV-based surveys, including the image collection, processing, and visual interpretation, were considerably faster and more cost-efficient than ground-based surveys.
4. *Synthesis and applications.* Unmanned aerial vehicle (UAV) image data of tree canopies can be easily captured and used to assess liana infestation at least as accurately as traditional ground data. This novel method promotes reproducibility of results and quality control, and enables additional variables to be derived from the image data. It is more cost-effective, time-efficient and covers larger geographical extents than traditional ground surveys, enabling more comprehensive monitoring of changes in liana infestation over space and time. This is important for assessing liana impacts on the global carbon balance, and particularly useful for

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forest management where knowledge of the location and change in liana infestation can be used for tailored, targeted, and effective management of tropical forests for enhanced carbon sequestration (e.g., REDD+ projects), timber concessions, and forest restoration.

KEYWORDS

drone, drone ecology, liana infestation, lianas, remote sensing, tropical forest canopy, unmanned aerial vehicles, visual image interpretation

1 | INTRODUCTION

Tropical forests and their canopies play a crucial role in the maintenance and provision of unique biodiversity and essential ecosystem services to all life on Earth (Lowman & Schowalter, 2012; Ozanne et al., 2003). One of the most important ecosystem services that tropical forests provide is their ability to store and sequester carbon (Pan et al., 2011). Managing tropical forests for carbon sequestration, therefore, provides a key opportunity to mitigate some of the effects of climate change resulting from increasing atmospheric CO₂ concentrations (Canadell & Raupach, 2008).

Lianas (woody vines) are conspicuous components of tropical forests, where they peak in abundance, biomass, and species richness (Schnitzer & Bongers, 2002). Lianas use the structural biomass of trees to deploy leaves in the canopy, thus investing relatively more resources in producing an extensive leaf canopy than in woody tissue. Lianas, therefore, disproportionately contribute to the forest canopy: liana leaves can comprise up to 30% of forest leaf area but only up to 5% woody stem biomass of tropical forests (van der Heijden, Schnitzer, Powers, & Phillips, 2013). Liana abundance and biomass have increased over the last few decades (Schnitzer & Bongers, 2011). Consequently, lianas have proliferated in the forest canopy, indicated by an increase in their contribution to leaf productivity as well as in the number of tree crowns infested (Ingwell, Wright, Becklund, Hubbell, & Schnitzer, 2010; Wright, Calderón, Hernández, & Paton, 2004). Partly due to their extensive canopies, lianas aggressively compete with trees, reducing tree growth (Ingwell et al., 2010; van der Heijden & Phillips, 2009), fecundity (e.g., Kainer, Wadt, & Staudhammer, 2014), survival (Ingwell et al., 2010; Phillips, Vásquez Martínez, Monteagudo Mendoza, Baker, & Núñez Vargas, 2005) and, consequently, forest biomass and net carbon uptake (van der Heijden, Powers, & Schnitzer, 2015). Lianas pose a particular problem for managed forests, where they can substantially hinder carbon sequestration and forest restoration (e.g., Marshall et al., 2017). Liana cutting is often used to enhance carbon uptake (Marshall et al., 2017; van der Heijden et al., 2015); however, this is expensive and labour intensive to perform over large extents. The ability to identify where liana management would be most beneficial would therefore help target management of tropical forests.

Being able to accurately monitor the presence and degree of liana infestation in forest canopies over time and space is, therefore, important for determining whether and where liana impacts

are high and/or may be increasing, particularly in managed tropical forests. Due to practical difficulties in accessing tropical forest canopies (Nakamura et al., 2017), assessing liana canopy infestation is traditionally done by ground-based surveys (e.g., van der Heijden, Feldpausch, Herrero, van der Velden, & Phillips, 2010). These are labour- and time intensive, and consequently limited in their spatial and temporal coverage, and lianas, therefore, remain understudied in tropical forests (Marvin, Asner, & Schnitzer, 2016). Furthermore, the stratified nature of tropical forests often limits the visibility of canopy and emergent tree crowns, affecting the reliability of ground-based estimates for them. As these larger trees tend to store and sequester the most carbon and, due to high light conditions in their crown, often harbour lianas (van der Heijden, Healey, & Phillips, 2008), reliable assessment of liana infestation for top-of-the-canopy trees is especially important.

Assessing lianas from a vantage point above the canopy should be feasible using remote sensing platforms which offer views of the canopy with much less obscuration by vegetation than possible from the ground (Nadkarni, Parker, & Lowman, 2011). However, satellite and many airborne platforms generally provide data too coarse in temporal or spatial resolution for this task, too expensive at very fine resolutions, and frequently suffer from cloud obscuration, especially in moist forests. Workarounds exist: using hyperspectral and LiDAR sensors, the Carnegie Airborne Observatory was able to accurately map heavy liana infestation across the forests of Panama (Marvin et al., 2016). The use of such sensors is very expensive and restricted to specialists, however, prohibiting their accessibility to the majority of researchers and forest managers. Furthermore, such remote sensing campaigns are typically carried out as one-time operations, so frequent monitoring is difficult (Xue & Su, 2017).

Unmanned aerial vehicles (UAVs) with sensors overcome most of the aforementioned limitations of remote sensing platforms (Cunliffe, Brazier, & Anderson, 2016). They can acquire remotely sensed data from relatively inaccessible environments, and thus are useful for measuring and (long-term) monitoring of forest canopies (Kachamba, Ørka, Gobakken, Eid, & Mwase, 2016; Paneque-Gálvez, McCall, Napoletano, Wich, & Koh, 2014; Zahawi et al., 2015; Zhang et al., 2016). Additionally, UAVs can capture data at even finer temporal and spatial resolutions than satellite and manned-airborne remote sensing (Nakamura et al., 2017). This is especially important because visually distinguishing lianas from trees requires ultra-fine resolution (mm–cm) image data: liana leaves grow among the leaves

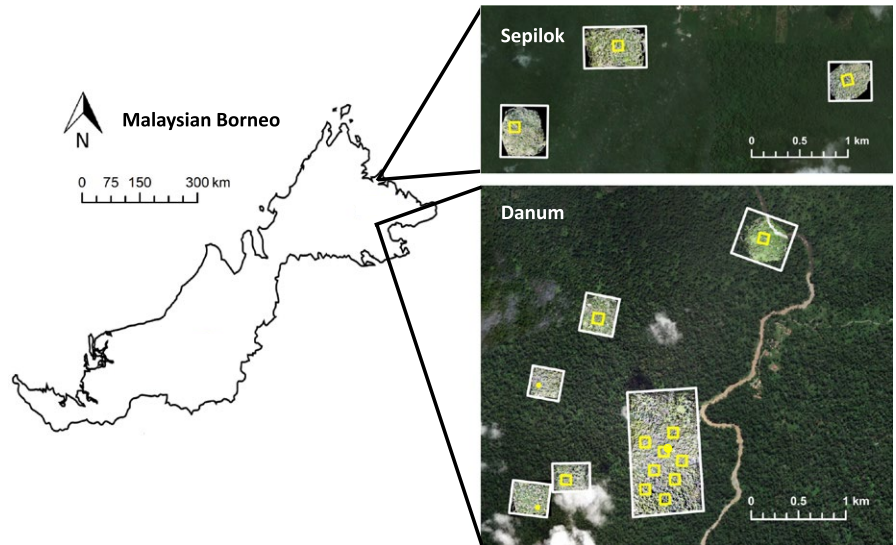


FIGURE 1 Location of the 2 study sites and 17 plots, which are in the state of Sabah, Malaysia, on the island of Borneo, Southeast Asia. The orthomosaics created from the UAV survey (150 ha) are shown outlined in white on top of satellite imagery, and the plots (14.15 ha) outlined in yellow. Satellite imagery source: DigitalGlobe WorldView2 RGB imagery

of the trees in which they are located, becoming embedded in the canopy, and are also heterogeneous in nature, as lianas are phylogenetically and functionally highly diverse (Burnham, 2004; Gentry, 1991). Because their physical traits vary, leaves of a given liana species may look very different or very similar to other liana species or the tree in which they are located. Additional textural context, such as leaf shape or arrangement, could allow improved discrimination of liana leaves from tree leaves in cases where spectral discrimination is unfeasible. Thus, UAVs and the enhanced spatial resolution they offer are potentially effective for assessing canopy-level liana infestation. However, even though UAVs have been used to study other canopy phenomena (e.g., Zahawi et al., 2015); thus far, they have not been used to study lianas.

Here, we examine, for the first time, the applicability of UAV-derived image data to assess the presence and degree of liana infestation in tropical tree canopies, using ground-based observations as a benchmark. Specifically, we aim to assess the validity of utilizing a consumer-grade UAV and camera as a new method for collecting data on liana infestation, by (a) assessing interobserver bias in classifying liana infestation from UAV images (*reproducibility between observers*); (b) evaluating the strength of the correlation between UAV- and ground-derived measures of liana infestation on individual tree- and plot levels, and for different canopy strata (*accuracy and reproducibility against benchmarked method*); and (c) comparing input time and costs between ground and UAV surveys of liana infestation (*efficiency against a benchmarked method*).

2 | MATERIALS AND METHODS

2.1 | Study sites

Ground and UAV-based surveys were conducted in two sites across eastern Sabah, Malaysia: Danum Valley Conservation Area (Danum) (4°57'N, 117°42'E) and Sepilok Forest Reserve (Sepilok) (5°52'N, 117°56'E) (Figure 1). Danum is characterized by lowland, evergreen

dipterocarp forest, covering ~43,800 ha, and Sepilok by alluvial lowland dipterocarp, sandstone hill dipterocarp, and kerangas forests, covering ~4,300 ha. We surveyed 17 plots: eight 1-ha plots located in the Center for Tropical Forest Science (CTFS) 50-ha plot, three additional 10-ha plots (Berry, Phillips, Ong, & Hamer, 2008), and three 0.05-ha circular plots (Foody et al., 2001) in Danum and three 1-ha plots in Sepilok located in the alluvial, sandstone hill, and kerangas forests (Nilus, 2004).

2.2 | Ground-based data collection and liana assessments

We classified the liana load carried by each tree ≥ 10 cm DBH within the plots using two methods: (a) crown occupancy index (COI) and (b) percentage liana cover (%LC). The COI expresses liana load in the tree crown on a simple 5-point ordinal scale: (0) no lianas in the crown, (1) 1%–25%, (2) 26%–50%, (3) 51%–75%, and (4) >75% of the crown covered by liana leaves (Clark & Clark, 1990). This index is widely used in liana research and accurately measures liana loads at both the individual tree- and site level with little interobserver bias (van der Heijden et al., 2010). %LC is a more detailed estimate, expressed as the mean of four compass quadrants into which the tree crown is visually split and percentage of the crown covered by lianas estimated to the nearest 5% (cf. Marvin et al., 2016).

The plot corners (or midpoints for the 0.05-ha plots) and individual trees ≥ 10 cm DBH within each plot were georeferenced using a handheld GPS unit (Garmin eTrex Vista HCx), allowing individual tree crowns to be identified and cross-referenced in the UAV images. We also assigned each tree ≥ 10 cm DBH a value indicating the light level its crown received using the crown illumination index (CII) (Clark & Clark, 1992). This ordinal scale index is more-or-less equivalent to canopy stature (1 = understory, 2 = lower canopy, 3 = mid canopy, 4 = upper canopy, 5 = emergent); it helped identify individual trees on the UAV image data and allowed comparison across different tree canopy statures.

The CII, COI, and %LC values were assigned by two independent observers, who discussed their estimates in the field and agreed final values for each tree. In one of the Danum plots %LC data were not collected, and in the Sepilok plots we only collected data for higher canopy-level trees.

2.3 | UAV data collection and liana assessments

We acquired images of the forest canopy using a lightweight, agile, inexpensive, commercially available quadcopter UAV: a DJI Phantom 3 Advanced equipped with an integrated three-waveband (RGB) camera, mounted on a three-axis, gyro-stabilized gimbal. The high-quality Sony EXMOR 1/2.3" 12-megapixel camera has a narrow 94° field of view lens (35 mm format equivalent: 20 mm) reducing "fish-eye" image distortion, and an f/2.8 aperture and 8s–1/8000s shutter speed reducing image blur. The UAV possesses GPS and GLONASS positioning to enable autonomous flights of up to ~23 min. Each image is geo-tagged with the GPS location and altitude of the UAV at the point of capture.

The plots were flown using the automatic mapping software Map Pilot, with predetermined flight plans with the same parameters (speed: 4 m/s; image overlap at ground-level: 90% forward, 90% side; altitude: 30 and 60 m above canopy surface) in parallel tracks that covered the plot and a "buffer" of surrounding vegetation to minimize edge-effects affecting the images of the plot in processing. High image overlap at ground-level was necessary to maintain adequate overlap for producing orthomosaics at canopy-level (for more information see Supporting Information Appendix S1.3). We identified canopy gaps large enough to allow the UAV to be launched/

landed, and manually piloted it through, to ensure maximal pilot control and minimal risk of collisions. The flights were conducted during calm conditions to prevent wind effects on leaves (McNeil, 2016) and, where possible, when there was even cloud cover to ensure diffuse radiation and minimize shadowing in the canopy—improving clarity in the images and aiding liana identification. All flights took place concurrently with the ground assessments in May and June 2016. Additional details on the UAV surveys, and our experiences and recommendations for using UAVs for research, are in Supporting Information Appendix S1.

In total, 6,094 and 1,344 images taken 30 and 60 m above the canopy were captured with spatial resolutions of ~10 mm/pixel and ~20 mm/pixel, covering ~150 ha and ~50 ha of forest, respectively, within which the plots cover 14.15 ha. The images were assembled to form a single two-dimensional orthorectified image (orthomosaic) for each plot, geo-referenced to the WGS84 UTM Zone 50N projected coordinate system, using Agisoft PhotoScan version 1.3.0. An example Agisoft PhotoScan output is in Supporting Information Appendix S2. The orthomosaics were exported into ArcGIS to identify individual trees (supplemented by the original images, to provide multiple views from different angles, where necessary). The 30 m data were used for all analyses; the 60 m data were used to compare different spatial resolutions.

For each individual tree, COI and %LC values were determined by visual image interpretation using the same method used on the ground but applied from above. Interpreting the images in this way is beneficial because it (a) matches the visual assessment used on the ground and (b) harnesses the power of human interpretation skills, which is especially important as no algorithm has been developed



FIGURE 2 An example image taken using the DJI Phantom 3 Advanced. Two sections of the image have been selected to show a (a) liana-free and (b) liana-infested tree crown (indicated by a white border). The yellow border in (b) indicates the liana leaves

to automate liana infestation identification in tree canopies from RGB image data. Any trees for which ground data were collected, but which were obscured by larger trees and not visible on the UAV image data, were excluded from further analysis on individual tree levels but retained for plot-level comparisons of UAV and ground surveys.

3 | RESULTS

Liana load data were collected in 17 plots across 4 forest types, via both ground- and UAV-based methods, for more than 3,500 trees. The ultra-fine spatial resolution (10 mm/pixel) of the UAV data rendered each tree crown recognizable and individual leaves clearly identifiable (Figure 2). Liana load could, therefore, be assessed: trees without liana infestation (Figure 2a) could be distinguished from liana-infested trees (Figure 2b). This remained true when using the coarser ~20 mm/pixel spatial resolution.

3.1 | Reproducibility (between observers)

We assessed interobserver bias in classifying liana load from the UAV image data; bias in ground-based surveys was examined previously by van der Heijden et al. (2010) and therefore not assessed here. Three independent observers with differing levels of experience in liana identification classified the COI and %LC for 200 randomly selected trees. We used Kendall's coefficient of concordance (Kendall's W) and Spearman's rank test, respectively, to assess the concordance of COI and %LC values recorded by different observers, finding high degrees of concordance for both measures (Table 1). The same COI was recorded by all observers on 75% of occasions and on only 2% of occasions did all observers classify liana load differently. When classifications differed, this was most often by only one class (86%).

3.2 | Reproducibility (against a benchmarked method)

There was high concordance of COI scores between UAV and ground surveys for the full dataset (Kendall's $W = 0.947$, $p < 0.001$, $N = 3,555$; Tables 2 and 3), with liana load scored the same on 71.1% of occasions. Classifications differed by one class for 26.1%, and by two or more classes for 2.8% of the trees. The most frequent differences between UAV and ground surveys (43.2% of trees that differed) were when COI was scored 0 (liana-free) by ground-based surveys and 1 (low infestation) by UAV surveys (Tables 2 and 3). Similar trends were found for Danum and the different forest types in Sepilok separately (Supporting Information Appendix S3.1).

We used Model II regression to test the relationship between the UAV and the ground-derived %LC values. Model II regression performs better than standard Model I (OLS) regression when there are errors associated with both variables (Legendre & Legendre, 1998), with the estimated model having the same slope and r^2 values

TABLE 1 Degree of concordance between different observers in independently assessing liana infestation of tree crowns in UAV image data using crown occupancy index (COI) and percentage liana cover (%LC). Differences in COI and %LC were assessed with Kendall's W and Spearman's rank tests, respectively

| | COI | | %LC | |
|------------|-------|--------|-------|--------|
| | W | p | r | p |
| All | 0.950 | <0.001 | | |
| Obs. 1 & 2 | 0.966 | <0.001 | 0.961 | <0.001 |
| Obs. 1 & 3 | 0.966 | <0.001 | 0.942 | <0.001 |
| Obs. 2 & 3 | 0.955 | <0.001 | 0.927 | <0.001 |

independent of which way round the axes are. To further evaluate the relationship between the UAV- and ground-based methods, we also calculated the RMSE with respect to the 1:1 line with lower RMSE values indicating greater concordance between the UAV and ground methods. We found a strong relationship between ground- and UAV-based assessments of %LC for the full dataset ($r^2 = 0.867$, $p < 0.001$, $N = 3,320$; Figure 3), for different forest types separately (Supporting Information Appendix S3.23) and when using a coarser spatial resolution (Supporting Information Appendix S3.3). Although UAV- and ground-based classifications were similar for more heavily infested trees, UAV-based %LC classification was higher for lightly infested trees, with the regression line significantly below the 1:1 line for %LC below 40% (Figure 3). This was mainly caused by the high number of tree crowns classed as liana-free by the ground survey but as low-level liana infestation by the UAV survey.

Since canopies of taller trees can be hard to see from the ground due to the stratified nature of tropical forests canopies, we also compared ground and UAV survey results for tree crowns located in different canopy strata. We found strong agreement between ground- and UAV-derived COI values (Kendall's $W > 0.9$) for all canopy stature classes except emergent trees (Kendall's $W = 0.750$; Table 2; Supporting Information Appendix S3.4a-d). The most common differences were again when COI was classed as 0 by the ground survey and 1 by the UAV survey, especially in the higher canopy strata (this was up to seven times more likely for emergent trees). Agreement between the two methods was greater for tree crowns in the lower canopy layers, and for more heavily infested individuals in upper canopy strata (Table 2; Supporting Information Appendix S3.4a-d). These patterns were also evident when comparing the %LC values; although ground- and UAV-derived %LC values were strongly related for all four canopy strata (Figure 4), the regression line deviated significantly from the 1:1 line for upper canopy and emergent trees. This was again caused by many trees classified as liana-free in the ground-based surveys and with low levels of liana infestation in the UAV-based surveys (Figure 4c,d).

At plot level, there was a strong, positive relationship between ground- and UAV-based classifications of (a) the proportion of liana-infested trees per plot, and plot level (b) mean COI and (c) %LC values ($r^2 = 0.719$, 0.899 , and 0.920 respectively; Figure 5). This indicates

TABLE 2 Percentage of trees in each of the crown occupancy index (COI) classes for the ground (G) and UAV surveys, and the degree of concordance between the surveys (Kendall's W) for the full dataset (All trees) and the dataset partitioned by canopy strata. $p < 0.001$ for all comparisons

| | N | W | COI 0 (%) | | COI 1 (%) | | COI 2 (%) | | COI 3 (%) | | COI 4 (%) | |
|-----------|-------|-------|-----------|------|-----------|------|-----------|------|-----------|------|-----------|------|
| | | | G | UAV | G | UAV | G | UAV | G | UAV | G | UAV |
| All trees | 3,555 | 0.947 | 44.6 | 34.5 | 13.0 | 24.7 | 12.3 | 11.4 | 12.1 | 12.8 | 18.0 | 16.6 |
| Lower | 1,841 | 0.968 | 33.9 | 31.6 | 16.2 | 22.0 | 15.2 | 13.5 | 13.1 | 14.0 | 22.0 | 19.0 |
| Mid | 989 | 0.936 | 44.5 | 29.6 | 11.0 | 26.7 | 11.2 | 11.7 | 13.6 | 14.3 | 19.5 | 17.7 |
| Upper | 412 | 0.909 | 61.2 | 39.6 | 10.2 | 28.9 | 7.8 | 7.0 | 10.0 | 10.2 | 10.9 | 14.3 |
| Emergent | 313 | 0.750 | 86.9 | 60.7 | 4.2 | 29.1 | 4.2 | 3.8 | 3.2 | 4.5 | 1.6 | 1.9 |

TABLE 3 Error matrix showing the number of trees classified in each crown occupancy index (COI) class for the ground and UAV surveys for the full dataset. Counts in bold indicate when the two methods produced the same score

| | | Ground data COI | | | | |
|--------------|---|-----------------|------------|------------|------------|------------|
| | | 0 | 1 | 2 | 3 | 4 |
| UAV data COI | 0 | 1,164 | 54 | 7 | 2 | 0 |
| | 1 | 390 | 358 | 109 | 16 | 5 |
| | 2 | 25 | 43 | 227 | 93 | 18 |
| | 3 | 9 | 6 | 85 | 259 | 96 |
| | 4 | 1 | 1 | 8 | 59 | 520 |

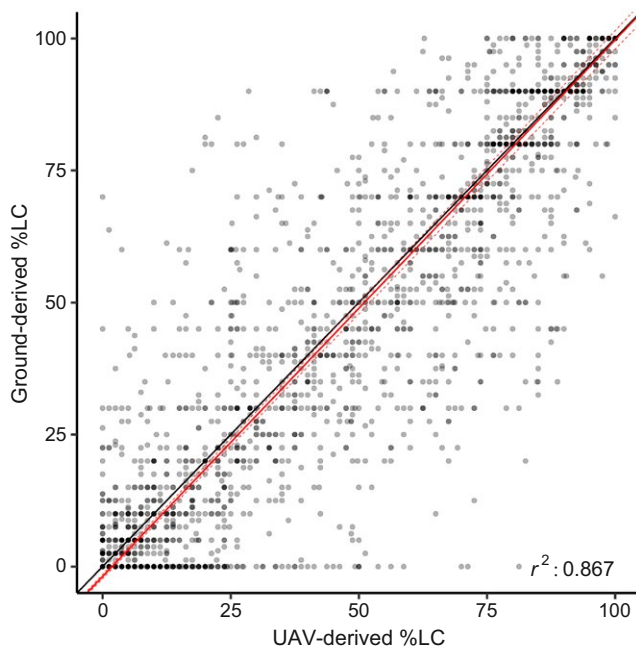


FIGURE 3 Relationship between the UAV-derived percentage liana cover (%LC) and the ground-derived percentage liana cover (%LC). The solid red line is the Model II regression line, and its associated r^2 is reported, dashed red lines are the 95% confidence intervals, and the black line is the 1:1 line (i.e., perfect match). $N = 3,320$; RMSE (with respect to the 1:1 line) = 12.73. Darker dots indicate more data points with similar ground and UAV values

that, although fewer tree crowns (of smaller trees) are discernible in the UAV image data (mean trees/ha: ground = 360; UAV = 270), the UAV method is nonetheless suitable for plot-level analysis. UAV-derived plot-level estimates of liana infestation were higher (i.e., under the 1:1 line in Figure 5) than ground-based estimates for almost all plots, with the difference more pronounced for plots with lower liana infestation.

3.3 | Efficiency

The UAV method was particularly time-efficient, with liana infestation assessment on average more than five times faster than the ground-based method, including both field and laboratory time (Table 4). Field campaigns are typically the most costly and time-limited phases of ecological research, and here the efficiency of the UAV survey over the ground survey is particularly enhanced. It reduces field time by 98.6% and the fixed costs of UAV hardware and software are recovered in the first 5.5 ha, with further UAV surveys costing 5.5% as much as the ground survey (Table 4). As fixed costs decrease with developments in UAV technology and popularity, the break-even point will occur even sooner than the 5.5 ha in this study.

4 | DISCUSSION

Here, we demonstrate, for the first time, that UAVs can be used as an accurate, accessible, agile, cost-effective, and time-efficient new tool for collecting data on liana infestation of tropical tree crowns, overcoming limitations of existing methods. Liana loads derived from UAV surveys and traditional ground surveys were strongly related at both individual tree- and plot level (Tables 2 and 3; Figures 3 and 4). Furthermore, we found little interobserver bias in visual classifications of liana loads derived from UAV image data, regardless of liana expertise or previous experience of liana surveys (Table 1), indicating high reproducibility of the UAV method. Additionally, the UAV method was much more time-efficient than the ground-based method, particularly in the field, and considerably more cost-efficient over multiple surveys (Table 4), with initial investment recouped within the first six plots. The UAV also remains cheaper than most suitable satellite or manned aerial survey image data.

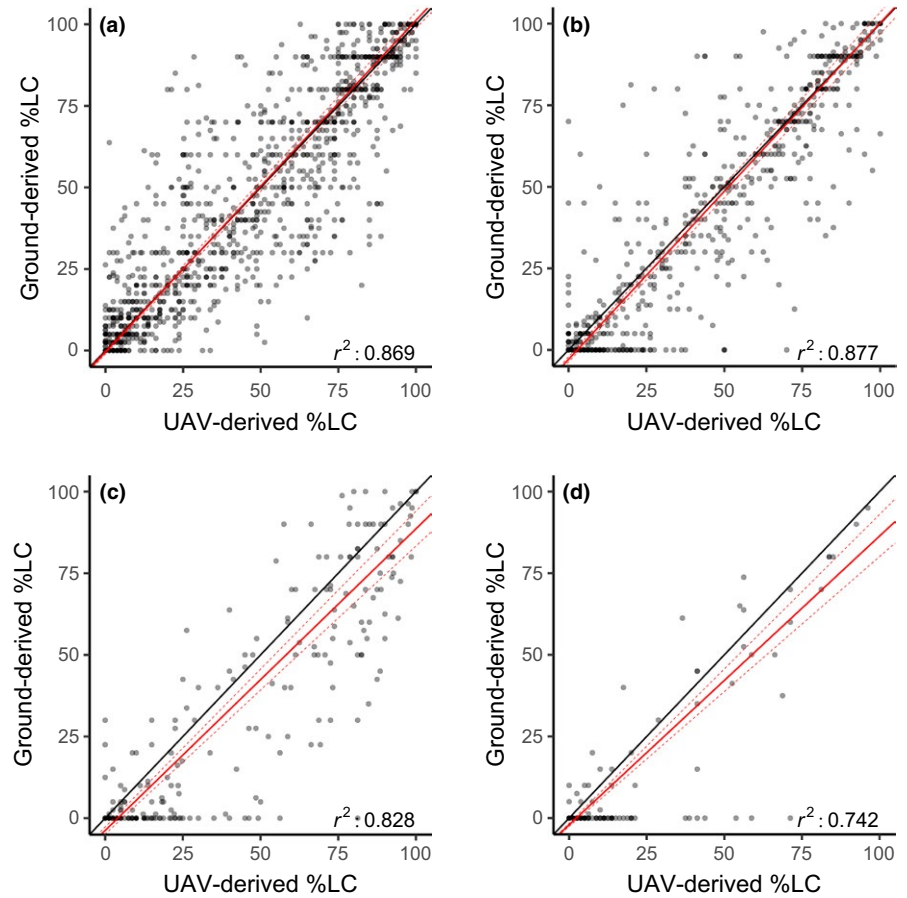


FIGURE 4 Relationships between the UAV-derived percentage liana cover (%LC) and the ground-derived percentage liana cover (%LC) for (a) lower canopy ($N = 1,711$; RMSE (with respect to the 1:1 line) = 12.79), (b) mid canopy ($N = 931$; RMSE (with respect to the 1:1 line) = 12.47), (c) upper canopy ($N = 380$; RMSE (with respect to the 1:1 line) = 14.96), (d) emergent trees ($N = 298$; RMSE (with respect to the 1:1 line) = 9.79). Solid red lines are the Model II regression lines with their associated r^2 s reported, dashed red lines are the 95% confidence intervals, and black lines are the 1:1 lines (i.e., perfect match). Darker dots indicate more data points with similar ground and UAV values

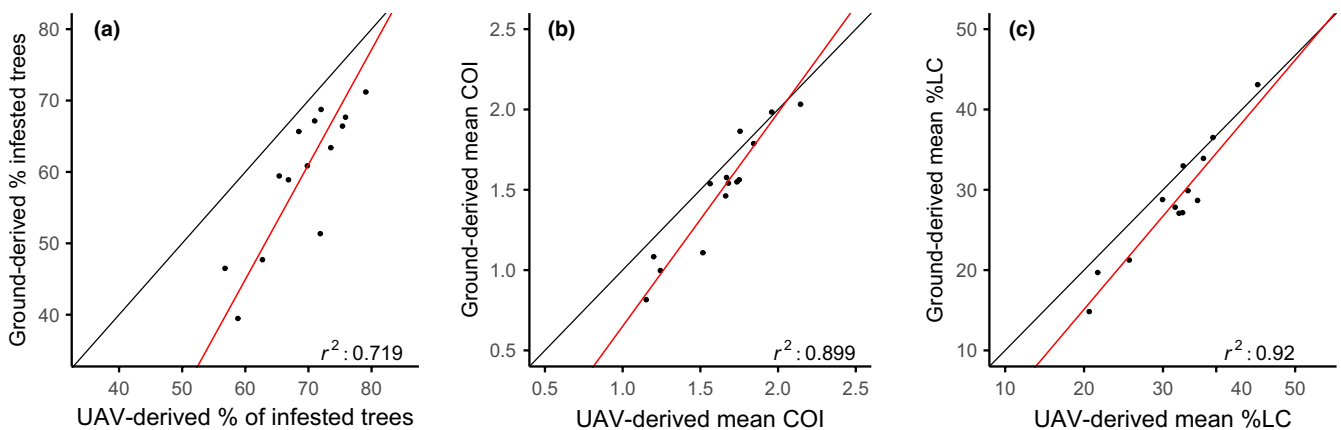


FIGURE 5 Relationships between ground and UAV-derived plot-level (a) proportion of infested trees (%; $N = 14$; RMSE (with respect to the 1:1 line) = 10.86), (b) mean liana crown occupancy index (COI; $N = 14$; RMSE (with respect to the 1:1 line) = 0.19), and (c) mean percentage liana cover (%LC; $N = 13$; RMSE (with respect to the 1:1 line) = 3.68) for the Danum Valley Conservation Area plots. The Model II regression lines are shown in red, with their associated r^2 s reported, and the 1:1 lines in black. The 1:1 line fell within the 95% confidence bands, but as intervals were large they were excluded from the graph

Thus, UAVs make liana data collection more accessible to a wider variety of researchers and forest managers and may, therefore, enable canopy monitoring and mapping of lianas on unprecedented spatial and temporal scales.

At the plot level, UAV-based surveys consistently classed percent liana infestation higher than ground-based surveys (Figure 5).

There are two explanations for this. Firstly, UAVs were better at recognizing low-level liana infestation (Tables 2 and 3; Figures 3 and 4). Secondly, plot-level estimates of liana infestation from ground surveys included understorey trees not visible on the UAV image data. As understorey trees are less frequently infested by lianas than larger trees (van der Heijden et al., 2008), their inclusion in

TABLE 4 Efficiency comparison of the time taken and costs required to collect crown occupancy index (COI) and percentage liana cover (%LC) using ground-based and UAV-based methods for a 1-ha plot, including the fixed costs (field and UAV equipment and processing software) required for the whole campaign (14.15 ha for ground; 150 ha for UAV). All timings are reported in “person-hours” (i.e., time taken to collect data considering number of people required) and exclude time to walk to the plots. All costs exclude international travel and costs/ha have been calculated based on number of days required at each plot with daily rates of £14.10 and £27.75 for accommodation/subsistence and field assistant costs, respectively. To replicate most grant budget costings, field assistant wages have been costed, whereas researcher input time has not

| | Ground | | | UAV | | |
|------------------------------------|-------------|-----------------|---------------|-------------|-----------------|-------------------|
| | Time/ha (h) | Fixed costs (£) | Cost/ha (£) | Time/ha (h) | Fixed costs (£) | Cost/ha (£) |
| Field^a | | | | | | |
| Accommodation/subsistence | – | – | 84.60 | – | – | 4.70 ^b |
| Field assistants | – | – | 166.50 | – | – | 9.25 ^b |
| UAV flight (inc. take-off/landing) | – | – | – | 0.5 | 1,336 | – |
| COI and %LC assessments | 40 | 450 | – | – | – | – |
| Laboratory | | | | | | |
| Data type up | 5 | – | – | – | – | – |
| Processing image data | – | – | – | 9 | 427.10 | – |
| Mapping trees on orthomosaics | – | – | – | 1 | – | – |
| COI and %LC assessment | – | – | – | 2 | – | – |
| Total | 45 | 450 | 251.10 | 12.5 | 1,763.10 | 13.95 |

^aTraining time is not included as it is not measured per ha. We found 5 hr ground and 2 hr UAV training was sufficient. Ground-measurement training must take place in the field; UAV training can take place beforehand, although some flight training in a tropical forest is recommended. ^bWe found it possible to survey three 1-ha plots, at two altitudes in a single day. To generate costs/ha, we have divided the daily accommodation/subsistence and field assistant costs by three.

ground surveys reduces plot-level values of percent liana infestation. Despite these differences between the ground- and UAV-based surveys, there was a strong positive relationship between their results for plot-level liana infestation. This suggests either method can be used to compare plot-level liana infestation rates across sites (cf. van der Heijden et al., 2010), provided that the same method is used.

The fine spatial resolution of UAV image data, combined with the top-of-the-canopy view, provides an enhanced perspective to study liana infestation. This makes UAVs particularly useful for silvicultural systems, where liana cutting is routinely performed for improving timber and fruit production (Kainer et al., 2014; Sist, Fimbel, Sheil, Nasi, & Chevillier, 2003; Verwer, Peña-Claros, Van Der Staak, Ohlson-Kiehn, & Sterck, 2008), and for forest management or restoration purposes, where liana cutting has been shown to regenerate biomass (Marshall et al., 2017). With UAVs, users can quickly, efficiently, and accurately pinpoint which trees or areas suffer from heavy liana infestation, and those at risk of heavy liana infestation in the future. This is feasible over much larger areas than normally possible with ground-based methods, enabling better targeting of management practices such as liana cutting, and saving time, effort, and money.

UAVs improve liana infestation assessment for canopy and emergent trees, compared to ground surveys (Table 2; Figure 4c,d; Supporting Information Appendix S3.4c,d). These tall trees store

and sequester the most carbon and are the main commercial species. Liana-induced changes in them may, therefore, be an important mechanism affecting forest-level and tree-level carbon storage and sequestration, for which UAVs represent a particularly useful management tool. Successful liana management may also help to increase timber and fruit productivity, and carbon storage and sequestration of degraded forests (van der Heijden et al., 2015). In particular, UAVs increased our ability to detect low-level liana infestation in these trees, which is particularly difficult from the ground as they are often partly obscured by shorter canopy trees (Table 3; Figure 4c,d). Although lianas exert limited effects at low levels (<50% crown coverage; for example Ingwell et al., 2010), identifying them quickly is important as infestation progression is likely as lianas utilize each other to climb into the tree crown (Putz, 1984), stressing the importance of repeated surveys of liana infestation.

Unmanned aerial vehicles answer this need, offering user-controlled deployment times, potential for high temporal frequency and an increased likelihood of recognizing low-level liana infestation (Table 2; Figure 4c,d). This allows for a flexible approach to liana management, tailoring it for trees or areas of forests at risk of heavy liana infestation. The new technique also facilitates monitoring and assessment of the success of management practices after they are put in place (Zahawi et al., 2015), including changing where management efforts are concentrated,

as spatial patterns of liana infestation change over time. It will also help track temporal changes, not only in liana infestation but also in wider canopy phenomena, such as tree crown shape and area, and timber, fruit, and forest-level biomass productivity and phenology, over shorter time-scales than is possible with ground-based surveys. The ability to track temporal changes enables investigation of the effects of short-term phenomena, such as drought events, on liana infestation and other processes in the canopy. The image data also represent an archive of detailed information about the forest canopy that allows (a) reproducibility, as people can check previous results; (b) additional metrics to be derived, for example, 3D models or digital elevation models (Supporting Information Appendix S2.5); (c) users to go back in time and measure variables that were not measured at the time but are later deemed important. For example, orangutan nests are clearly visible in our imagery (Supporting Information Appendix S3.5).

Advances in UAV technology and competitive price pressures are likely to improve the current UAV method and expand its applicability for forest management. We cannot specify at what resolution lianas (or other canopy phenomena) become indistinguishable (lianas remained clearly identifiable in our coarser spatial resolution images; Supporting Information Appendix S3.3), but the advent of newer UAVs with larger high-resolution image sensors, bright lenses, and zoom lens technology will enable even higher flights while retaining the ability to identify lianas, which may increase areal coverage (it is unlikely that this will be possible using satellite data in the next few decades). Further research could usefully investigate this for lianas, as well as for other canopy phenomena. The wide array of UAV platforms and sensors already available (Pajares, 2015) allows tailoring of system choice towards individual research and/or monitoring requirements. Additionally, rapid advances in the miniaturization of hyperspectral and LiDAR sensors increasingly enable them to be mounted on UAVs (Sankey, Donager, McVay, & Sankey, 2017) alongside RGB cameras and predicted future price drops will increase their accessibility. While RGB images allow visual species identification (Baena, Boyd, & Moat, 2018; Getzin, Wiegand, & Schöning, 2012), multispectral or hyperspectral sensors may allow this to be automated (Baena, Moat, Whaley, & Boyd, 2017; Sankey et al., 2018), further increasing the speed and ease of liana identification. Future work could test whether a suitably equipped UAV could automate mapping of liana infestation and changes in infestation similar to the approach adopted by Marvin et al. (2016) using airborne-collected data, but at much finer spatial and temporal resolutions, and at a small fraction of the cost. Also, as liana and tree species differ spectrally (e.g., Sánchez-Azofeifa et al., 2009), hyperspectral UAVs may help discern liana and tree species, supporting monitoring of tropical forest biodiversity, which is particularly important for the management of degraded forests (e.g., Marshall et al., 2017). With the emergence of a new platform and sensor capabilities, the opportunities for using UAVs in both liana, and canopy research more generally, will increase. Thus, the UAV method presented here offers a

wealth of opportunities for forest canopy research and monitoring, including liana monitoring, over space and time to assist with tailored management of tropical forests, and forms a firm foundation for exploiting future advances.

5 | CONCLUSIONS

The recent proliferation of lianas, coupled with their large impacts on the carbon balance and cycle of tropical forests, has made it important to study liana infestation of tree canopies more comprehensively and frequently than feasible with current methods. Here, we show, for the first time, how capturing RGB images of tree canopies via an inexpensive, lightweight UAV can be used accurately and efficiently to assess liana infestation and help make such data collection more accessible. Liana infestation data derived from UAV image data are at least as accurate as traditional ground data, and superior in assessing liana infestation of tree crowns in upper canopy layers, enabling future advances in liana and tropical forest ecology research. The support for frequent surveys, data archiving, wealth of additional data captured, and larger geographical extent covered will enable more detailed monitoring of liana infestation and forest canopies over space and time with the potential to revolutionize both liana and canopy research. These advantages will be enhanced by rapidly developing protocols for UAV use in science (Duffy et al., 2018) and the potential for additional sensors offered by UAV platforms. UAVs also provide potential for tailored and targeted liana management protocols to effectively manage liana infestation to aid restoration of degraded forests, silvicultural systems, and projects designed to increase carbon storage and sequestration in tropical forests.

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AUTHORS' CONTRIBUTIONS

C.E.W., G.M.F.v.d.H., R.F., and D.S.B. designed the research; C.E.W. performed UAV data capture and processing, analysed data, and wrote the paper; G.M.F.v.d.H. was responsible for ground data collections; all authors developed the analytical approach, contributed to manuscript revisions, and approved publication. This work is a component of C.E.W.'s PhD which is supervised by D.S.B. and R.F.

DATA ACCESSIBILITY

Data available via the Dryad Digital Repository <https://doi.org/10.5061/dryad.21t1805> (Waite, van der Heijden, Field, & Boyd, 2019).

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SUPPORTING INFORMATION

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