REVIEW

Grime Review: What can remote sensing do for plant ecology?

Making (remote) sense of lianas

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Abstract

1. Lianas (woody vines) are abundant and diverse, particularly in tropical ecosystems. Lianas use trees for structural support to reach the forest canopy, often putting leaves above their host tree. Thus they are major parts of many forest canopies. Yet, relatively little is known about distributions of lianas in tropical forest canopies, because studying those canopies is challenging. This knowledge gap is urgent to address because lianas compete strongly with trees, reduce forest carbon uptake and are thought to be increasing, at least in the Neotropics.

2. Lianas can be difficult to study using traditional field methods. Their pliable stems often twist and loop through the understorey, making it difficult to assess their structure and biomass, and the sizes and locations of their crowns. Furthermore, liana stems are commonly omitted from standard field surveys. Remote sensing of lianas can help overcome some of these obstacles and can provide critical insights into liana ecology, but to date there has been no systematic assessment of that contribution.

3. We review progress in studying liana ecology using ground-based, airborne and space-borne remote sensing in four key areas: (i) spatial and temporal distributions, (ii) structure and biomass, (iii) responses to environmental conditions and (iv) diversity. This demonstrates the great potential of remote sensing for rapid advances in our knowledge and understanding of liana ecology. We then look ahead, to the possibilities offered by new and future advances. We specifically consider the data requirements, the role of technological advances and the types of methods and experimental designs that should be prioritised.

4. *Synthesis.* The particular characteristics of the liana growth form make lianas difficult to study by ground-based field methods. However, remote sensing is well suited to collecting data on lianas. Our review shows that remote sensing is an emerging tool for the study of lianas, and will continue to improve with recent developments in sensor and platform technology. It is surprising, therefore, how little liana ecology research has utilised remote sensing to date—this should

rapidly change if urgent knowledge gaps are to be addressed. In short, liana ecology needs remote sensing.

KEYWORDS

forest canopies, global change ecology, lianas, remote sensing, tropical forests

1 | INTRODUCTION

Advances in remote sensing now allow the study of tropical forests at local, regional and global scales. Importantly, remote sensing enables the study of the difficult-to-access forest canopy layer. This helps quantify above-ground biomass and diversity (e.g. Asner et al., 2017; Saatchi et al., 2011), as well as responses of tropical forests to environmental change and human disturbances (e.g. Reiche, Verbesselt, Hoekman, & Herold, 2015; Wigneron et al., 2020). The vast majority of remote sensing research in tropical forests has focussed exclusively on trees (e.g. Gillespie, Foody, Rocchini, Giorgi, & Saatchi, 2008; Saatchi et al., 2011; Wigneron et al., 2020), which overlooks the fact that tropical forests contain many plant growth forms. For example, lianas (woody vines) commonly contribute 25% of the rooted woody stems and 35% of the woody plant species (Gentry, 1991; Schnitzer et al., 2012; Schnitzer & Bongers, 2002; van der Heijden, Schnitzer, Powers, & Phillips, 2013). They are a particularly common feature of tropical canopies (Chandler, van der Heijden, Boyd, Cutler, et al., 2010; Ingwell, Joseph Wright, Becklund, Hubbell, & Schnitzer, 2010; Waite, van der Heijden, Field, & Boyd, 2019).

Unlike trees, lianas are not self-supporting past their juvenile stage, and instead use the structure of adjacent trees to reach the forest canopy (Putz, 1984; Stevens, 1987). Due to their lack of self-supporting architecture, few lianas reach diameters greater than 10 cm (Schnitzer et al., 2012). However, their stem lengths can be very long, and most lianas ≥2 cm diameter have already reached the forest canopy (Kurzel, Schnitzer, & Carson, 2006). Moreover, lianas often support a large leaf area relative to their diameter (Hegarty & Caballé, 1991; Medina-Vega, Bongers, Schnitzer, & Sterck, 2021; Putz, 1983) and can contribute 40% of the forest leaf area (van der Heijden et al., 2013). Lianas therefore contribute disproportionately (relative to stem diameter) to forest canopy productivity and leaf area (van der Heijden et al., 2013; van der Heijden, Powers, & Schnitzer, 2015).

As liana–tree competition is often stronger than tree–tree competition (Tobin, Wright, Mangan, & Schnitzer, 2012), trees hosting lianas tend to experience reduced growth (van der Heijden & Phillips, 2009), increased mortality risk (Ingwell et al., 2010; Phillips et al., 2005) and reduced reproductive success (García León, Martínez Izquierdo, Mello, Powers, & Schnitzer, 2018). Lianas thereby negatively affect the forest carbon balance and cycle (van der Heijden et al., 2013, 2015) and ecosystem productivity (Meunier et al., 2022), as well as gap-phase regeneration and forest succession (Estrada-Villegas, Hall, Breugel, & Schnitzer, 2020; Schnitzer, Dalling, & Carson, 2000). However, lianas maintain faunal diversity and may contribute to complex trophic interactions in tropical

forests (Schnitzer, 2018). As lianas influence many ecosystem processes in tropical forests (Collins, Wright, & Wurzburger, 2016; Hättenschwiler, Tiunov, & Scheu, 2005; Reichstein, Bahn, Mahecha, Kattge, & Baldocchi, 2014), studying lianas is important. Such research not only provides further insight into lianas themselves, but also fundamentally improves our understanding of the functioning and diversity of the entire tropical ecosystem (Schnitzer, 2018).

The recent realisation that lianas are important contributors to tropical forest dynamics and processes highlights the need to develop methods for measuring and monitoring them. However, tropical forests are complex and often hard-to-access ecosystems, presenting numerous difficulties for field-based research (Balzotti, Petersen, Terry, Scherer, & Golden, 2010). Traditionally, liana-focussed studies have utilised time- and labour-intensive, field-based data collection methods that rely on human surveying from the ground (van der Heijden, Feldpausch, de la Herrero, van der Velden, & Phillips, 2010), usually in field plots. Although liana stem diameters can be measured accurately from the ground, limited visibility means that assessing liana occupancy in the canopy is exceedingly difficult and error-prone (Waite et al., 2019). In short, although the need for data on lianas is clear, the status quo on liana data capture does not meet this demand.

Remote sensing offers new solutions that can complement and expand upon ground-based field methods, providing data on lianas that have been previously obscured or unobserved. Remote sensing provides a synoptic view of tropical forests at greater spatial and temporal scales than ground-based measurements (Foody, 2003; Lechner, Foody, & Boyd, 2020) and allows measurements of the plant life forms within them (Calders et al., 2020). It also enables improved repeatability at lower operational cost per unit area (Carr & Slyder, 2018; Watts, Ambrosia, & Hinkley, 2012). Recent advances in both the spectral and spatial domains of airborne, space-borne and ground-based remote sensing may therefore offer critical insights into lianas' geography and levels of forest canopy infestation, and the changes in their canopy infestation over time. These are challenging with traditional ground-based measurements.

While liana ecology would benefit from remote sensing to meet pressing information needs, efforts to make remote sense of lianas are still limited in number (see Table 1). Furthermore, to date there has been no systematic assessment of how remote sensing can contribute to these needs. This review aims to (1) facilitate understanding of the possibilities and challenges to studying lianas offered by current and future remote sensing technology, and (2) outline how remote sensing can advance tropical forest ecology by elucidating the role of lianas in tropical forests. For simplicity, herein we make (remote) sense of lianas with respect to four main areas of liana

Sensor	Platform	Citation
UniSpec Spectral Analysis System (306–1138 nm @ <10 nm sampling)	Laboratory analysis	Castro-Esau, Sánchez-Azofeifa, and Caelli (2004)
UniSpec Spectral Analysis System (306–1138 nm @ <10 nm sampling)	Laboratory analysis	Guzmán and Sánchez-Azofeifa (2021)
1. UniSpec Spectral Analysis System (306–1138 nm @ <10 nm sampling); 2. Agilent 4100 ExoScan Fourier Transform Infra-Red (FTIR) spectrometer (8000–11,000 nm across 301 wavebands)	Laboratory analysis	Guzmán, Rivard, and Sánchez-Azofeifa (2018)
ASD FieldspecFR Spectrometer (350–2500 nm @ 1.4 nm sampling between 350 and 1050 nm and 2 nm between 1000 and 2500 nm)	Field Sampling by hand	Hesketh and Sánchez-Azofeifa (2012)
ASD FieldspecFR Spectrometer (350–2500 nm @ 1.4 nm sampling between 350 and 1050 nm and 2 nm between 1000 and 2500 nm)	Field sampling by hand	Kalacska, Bohlman, Sanchez-Azofeifa, Castro-Esau, and Caelli (2007)
Portable Spectrometer (400–1100 nm @ 10 nm sampling)	Field sampling by hand	Sánchez-Azofeifa et al. (2009)
RIEGLVZ400 terrestrial laser scanner (multiple return time-of-flight; narrow infrared laser beam @ 1550 nm)	Field sampling using tripod	Bao, Moorthy, and Verbeeck (2018)
RIEGLVZ400 terrestrial laser scanner (multiple return time-of-flight; narrow infrared laser beam @ 1550 nm)	Field sampling using tripod	Krishna Moorthy, Bao, Calders, Schnitzer, and Verbeeck (2019)
RIEGLVZ400 terrestrial laser scanner (multiple return time-of-flight; narrow infrared laser beam @ 1550 nm)	Field sampling using tripod	Krishna Moorthy, Raumonen, Van den Bulcke, Calders, and Verbeeck (2020)
UniSpec Spectral Analysis System (306–1138 nm @ <10 nm sampling)	Construction Crane	Sánchez-Azofeifa and Castro-Esau (2006)
Integrated three-waveband (RGB) high- quality Sony EXMOR 1/2.3″ 12- megapixel camera, with a narrow 94° field of view lens (35 mm format equivalent: 20 mm)	DJI Phantom 3 Advanced Quadcopter UAV	Waite et al. (2019)
Micasense RedEdge 3 camera with five wavebands (@ 475 nm; 560 nm; red 668 nm; 717 nm and 840 nm)	RotorKonzept® RK-8x multicopter UAV	Li, Campos-Vargas, Marzahn, and Sanchez-Azofeifa (2018)
1. Micasense RedEdge 3 camera with 5 wavebands (@ 475 nm; 560 nm; red 668 nm; 717 nm and 840 nm); 2. FLIR TAU® 2 FLIR 640 broadband camera (@ 7500 to 13,500 nm).	RotorKonzept® RK-8x multicopter UAV	Yuan, Laakso, Marzahn, and Sanchez-Azofeifa (2019)
1. Leica ALS50-II - 8 W class 4 laser with radiation at 1064 nm recording up to four discrete returns for each emitted pulse. Twenty-two centimetre pulse footprint and point density ranging between 2.80 and 3.16 per m^2; 2. Specim FENIX hyperspectral sensor (380–2500 nm), with 448 contiguous channels, sampled at (2.9 nm) in the visible-to-near infrared (VNIR) ranged from 380 to 970 nm with a spectral resolution of 3.5 nm; in the shortwave infrared (SWIR) spectra were sampled (5.7 nm) from 970 to 2500 nm with a spectral resolution of 12 nm	UK's Natural Environmental Research Council's Airborne Research Facility (NERC-ARF) Dornier 228–201 airplane, flying at 65.6–71.6 ms^{-1} at an altitude of 2335–2429 m	Chandler, van der Heijden, Boyd, Cutler, et al. (2021)

TABLE 1 (Continued)

Sensor	Platform	Citation
1. Full-spectral range (visible-to-shortwave infrared) imaging spectrometer spectral radiance in 481 contiguous channels spanning the 252–2648 nm wavelength range; 2. Visible-to-near infrared (VNIR) imaging spectrometer, The VNIR imaging spectrometer collects 288 contiguous spectral bands over a smaller range (365–1052 nm); 3. Full waveform light detection and ranging (LiDAR)—a dual laser, scanning waveform system capable of operating at 500,000 laser shots per second. The LiDAR point density was 2 shots m^{-2}	Carnegie Airborne Observatory (CAO) Airborne Taxonomic Mapping System (AToMS)	Marvin, Asner, and Schnitzer (2016)
1. Hyperion hyperspectral sensor (400–2500 nm) across 220 wavebands at a spatial resolution of 30 m; 2. ETM+ multispectral sensor with eight wavebands across 400–2400 nm and 10,700–12,700 nm and spatial resolutions of 15 m (panchromatic); 30 m (visible/NIR/SWIR) and 60 m (thermal)	1. EO-1 satellite 2. Landsat-7 satellite	Foster, Townsend, and Zganjar (2008)
TM multispectral sensor with seven spectral bands across 450–2350 nm and 1040–1250 nm and spatial resolutions of 30 m in the reflective bands and 120 m in the thermal band	Landsat-5 satellite	Tymen et al. (2016)
Multispectral Instrument (MSI) hyperspectral sensor with 13 wavebands across 443–2190 nm) and spatial resolutions of 10, 20 and 60 m	Sentinel-2 satellite	Chandler, van der Heijden, Boyd, & Foody (2021)

ecology: (i) spatial and temporal liana distributions; (ii) liana structure and biomass; (iii) responses of lianas to environmental conditions; and (iv) liana species diversity. Measuring and monitoring these four areas can be largely achieved by airborne and space-borne sensors. Remote sensing can also be performed below the canopy (e.g. from the forest floor); this can be linked to the above-canopy view to better understand the distribution of lianas throughout all the forest strata (Figure 1).

2 | SPATIAL AND TEMPORAL DISTRIBUTIONS OF LIANAS

2.1 | Why use remote sensing?

Liana distributions vary considerably between forests, both within and among continents (DeWalt et al., 2015; DeWalt et al., 2010; Gentry, 1991; Schnitzer, 2005; van der Heijden & Phillips, 2008, 2009). Similarly, although lianas have proliferated across the Neotropics (Phillips et al., 2002; Schnitzer & Bongers, 2011), there is some evidence that this may not be a universal trend across the tropics (Bongers, Ewango, Sande, & Poorter, 2020; Schnitzer & Bongers, 2011; Wright, Sun, Pickering, Fletcher, & Chen, 2015). We know very little about current trends in liana abundance through

time across the tropics. The drivers responsible for changes in liana abundance are also largely unknown, although several putative mechanisms have been put forward (Parolari et al., 2020; Schnitzer & Bongers, 2011).

It is important to know what drives spatial and temporal variation in liana distribution because lianas reduce the ability of both mature and secondary tropical forests to absorb and store carbon (Estrada-Villegas et al., 2020; Tymen et al., 2016; van der Heijden & Phillips, 2009; van der Heijden et al., 2015; van der Heijden, Powers, & Schnitzer, 2019). These liana-induced changes in the carbon balance of tropical forests probably differ across forests, so we need data both within forests and across the tropics. For example, liana–tree competition is greatest in younger forests (Estrada-Villegas et al., 2020) and may depend on liana abundance (Durán & Gianoli, 2013). Increasing our knowledge about what drives spatial and temporal distributions in liana abundance across tropical forests will therefore improve our understanding of liana ecology and biogeography. Changes in liana abundance may have a knock-on effect on the carbon sink function of tropical forests, with potentially important ramifications for global change (van der Heijden et al., 2015). So better data on lianas will also help us generalise about liana-induced effects on the carbon dynamics of tropical forests.

Our knowledge of liana distributions comes from rather few field-based liana studies with limited spatial coverage and
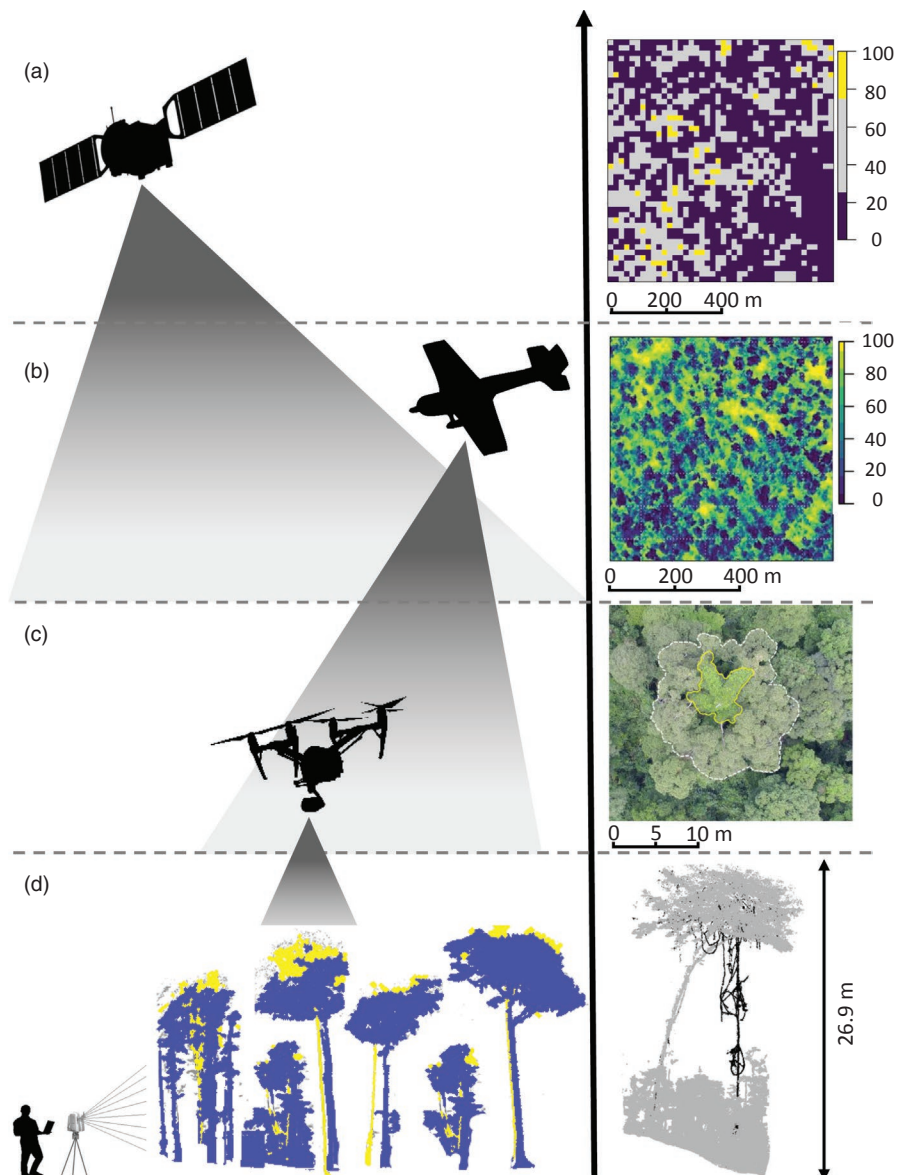
FIGURE 1 To make remote sense of lianas, different combinations of sensors and platforms are (to be) used. For example: Spatial and temporal liana distributions (section 2) can benefit from Sentinel-2 satellite data (Chandler, van der Heijden, Boyd, & Foody, 2021; see panel [a]) and airborne hyper-spectral and LiDAR data (e.g. Chandler, van der Heijden, Boyd, Cutler, et al., 2021; see [b]). Insight into liana species diversity (section 5) may come from UAV data (e.g. Waite et al., 2019; see [c]). For liana structure and biomass measures (section 3), terrestrial laser scanning (e.g. Krishna Moorthy et al., 2020; see [d]) is useful. For understanding responses of lianas to environmental conditions (section 4) a proximal sensor mounted on a pole or work using a field spectroradiometer may provide suitable data—See (d). The examples given here are not exhaustive; selection of suitable remote sensing approaches will be determined by underpinning data available, access to relevant technologies and method and experimental design

relatively long census intervals (e.g. Ingwell et al., 2010; Wright et al., 2015). This information is biased, focussing predominantly on large lianas (≥ 10 cm diameter; Phillips et al., 2002) and the Neotropics (Phillips et al., 2002; van der Heijden & Phillips, 2008). These data limitations also restrict our ability to understand the effects of lianas on tropical forest functioning. Disturbance history (via Landsat; Pflugmacher, Cohen, & Kennedy, 2012) and drought (via metrics like standardised precipitation evaporation index [SPEI]; Marín, Julio, Dante Arturo, & Daniel Jose, 2018) can be remotely sensed. Together with other environmental variables, these can be correlated with spatial or temporal changes in liana abundance. Using remote sensing to map and monitor lianas over much broader geographical scales, including across environmental gradients and forest types, and with higher temporal frequency, than is currently possible with field-based studies alone, is therefore key for advancing liana ecology.

2.2 | Current remote sensing progress

Some excellent progress to facilitate remote sensing of spatial and temporal liana distributions has been made over the last decade. One important advance is in the ability to discriminate lianas from trees. The ability of the sensors to detect liana infestation in the forest canopy determines the feasibility of utilising the contiguous and frequent coverage afforded by remote sensors, especially those that are space-borne. In particular, the view from above must have sufficiently fine spatial resolution. Several studies have now indicated that lianas can indeed be differentiated from trees in the spectral domain. Despite some overlap between liana and tree spectra, most studies indicate that liana leaves, on average, have higher reflectance around 550 nm (green) and 2500 nm (short-wave infrared; SWIR), and present more distinctive peaks and troughs than trees in the medium and longwave infrared region (MLWIR: 3000–14,000 nm). Meanwhile, trees may have higher reflectance in the

near infrared (NIR: 800–1200 nm) (Castro-Esau et al., 2004; Guzmán & Sanchez-Azofeifa, 2021; Guzmán et al., 2018; Hesketh & Sánchez-Azofeifa, 2012; Kalacska et al., 2007; Sánchez-Azofeifa et al., 2011; Sánchez-Azofeifa & Castro-Esau, 2006; Figure 2a, b). Most of these leaf-level differences remain discernible at the canopy scale, which allows differentiation between liana-infested and liana-free trees in remotely sensed imagery (Chandler, van der Heijden, Boyd, Cutler, et al., 2021; Marvin et al., 2016; Figure 2c).

The differences in tree and liana spectral response have been used to provide landscape-scale maps of liana presence in tree canopies based on differences in spectral reflectance between liana-free and liana-infested tree canopies. By combining hyperspectral data and LiDAR data from an airborne sensor within a machine learning framework, high liana presence could be accurately mapped in the forest canopy of seasonally dry forests (Marvin et al., 2016). This can also be done in aseasonal forests where spectral properties of liana and tree leaves tend to converge (Avalos, Mulkey, & Kitajima, 1999; Chandler, van der Heijden, Boyd, Cutler, et al., 2021). The latter is particularly important as it indicates the potential to estimate liana abundance in tropical forests world-wide (Chandler, van der Heijden, Boyd, Cutler, et al., 2021) and should enable landscape-scale comparisons of liana infestation across different forest landscapes. However, more subtle differences in liana infestation have so far proved more difficult to discern (Marvin et al., 2016; Chandler, van der Heijden, Boyd, Cutler, et al., 2021). Multispectral or hyperspectral data may also assist in assessing the drivers of spatial distribution of liana infestation on the landscape scale by using variables such as disturbance, forest structural and topographical measures as predictor variables (cf. Marvin et al., 2016). With repeated sampling, the rates of change in liana abundance across large swaths of tropical forests can be assessed, and insights gained into the potential drivers.

Opportunities for measuring liana presence and degree of liana infestation have arisen through the recent proliferation of unoccupied aerial vehicle (UAV) or drone technology, one of the more affordable and accessible remote sensing platforms. Lianas have been successfully detected in forest canopies and gaps by using UAVs fitted with standard cameras because of the ultra-fine resolution, down to centimetre, of the imagery obtained (Waite et al., 2019). Using visible to NIR (Li et al., 2018) and thermal sensors (Yuan et al., 2019) has also proved successful. Waite et al. (2019) went beyond detecting liana presence in tree canopies, also assessing the degree of liana infestation in tree canopies. Although the spatial extent over which UAV technology can be used for monitoring liana presence is limited, its main advantages lie in its capacity for high-frequency deployment to monitor temporal changes in liana infestation, its utility during cloudy conditions (by flying under the clouds) and its usefulness in calibrating the imagery acquired by airborne and satellite sensors.

Whereas both occupied and unoccupied airborne sensors have the potential to provide fine resolution imagery to detect liana presence and abundance, they are realistically limited to landscape-scale studies (<10,000 km^2). At larger scales (e.g. regional, continental, global), satellites remain the only platform with the capacity for comprehensive and temporally frequent assessment of liana infestation. Given the relatively coarse resolution, only a few studies have used satellite data to identify liana infestation and assess temporal patterns in liana infestation (e.g. Foster et al., 2008 – EO-1 Hyperion and Landsat TM and ETM+, Tymen et al., 2016 – Landsat TM). These studies were either based on dry season images and/or limited to detecting liana-dominated patches. It is unclear whether these techniques can feasibly be transferred to assess liana infestation across broad geographical scales. In an exploratory study, Chandler, van der Heijden, Boyd & Foody (2021) demonstrated that liana infestation was positively related to Sentinel-2 MSI greenness (at 10 m spatial resolution) across primary and selectively logged aseasonal forest of Sabah, Borneo. Given the temporal frequency afforded by the constellation of Sentinel-2 satellites (and other constellation systems with similarly fine spatial resolutions, e.g. PlanetScope, Pléiades

FIGURE 2 Characteristic reflectance spectra: (a) visible (VIS) to near-infrared (NIR) to short-wave infrared (SWIR; adapted from Kalacska et al., 2007) reflectance of liana and tree leaves; (b) mid- to long-wave infrared (MLWIR; adapted from Guzmán & Sanchez-Azofeifa, 2021) of liana and tree leaves; (c) VIS–NIR-SWIR reflectance for liana-infested (≥75% crown covered by lianas) and liana-free tree crowns (adapted from Chandler, van der Heijden, Boyd, Cutler, et al., 2021). Black arrows in (a) indicate the areas where literature indicates there is greatest spectral separability between liana (orange lines) and tree (blue lines) leaves
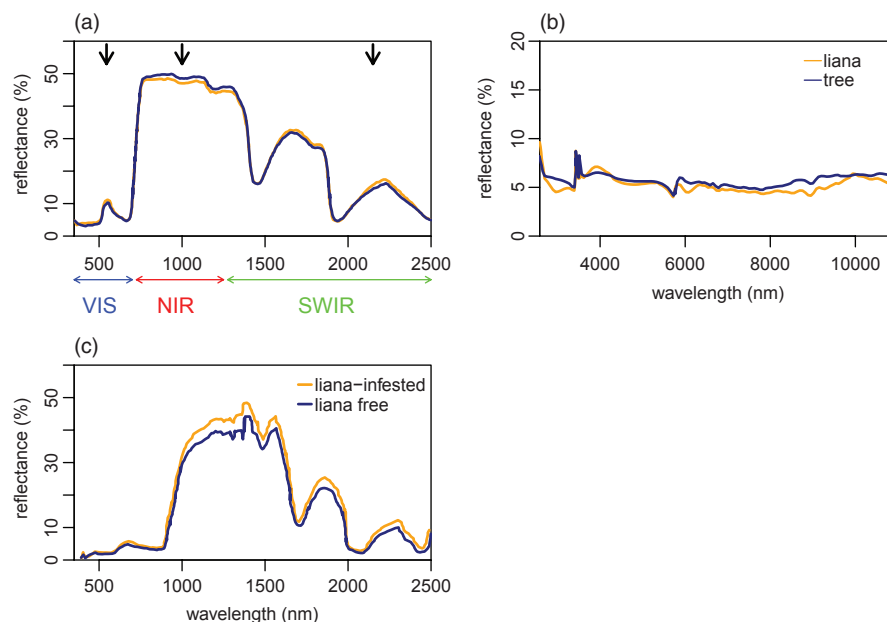
Neo), this bodes well for monitoring infestation across regions and continents in the future. Importantly, it improves the chances of cloud-free data at desired repeat rates, for example, prior to, within and after an ENSO event.

2.3 | Remote sensing challenges and aspirations

To measure liana distributions over time and space, cutting-edge space-borne systems with improved spatial resolution, coupled with enhanced spectral and radiometric resolution, are essential. The coarse resolution of many freely available satellite datasets, such as Landsat and Sentinel-2, can be problematic as one single pixel may be occupied by multiple tree crowns. In a single pixel, the liana spectral signal itself may be unclear because liana infestation can be patchy and a single tree crown can be infested by multiple liana species. Furthermore, forests growing in different environmental regimes have different reflectance; this makes it harder to detect liana infestation over larger geographical scales, especially if differences in reflectance between liana-infested and non-infested pixels are smaller than differences between forest types. For this purpose, textural and contextual information can be important sources of information beyond the spectral (Mather & Koch, 2011). Cloud-free satellite data from tropical forests can be also difficult to obtain (Foster et al., 2008; Tymen et al., 2016), which may limit the ability to assess changes in liana infestation, depending on the temporal resolution of the system.

Despite this set of challenges, several satellite sensor developments hold promise for improved liana detection. These include hyperspectral missions such as DESIS and PRISMA. Others on the horizon promise routine capture of hyperspectral data (e.g. https://news.satnews.com/2021/03/18/pixxel-to-build-worlds-highest-resolution-hyperspectral-satellite-array/) and capture of thermal emission from canopies at a much finer spatial resolution than currently (e.g. from Landsat TIRS, Terra ASTER). These tend to be commercial satellites (e.g. Satellite Vu - https://www.satellitevu.com/), so they would need substantial investment to be used at the continental scales for which they would bring most benefit to liana ecology (https://news.mongabay.com/2020/09/new-partnership-brings-high-resolution-satellite-imagery-of-the-tropics-to-all/). Nonetheless, these could be used locally to use spectral data across the spectrum, at high spatial resolution: (i) for measuring liana infestation, (ii) for monitoring areas of known liana infestation to better understand their dynamics and function and iii) to serve as a data input for scaling from plots to other satellites. Occupied and unoccupied platforms carrying a suite of sensors would also be useful here. NASA Goddard's G-LiHT—an airborne system with LiDAR, Hyperspectral and Thermal Imaging (Cook et al., 2013)—is one such example and was designed to simultaneously estimate biochemical and structural data from forests.

To improve liana detection from remotely sensed data, a critical component is appropriate ground truthing data. We need to expand the underpinning data on liana distributions, both geographically and temporally. The key challenge is how to do this efficiently and, for optimal impact, within a framework that enables data sharing for mutual collaboration between all involved. Existing plot networks and initiatives could be used for this purpose. Currently, the only exclusively liana-focussed plot network is the Global Liana Database (DeWalt et al., 2015). In addition, some tree-focussed networks contain standardised liana measurements across plots, such as stems ≥10 cm (e.g. Phillips et al., 2002) or crown occupancy index (e.g. van der Heijden et al., 2010). These include ForestGEO (Davies et al., 2021) and ForestPlots.net (2021). Although these plots are often used to support remote sensing studies (e.g. Marselis et al., 2020), even plots as large as 50 ha may be too small for airborne and satellite-based remote sensing (Réjou-Méchain et al., 2014). Additional investigation to determine standards for appropriate plot sizes and/or shapes for liana and tree censuses would, therefore, be beneficial.

3 | LIANA STRUCTURE AND BIOMASS

3.1 | Why use remote sensing?

To better understand the role that lianas play in the carbon balance and cycle of tropical forests, we must be able to accurately quantify liana biomass. The negative effects of lianas on tree above-ground biomass and biomass growth in tropical forests are well-established (van der Heijden et al., 2013, 2015). However, evidence that lianas themselves do not offset all the displacement of tree carbon that they cause (van der Heijden et al., 2013) is generally based on both assumptions of liana biomass allocation patterns and liana allometric models to calculate liana biomass and biomass change.

Our ability to accurately quantify the contribution of lianas to above-ground biomass and biomass change in forests is constrained by the limited number of studies investigating liana allometry (Addo-Fordjour & Rahmad, 2013a, 2013b; Gehring, Park, & Denich, 2004; Schnitzer, DeWalt, & Chave, 2006). Liana biomass estimates diverge considerably, depending on the allometric model used (Miao, Koerner, Medjibe, & Poulsen, 2016). The estimates are usually based on small numbers of liana stems, and hence only sparsely replicate across species, and include very limited numbers of large lianas (Schnitzer et al., 2006). The large variation in liana allometric models between studies may also indicate that liana allometry and biomass allocation patterns change with species identity, climate, edaphic conditions, disturbance history and/or forest type (Schnitzer et al., 2006; Smith-Martin, Xu, Medvigy, Schnitzer, & Powers, 2020).

Lianas are often assumed to allocate more biomass to leaves than to stems (Castellanos, Mooney, Bullock, Jones, & Robichaux, 1989; Putz, 1983; van der Heijden et al., 2015, 2019; Wyka, Oleksyn, Karolewski, & Schnitzer, 2013). However, recent research has indicated that lianas may invest proportionally as much biomass in stems as trees do by making up what they miss in stem diameter by extended stem length (Smith-Martin et al., 2020). The relationship between diameter and biomass may therefore not be as strong

for lianas as it is for trees (Krishna Moorthy et al., 2020; Schnitzer et al., 2006; Figure 3b). Consequently, above-ground liana biomass estimates based on diameter measurements may be subject to considerable error. Due to the complex growth form of lianas (Figure 3), liana length is much more difficult to measure in the field than liana diameter. However, to accurately quantify the contributions of lianas to forest biomass, and to fully understand the role of lianas in forest processes, we urgently need more information on liana structure and biomass allocation patterns from a range of forests world-wide. This plays to the strengths of remote sensing technologies and methods, because they can more directly measure liana biomass.

3.2 | Contribution of remote sensing—Current progress and aspirations

Terrestrial laser scanning (TLS) can be used to measure structural parameters such as height, diameter, above-ground wood volume and leaf area index (LAI) from LiDAR-derived 3D point clouds (Atkins et al., 2018; Béland, Baldocchi, Widlowski, Fournier, & Verstraete, 2014; Calders et al., 2015; Strahler et al., 2008). This remote sensing technique has advanced swiftly in the last decade (Calders et al., 2020; Dassot, Constant, & Fournier, 2011; Owen,

Flynn, & Lines, 2021; Richardson, Monika Moskal, & Bakker, 2014). Although the use of this technology to study lianas has lagged behind that for trees (Krishna Moorthy et al., 2019), TLS now enables us to distinguish liana stems from trees in point cloud data with great precision and accuracy (Bao et al., 2018; Krishna Moorthy et al., 2019). Thus, TLS is progressing the study of liana allometry and quantification of liana biomass (Krishna Moorthy et al., 2020). Liana extraction from co-registered point clouds is still challenging (Krishna Moorthy et al., 2019), but work in French Guiana has shown that by obtaining detailed information on liana structure below the canopy, TLS methods may provide more accurate liana biomass estimations than traditional field-based methods (Krishna Moorthy et al., 2020).

A TLS-based methodology, in combination with a machine learning-based algorithm to semi-automatically extract liana woody points from plot-level TLS data, could facilitate long-term, reliable monitoring of liana wood volume. This would enhance understanding of the dynamics of plot-based liana infestation, structure and biomass (Krishna Moorthy et al., 2019; Krishna Moorthy et al., 2020). Currently, the main problem with TLS data is that occlusion prevents detection of smaller liana structures, such as small branches or leaves, in the forest canopy. However, combining TLS data with top-of-the canopy measures from airborne or UAV platforms to assess liana leaf area has the potential to assess the
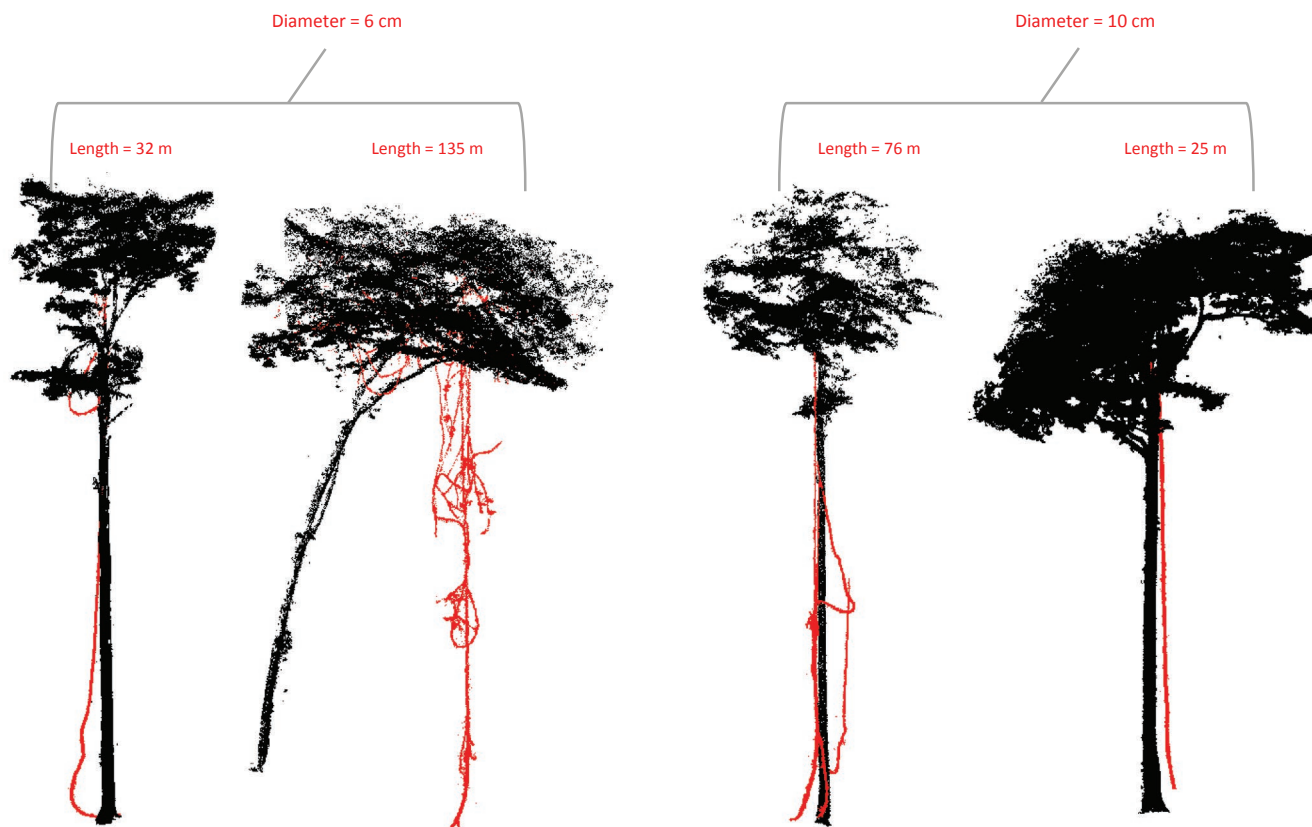

FIGURE 3 TLS imagery of four lianas from Nourages, French Guiana, having similar diameters (6 or 10 cm), but exhibiting different structures, length and biomass, which illustrates the complex and variable growth form of lianas compared to trees (adapted from Krishna-Moorthi et al. 2020). Please note, although the liana infesting tree 4 is shorter compared to the liana in tree 3, its higher wood density, slightly larger diameter and slower taper results in it having a higher biomass

complete above-ground liana structure. This could be an invaluable tool to comprehensively investigate allometric scaling relationships in lianas (cf. Krishna-Moorthy et al. 2020). It would enable us, for example, to include both diameter and length (or length only) in allometric relationships to calculate liana biomass.

4 | LIANA RESPONSES TO ENVIRONMENTAL CONDITIONS

4.1 | Why use remote sensing?

Our understanding of how lianas respond to their environment has increased over the last few decades. However, there are two main areas where our understanding is still lacking, but which are important to understand and predict how changing environmental conditions may affect lianas in the future. The first concerns the response of lianas to elevated atmospheric CO_2 conditions, which is one of the hypotheses for the observed liana proliferation (e.g. Schnitzer & Bongers, 2011). Although some CO_2 enrichment experiments have shown a strong response of lianas to elevated CO_2 (Granados & Körner, 2002; Marvin, Winter, Burnham, & Schnitzer, 2015; Zotz, Cueni, & Korner, 2006), not all studies have shown a stronger effect for lianas than trees (e.g. Marvin et al., 2015). Furthermore, if lianas are not proliferating in the Palaeotropics (we are not yet sure), then the role of CO_2 may be limited, or may be offset by other mechanisms regionally. How lianas respond to elevated CO_2 concentrations, whether their response is different from trees, and whether this could be a direct driver of liana proliferation in some parts of the tropics, are therefore questions in need of further research.

The second area concerns the role of water stress. Climate change is expected to increase this in many parts of the tropics, and numerous studies have shown that lianas grow well during periods of prolonged water stress (Cai, Schnitzer, & Bongers, 2009; Chen et al., 2015; Maréchaux, Bartlett, Iribar, Sack, & Chave, 2017; Schnitzer & van der Heijden, 2019; van der Heijden et al., 2019; Zhu & Cao, 2010). Lianas may deal with drought by tapping into deeper water sources (e.g. Chen et al., 2015; Holbrook & Putz, 1996) or by efficiently capturing any precipitation in the dry season (De Deurwaerder et al., 2018; Smith-Martin et al., 2020). They may also reach maximum photosynthesis early in the day, and then close their stomata to prevent water loss during the hottest parts of the day (Schnitzer, 2018). However, the exact strategies employed by lianas to thrive during periods of drought stress remain unknown. Similarly, the limits to the water stress advantage to lianas are not clear—some types of drought conditions may favour lianas while others may not.

To assess such liana responses to environmental conditions, and to compare them with co-occurring trees, often needs monitoring of many individuals with high temporal frequency. Remote sensing, which allows routine measurements, including in areas of restricted access, offers huge promise.

4.2 | Contribution of remote sensing—Current progress and aspirations

Responses to water stress and CO_2 are evident in the leaf spectral reflectance (Chemura, Mutanga, & Dube, 2017; Chou et al., 2017; Gray, Dermody, & Delucia, 2010; Ihuoma & Madramootoo, 2019; Nunes et al., 2019; Figure 2a). Indeed, hyperspectral remote sensing is showing promise for estimating photosynthesis in periods of stress (Barnes et al., 2017). The use of proximal sensors to record frequent spectral information above the forest canopy could provide information on the timing of water uptake and photosynthesis. Furthermore, high-resolution hyperspectral (visible through to thermal wavelengths) data can be used to monitor, for example, evapotranspiration of lianas and trees in drought and free air CO_2 enrichment (FACE) experiments in which lianas are present, or during natural phenomena such as El Nino events (e.g. van der Heijden et al., 2019). This allows us to investigate whether lianas and trees differ in their responses to environmental change. Combining data on liana growth, survival, reproduction, recruitment and leaf phenology with data from remote sensing could therefore prove essential in understanding which environmental conditions favour lianas over trees.

Building up remote sensing capability in the already-running experimental plots that feature lianas (serendipitously or otherwise) would be extremely beneficial. Data from networks of sensors can be combined with the detailed ground measurements already being made. As part of this, we can build understanding of optimal scaling methods and any links between remotely sensed responses observed below the canopy and above the canopy. Protocols for remotely sensed measurements of lianas can be developed (in the same way as for other metrics and traits of forests, e.g. Duncanson et al., 2021). These can be combined with research to harness the potential for liana ecology of upcoming, novel space-borne systems (e.g. FLEX (Drusch et al., 2017), EnMAP (Guanter et al., 2015), Zhuhai-1 (Jiang et al., 2019) and GEDI (Dubayah et al., 2020)).

5 | LIANA SPECIES DIVERSITY

5.1 | Why use remote sensing?

A key challenge in ecology is to increase our understanding of the mechanisms behind the broad-scale species distributions and composition (Schnitzer, 2018). However, we still know little about what controls liana species diversity and composition across space and time. Most of what we know comes from small plot-based studies (many 0.1 ha), several larger plots of up to 50 ha (DeWalt et al., 2010; Gentry, 1991; Schnitzer et al., 2012) and field occurrence collections (Meyer, Kissling, Lohmann, Hortal, & Diniz-Filho, 2020). However, the spatial coverage of these studies is limited and studies focussing on temporal patterns of liana diversity and composition are still scarce (Caballé & Martin, 2001; Swaine & Grace, 2007). With global warming driving pronounced changes in both climatic conditions

and disturbance across the tropics (Garcia, Cabeza, Rahbek, & Araujo, 2014), investigating the responses of liana species to these changes is crucial if we are to predict future liana species distributions. Furthermore, we do not yet know whether the liana proliferation observed in Neotropical forests is consistent across taxa, or instead driven by the proliferation of certain taxa only. Including lianas in biodiversity mapping would also aid conservation efforts: despite their importance for forest composition and diversity, lianas are still typically overlooked in management, conservation and restoration actions. If liana species do diverge in their response to changing environmental conditions, phylogenetic differences in liana communities may help explain the different rates of liana proliferation across the world (Schnitzer & Bongers, 2011).

Plot-based studies are limited in the extent to which they can meet these research needs. Field identification of lianas is often difficult and time-consuming, as fruits and flowers of lianas, which are often needed for identification, are typically high up in the forest canopy. Furthermore, most liana species are locally rare (e.g. Mascaro, Schnitzer, & Carson, 2004), and therefore absent from relatively small field plots. Remote sensing offers the potential for wall-to-wall assessments, and for those to be repeated quite frequently. The view of the top of the canopy makes species identification from flowers and fruits feasible, given sufficient image resolution. Remote sensing technologies would therefore enable liana diversity mapping across the landscape and over time, leading to a step-change in our understanding of the contribution of lianas to plant diversity in the tropics.

5.2 | Contribution of remote sensing—Current progress and aspirations

Remote sensing technologies, in combination with machine learning algorithms, have been used to map tree species richness and composition, and also distributions of individual tree species in tropical forest canopies, mainly based on differences in spectral patterns (e.g. Féret & Asner, 2012; Ferreira, Wagner, Aragão, Shimabukuro, & de Souza Filho, 2019; Foody & Cutler, 2006). There is some evidence that liana species can be differentiated from each other, as well as from tree species, based on their spectral reflectance (Hesketh & Sánchez-Azofeifa, 2012). However, there have, so far, been no attempts to use remote sensing to either map liana diversity or identify liana species. Reasons include the difficulties of reliably distinguishing tree from liana leaves in the forest canopy, and of differentiating between liana species—multiple liana species can be present in the crown of a single tree.

Building an accessible database of foliar reflectance spectra of the most abundant liana species would allow us to assess whether lianas species can be uniquely identified by their spectra, and which aspects of those spectra are phylogenetically conserved (e.g. Meireles et al., 2020). Both would aid in measuring liana diversity and forest-level species diversity. Our current knowledge on spectral properties of lianas comes mainly from deploying field-based

instrumentation within forests (e.g. as per Nunes et al., 2019 on trees), destructively sampling to enable laboratory-based measurements (Asner & Martin, 2012) and extracting spectra from airborne hyperspectral instrumentation (Chandler, van der Heijden, Boyd, Cutler, et al., 2021; Marvin et al., 2016). In the latter, the extracted spectra are often not linked to specific liana species, so are of limited use. Overall, spectral knowledge across liana species is currently lacking. Existing spectral libraries, such as the ECOSTRESS spectral library (https://speclib.jpl.nasa.gov/; Meerdink et al., 2019), the EcoSIS database (https://ecosis.org/) and the USGS spectral library (Kokaly et al., 2017), do not contain any liana species and only a very limited number of tropical tree species. Furthermore, many leaf and canopy traits vary systematically among plant groups in relation to life history and leaf phenology, but this variation may be small in comparison to the large variability due to interspecific, intraspecific, phenotypic and ontogenetic differences within natural vegetation (Detto & Xu, 2020; Werden et al., 2018; Wu et al., 2018). Thus, enhancing the knowledge base of spectral responses of both lianas and trees is a research priority.

We can improve and tailor the design of liana-specific remote-sensing platforms and sensors. This is best done iteratively, as we develop our knowledge of liana diversity and liana structural and functional properties. In some cases, specific liana/tree assemblages may be discerned at specific wavelength combinations, and thus inform custom-built systems—either for proximal or airborne/spaceborne sensing. This approach is common at European flux sites, where the goal is to fuse eddy covariance and tower-based optical measurements (Balzarolo et al., 2011). The optical measurements are made by multi- or hyperspectral systems, which incorporate discrete wavebands, each sensitive to a specific vegetation parameter. Existing systems, such as the Cropscan and Cimel radiometers, could be adapted and customised, or novel sensors produced to be able to detect and differentiate between liana species (e.g. use of light emitting diodes for monitoring vegetation reflectance in narrow spectral bands—Ryu et al., 2010). The manufacture of remote sensing systems is becoming ever more democratised through expansion in capability and access to UAVs, cubesats, etc (Baena et al., 2018; Santilli et al., 2018). This should enable us to adapt existing technologies for detecting lianas in general, or liana species specifically. Increasing spectral data will also allow radiative transfer modelling, which will help to increase our understanding of what might be possible using remote sensing (Meunier et al., 2020; Visser et al., unpublished data). This would guide next steps in a much more informed fashion.

6 | SO, CAN WE MAKE REMOTE SENSE OF LIANAS?

The short answer is not quite yet. The long answer is more nuanced. We argue that current remote sensing capability should play a key role in liana ecology, and this will be enhanced by future developments. Remote sensing will help fill many of the knowledge gaps in liana ecology by enabling research at unprecedented spatial and

temporal scales, and in detail. However, we have also indicated where the use of remote sensing in liana ecology requires further technological innovations, methods and experimental design or underpinning field-based data. In particular, three principal sets of underpinning data are required for advancing remote sensing of lianas: (i) spectral reflectance data for a wide range of liana species; and field-based measurements of (ii) liana traits, such as leaf and wood traits, and (iii) liana abundance, diameter and species identity across sites. Additionally, various types of remotely sensed baseline data would be useful; for example, there are very few TLS data on trees infested with lianas.

The slow but important increase in capture of tropical forest by ultra-fine resolution remote sensing technologies, such as TLS and UAVs, still mostly relies on visual interpretation of the data to extract meaningful metrics relating to liana ecology. Sharing of these datasets would be beneficial, and would aid development of computational methods for more automated extraction of liana metrics. These data are required to train models of the interactions between the liana property of interest and the remote sensing data being used. Once these models are established, they can be applied to produce liana data across the rest of the remotely sensed datasets used. If the models are fully calibrated, extrapolation can be achieved beyond the time periods and locations used for model training.

This review focusses on four key areas of liana ecology, but as our understanding of the ecological systems within which lianas thrive increases, this will also open up novel possibilities for use of remote sensing to improve our understanding of liana ecology. For example, a role for radar systems is not immediately obvious at present. However, ground-penetrating radar (e.g. Zou et al., 2020) may prove useful for understanding the effects of lianas on belowground processes, of which little is currently known. We expect that the ability to accurately map liana abundance over time, in combination with future missions to estimate biomass in tropical forests (e.g. BIOMASS - Quegan et al., 2019), will be particularly useful for understanding the effects of lianas on forest structure and biomass. In turn, such studies could inform liana ecology directly. Furthermore, improvements in identifying tree and liana species using remote sensing will enable monitoring of liana-driven changes in forest species composition. Understanding of all these liana impacts is essential for better predicting the fate of tropical forests, their diversity and their carbon balance in a changing climate.

Efforts to overcome current constraints need liana ecologists and remote sensing experts to collaborate to make (remote) sense of both lianas and tropical forests as a whole. In the long term, determining the optimal remote sensing approaches for liana ecology will need innovation in methods to extract the required information from the data and understand its quality, in conjunction with appropriate experimental designs to collect underpinning ground data. This requires developments in areas such as pattern recognition, data fusion and super-resolution analyses (e.g. Kaya et al., 2019; Ling et al., 2020). Recent advances in spatial data science using machine learning and deep learning algorithms (Ma et al., 2019), and mechanistic models (e.g. Meunier et al., 2020), offer new opportunities to improve existing methods and develop new ones specifically for liana ecology. However, we should not underestimate the challenges involved. For example, some of the machine learning methods are data hungry and require data that we still do not have, while the more black-box methods are challenging to interpret (Rudin, 2019). Nonetheless, as the number of studies using remote sensing for liana ecology increases, these techniques may help improve transferability to other contexts of models developed for particular climatic conditions and floristic compositions (e.g. Foody, Boyd, & Cutler, 2003). If all this were accomplished, might there be a call for a liana ecology-specific satellite sensor? This would be a major leap forward from regarding lianas as an impediment to remote sensing of tropical forests, benefitting not only liana ecology but also the general field of tropical ecology.

It is fair to say that, to date, remote sensing of tropical forests has mainly ignored lianas. This is problematic because lianas affect forest dynamics and can respond differently than trees to changes environmental conditions (e.g. Schnitzer et al., 2000; van der Heijden et al., 2019); and the presence of lianas may alter the signal of the forest being remotely sensed (e.g. Chandler, van der Heijden, Boyd, Cutler, et al., 2021; Figure 2). In turn, lianas may distort efforts to remotely sense tropical forests, leading to potentially large measurement error in the biophysical parameters of trees, given that the ground data used to validate remote sensing data have tended not to take lianas into account. Satellite-observed changes in spectral reflectance in response to climatic changes (e.g. Saleska, Didan, Huete, & Da Rocha, 2007) may therefore be complicated (cf. Anderson et al., 2010) by the differential responses of lianas and trees. Given that lianas are here to stay, we hope this review prompts much needed activity within a new sub-field of remote sensing, or is it ecology.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest.

AUTHORS' CONTRIBUTIONS

D.S.B and G.M.F.vdH. conceived the idea. D.S.B., G.M.F.vdH. and A.D.C.P. wrote the manuscript with critical contributions from all other authors. A.D.C.P. is a MRes student supervised by G.M.F.vdH. and D.S.B. and this work forms part of his MRes thesis.

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DATA AVAILABILITY STATEMENT

This study does not include or use any data.

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