Monitoring restored tropical forest diversity and structure through UAVborne hyperspectral and lidar fusion

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1 Monitoring restored tropical forest diversity and structure through UAV-borne 2 hyperspectral and lidar fusion

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- 54 ABSTRACT
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56 Remote sensors, onboard orbital platforms, aircraft, or unmanned aerial vehicles (UAVs) have 57 emerged as a promising technology to enhance our understanding of changes in ecosystem 58 composition, structure, and function of forests, offering multi-scale monitoring of forest 59 restoration. UAV systems can generate high-resolution images that provide accurate 60 information on forest ecosystems to aid decision-making in restoration projects. However, 61 UAV technological advances have outpaced practical application; thus, we explored combining 62 UAV-borne lidar and hyperspectral data to evaluate the diversity and structure of restoration 63 plantings. We developed novel analytical approaches to assess twelve 13-year-old restoration 64 plots experimentally established with 20, 60 or 120 native tree species in the Brazilian Atlantic Forest. We assessed (1) the congruence and complementarity of lidar and hyperspectral-65 derived variables, (2) their ability to distinguish tree richness levels and (3) their ability to 66 67 predict aboveground biomass (AGB). We analyzed three structural attributes derived from lidar 68 data-canopy height, leaf area index (LAI), and understory LAI-and eighteen variables 69 derived from hyperspectral data-15 vegetation indices (VIs), two components of the 70 minimum noise fraction (related to spectral composition) and the spectral angle (related to 71 spectral variability). We found that VIs were positively correlated with LAI for low LAI values, 72 but stabilized for LAI greater than 2 m²/m². LAI and structural VIs increased with increasing 73 species richness, and hyperspectral variability was significantly related to species richness. 74 While lidar-derived canopy height better predicted AGB than hyperspectral-derived VIs, it was 75 the fusion of UAV-borne hyperspectral and lidar data that allowed effective co-monitoring of 76 both forest structural attributes and tree diversity in restoration plantings. Furthermore, 77 considering lidar and hyperspectral data together more broadly supported the expectations of 78 biodiversity theory, showing that diversity enhanced biomass capture and canopy functional 79 attributes in restoration. The use of UAV-borne remote sensors can play an essential role during

- 80 the UN Decade of Ecosystem Restoration, which requires detailed forest monitoring on an
- 81 unprecedented scale.
- 82
- 83 Keywords: forest landscape restoration, tropical forests, drones, lidar remote sensing,
- 84 hyperspectral remote sensing, leaf area density, vegetation indices

1. INTRODUCTION

87 An ambitious restoration agenda has been set to increase forest cover in deforested and 88 degraded landscapes, to improve their multifunctionality and capacity to provide essential 89 ecosystem services, such as maintaining biodiversity, water supply and carbon storage 90 (Erbaugh & Oldekop 2018). Forest monitoring will play a crucial role to track the success of 91 these goals and also support adaptive management (Brancalion & Holl 2020; Fagan et al. 2020), 92 given the widespread failures in ecosystem restoration and the unprecedented scale of 93 restoration pledges (Versluijs et al. 2019; Chagas et al. 2020). Currently, there is a pressing 94 need to develop social collaborative and effective technologies for monitoring ecosystem 95 recovery over large areas (hundreds to millions of hectares) using multiple key ecological indicators (Guariguata & Evans 2020; Höhl et al. 2020). Remote sensors onboard orbital 96 97 platforms, aircraft, or unmanned aerial vehicles (UAVs) have emerged as promising 98 technologies to upscale forest restoration monitoring. Particularly, UAV systems can generate 99 high-resolution images that provide accurate information on forest stands with or without the 100 need for ground-based data (e.g., calibration or validation) to estimate important forest 101 attributes such as the number of trees, aboveground biomass, or canopy openness (Almeida et 102 al. 2020a, Kotivuori et al. 2020; Ferreira et al. 2020).

103 Accurate methods to estimate forest attributes to support decision-making are required 104 for the effective remote monitoring of forests undergoing restoration (Almeida et al. 2019a). 105 For example, forest cover, biomass stock and tree species diversity vary along forest 106 successional sequences and are commonly employed to monitor forest restoration (Wortley et 107 al. 2013). To this aim, multispectral sensors have proven useful, offering estimates of these 108 critical variables. However, a high leaf area index (LAI) saturates most vegetation indices (VIs) 109 derived from remote sensing (Turner et al. 1999). This saturation complicates their use to 110 monitor structural attributes (such as aboveground biomass - AGB) in high-LAI tropical 111 forests, which account for a large portion of global restoration commitments (Timothy et al. 112 2016, Crouzeilles et al. 2019). On the other hand, the light detection and ranging (lidar) sensor 113 has been hailed as a promising technology for retrieving forest canopy structural attributes, 114 regardless of canopy leaf area density. Lidar enables the estimation of canopy structural 115 attributes with high precision and accuracy, such as vegetation density in the understory, LAI, 116 tree height, the identification and measurement of forest gaps, and AGB (Almeida et al. 2019b, 117 da Costa et al. 2020, Valbuena et al. 2020, Dalagnol et al. 2021). On the other hand, lidar 118 technology is of limited use for assessing tree species diversity, for which hyperspectral has 119 shown greater potential (Asner & Martin 2009).

120 Assessing the different facets of forest diversity, such as tree richness, functional 121 diversity, and composition, is one of the most important but challenging modern remote sensing 122 tasks (Asner et al. 2015). With lidar, one approach is to use canopy structural attributes as 123 predictive variables for indirectly estimating tree species diversity (Hernández-Stefanoni et al. 124 2014, Ali et al. 2019, De Cáceres et al. 2019, Adhikari et al. 2020). Notably, a more species-125 rich forest is expected to have a more heterogeneous and complex canopy structure (Zellweger 126 et al. 2019, Mensah et al. 2020). Secondary forests with higher biomass are expected to have 127 reached a later stage of succession, supporting more tree species (Gamfeldt et al. 2013, Lasky 128 et al. 2014, Finegan et al. 2015, Poorter et al. 2015). However, structure-richness relationships 129 are not ubiquitous and depend on a wide range of factors, such as forest type, management, use 130 and disturbance history. Consequently, the lidar approach has so far demonstrated a limited 131 ability for local scale prediction of species richness, especially in hyper-diverse tropical biomes 132 (Marselis et al. 2020, Almeida et al. 2019a, Valbuena et al. 2020).

Hyperspectral imaging (HSI) has a significant potential for estimating or measuring
taxonomical and functional diversity of highly diverse tropical forests (Feret & Asner 2014;
Vaglio Laurin et al. 2016; Durán et al. 2019). HSI measures reflected radiation from the forest

136 canopy over hundreds of narrow spectral bands (or channels) within the visible- to short-wave 137 infrared wavelength range (VSWIR, 400-2500 nm). The rationale for using hyperspectral 138 sensors to discriminate species-richness is that each species (or group of species) has specific 139 combinations of spectral features. These include absorption by specific chemical constituents 140 of leaves and non-photosynthetic elements and scattering driven by vegetation structure at 141 different scales, such as leaf anatomy, leaf area index, leaf angle distribution function (Ferreira 142 et al. 2016). However, this combination of spectral traits does not necessarily result in a unique 143 species-specific spectral identity (and thus perfect discrimination among species), as significant 144 intraspecific variability in spectral traits was evidenced (Amaral et al. 2018; Camarretta et al. 145 2020). For example, a single species' spectral characteristics can vary widely depending on 146 environmental variables (e.g., water availability) or species and community attributes (e.g., leaf 147 amount and leaf age) (Yan et al. 2018; Ferreira et al. 2019; Gonçalves et al. 2020). Another 148 rationale is that the spectral heterogeneity is related to tree species diversity and composition 149 (Rocchini et al. 2010; Féret and Asner, 2014; Asner et al. 2017; Laliberté et al. 2020). HSI also 150 enables linking canopy reflectance to biophysical and chemical properties using various 151 approaches, including narrow-band vegetation indices, which are designed to be used as 152 proxies for both structural (e.g., vegetation density) and physiological (e.g., leaf chemical 153 composition and water stress) properties (Zhao et al. 2018).

Using HSI data to study species diversity or the retrieval of canopy chemical properties is still challenging, particularly in tropical ecosystems due to their high biodiversity and structural complexity (Féret and Asner 2013). HSI data acquisition with airborne surveys is usually costly, planning intensive, and may be operationally prohibitive in places with poor infrastructure and resources, such as in some tropical forest regions. Conversely, restoration practitioners face the challenges of monitoring tree diversity in tropical forest regions (Crouzeilles et al. 2019), given the difficulty of properly identifying hundreds of tree species and the reduced accessibility of restoration areas for forest inventories (Keil et al. 2019). As
 restoration programs are usually composed of several small to mid-size polygons scattered
 across large and heterogeneous areas, airborne surveys are less viable.

164 Recent technological developments have allowed for manufacturing UAV-compatible 165 HSI sensors, a promising approach to mainstreaming the common use of HSI in tropical forest 166 restoration monitoring. UAVs are a technological frontier of remote sensing data acquisition 167 and may constitute an alternative to high-cost airborne hyperspectral and lidar campaigns. The 168 use of UAV-borne remote sensors, both lidar and HSI, nonetheless presents pros and cons. The 169 main advantage is the higher spatial resolution. Point cloud density from airborne lidar usually 170 ranges between 0.4 and 30 points per m² (ppm²), whereas UAV lidar acquisitions can reach 171 100-1000 ppm² (d'Oliveira et al. 2020; Prata et al. 2020). The high point density increases the 172 accuracy of estimating structural parameters, such as vertical profiles of leaf area density 173 (Almeida et al. 2019c). It can even allow the individualization of trees and measurement of 174 stem volume in open-canopy forests such as eucalyptus plantations (Corte et al. 2020) and 175 temperate forests (Krůček et al. 2020). For UAV-HSI, the centimetric resolution of the pixels 176 allows a better characterization of target objects, detecting vegetation-free patches, removing 177 background contribution, and capturing the spectral variability within and among crowns. 178 Conversely, flight instability of the UAV, changing view and illumination geometry and 179 changing sky conditions make the use of these images challenging. HSI reflectance retrievals 180 from UAVs require a matched incident radiance HSI sensor and non-trivial pre-processing 181 steps, including corrections for bidirectional reflectance distribution function (BRDF) and atmospheric effects (Jia et al. 2020). 182

183 To date, few investigations have assessed the potential of UAV-lidar-HSI systems in 184 tropical forest monitoring. Sankey et al. (2017) and Lin et al. (2019) used UAV-lidar-HSI 185 systems to monitor semi-arid and pine forests, respectively. Here, we explored the fusion of 186 UAV-borne lidar and hyperspectral data to remotely access the structure and diversity of 187 restored tropical forests. We developed a novel analytical approach for a mixed-species, 13-188 year-old restoration plantation experimentally established with 20, 60, and 120 native tree 189 species in the Brazilian Atlantic Forest. Specifically, we assessed (1) the congruence of lidar 190 and hyperspectral variables, (2) their usefulness to distinguish tree species richness levels, and 191 (3) their ability to predict aboveground biomass. Our work goes well beyond traditional 192 measurements based on sampling plots, providing high-accuracy and precision information for 193 upscaling field variables to satellite-based hyperspectral and lidar observations, representing 194 an effective strategy for large-scale forest restoration monitoring during the United Nations 195 Decade on Ecosystem Restoration (2021-2030).

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2. METHODS

2.1. Experimental site and field data

202 We used an experimental mixed-species restoration plantation with three diversity 203 levels to explore the potential and limitations of fusing UAV-borne lidar and hyperspectral data 204 to assess structure and diversity. The experimental plots were established in May 2006 in 205 Anhembi-SP, southeastern Brazil, in a completely randomized design with 20, 60, and 120 206 native tree species (hereafter sp.), each with four replicates, in 45 x 48 m plots. The area was 207 previously covered by pastures, with no regeneration of native tree species. Tree seedlings were 208 randomly planted with 3 x 1.5 m spacing and ensuring a homogeneous density across species. 209 The species pool present in the treatments with the lowest richness was contained in the 210 treatments with higher richness, i.e., species of the treatment of 20 species are contained in the 211 treatment of 60 species, which are also contained in the treatment of 120 species. Extensive 212 information on the study site and experiment is provided by Duarte et al. (2021). Due to the 213 low coverage of HSI in one plot, the treatment of 120 species had only three replicates for the 214 analysis using HSI data. Forest inventory field data were collected in November 2019, when 215 the plantation was 13.5 years old. At this time, 58 and 114 species had survived in the 60- and 120 species treatments, respectively. For all living stems, we identified the tree species in this 216 217 inventory, measured diameter 30 cm above the ground and measured total height. We used the 218 allometric equation developed by Ferez et al. (2015) for a neighboring restoration plantation to 219 estimate aboveground woody biomass of each individual (equation 1). Wood densities were 220 obtained for all tree species based on wood discs (cross-sections from the stem) sampled in 221 destructive plots established, using three individuals per species (see Ferez, 2012 for more 222 details).

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$$\ln(AGB_W) = 6.039 + 0.945 \times \ln(SA) + 0.961 \times \ln(Ht) + 1.022 \times \ln(\rho)$$
 (1)
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226 Where: AGBw = Aboveground woody biomass (Mg/ha); SA: sectional area of the stem (m²);

227 Ht: total height (m); ρ = wood density (g/cm³).

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- **Figure 1** Study area and plot designs. Left) site location; upper right) sample design and lidar
- point cloud example of one plot; bottom right) hyperspectral image colored by a false RGB
- composition using the first components from the minimum noise fraction transformation.

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234 2.2. UAV-borne lidar and hyperspectral data

Data were collected using the GatorEye Unmanned Flying Laboratory, consisting of a hardware system with custom algorithm workflows incorporating lidar, hyperspectral, thermal, and visual (RGB) sensors. The hardware and processing workflows are described in detail in the GatorEye overview manuscript (Broadbent et al. 2021) available at <u>www.gatoreye.org</u>. The data is also available under the section "2019 Brazil Sao Paulo State August/082819".

241 The system uses a DJI Matrice 600 Pro hexacopter platform, with mission planning 242 conducted using Universal Ground Control Station (UGCS) software. GNSS base station data 243 are collected within 3 km of data collection areas, then post-processed online via the Trimble 244 CenterPoint RTX platform, providing typically < 2cm 3D uncertainty within a 2-hour 245 collection period (and < 0.25 cm within 4+ hour collections). The computational sensor core is based on a Phoenix Ultra Scout, a Novatel STIM 300 IMU tactical grade and differential GNSS 246 247 system. Integrated into this is a (a) Velodyne VLP-32c Ultra Puck LiDAR sensor, (b) Nano VNIR Hyperspectral Headwall sensor (640 pixels x 270 spectral bands in a 100-hertz line scan 248 249 approach), (c) high-resolution RGB camera, (d) radiometric thermal camera, and (e) time-250 synchronized downwelling hyperspectral Ocean Optics Flame (upward viewing spectrometer, 251 400-1025nm wavelength range, and 1.70 nm spectral resolution) (Figure S1). See Broadbent 252 et al. (2021) for more details.

The Velodyne Ultra Puck sensor features 32 individuals 905 nm lasers, situated to provide a 360° horizontal (cross-track) and 40° vertical (along-track) field of view. The Ultra Puck fires 600,000 times per second, recording for each pulse the strongest and the last (dual) return, for a theoretical points/sec of 1,200,000 at a range of up to 200 meters. The Headwall Photonics Nano VNIR 270 spectral band lab-calibrated radiance hyperspectral sensor acquires 1400 spectral bands from 400-1000 nm every 0.5 seconds and allows conversion of radiance to reflectance by ratioing with the spectral bands most similar in wavelength from the upward-facing Ocean Optics Flame sensor (Broadbent et al. 2021).

261 The GatorEye overflew the experimental area 27-30 Aug of 2019 at approximately 262 solar noon at an aboveground mean altitude of 100 meters. The local solar zenith angle was 32 263 degrees at solar noon (based on the date 28 Aug 2019, lat, long = -22.75, -48.11). Four flight 264 lines were acquired to cover the majority of plots. The speed was 12-14 m/s, resulting in a 265 forward pitch of approximately 12 degrees during flight. Acquisitions were performed under 266 clear sky conditions with no atmospheric haze. The specific lidar and hyperspectral GatorEye 267 deliverables used in this study were: (a) the Canopy Height Model (CHM), (b) the cleaned lidar 268 point cloud, and (c) the 'reflectance-calibrated hyperspectral shade-filtered orthomosaic' (e.g., 269 HSI image).

Lidar flight lines were processed to standard products using the GatorEye Multi-scalar Post-Processing workflow -- using the software Lastools (Isenburg, 2020) and "lidR" R package (Roussel & Auty, 2019). This procedure automatically merges flight lines, classifies ground points and removes noise -- to generate the cleaned point clouds and the rasters DTM (digital terrain model), DSM (digital surface model) and CHM. More details are given in Almeida et al. (2019b and 2020). The point density of the final lidar point cloud was 360 ± 137 (mean \pm *SD*) ppm², of which 80.4% were first returns.

Hyperspectral data were processed in three steps. (1) The non-orthorectified timesynchronized lab-calibrated radiance data from the downward-facing boresighted Nano hyperspectral camera was projected onto the DSM from the lens using a ray-tracing algorithm. (2) The radiance bands were then converted to reflectance using the also time-synchronized and lab-calibrated upward-facing Flame hyperspectral irradiance sensor. (3) The shade was removed through a separate process where solar geometry was calculated and then applied, through a ray tracing algorithm (Broadbent et al. 2021), to map portions of the DSM to be 284 either in full sunlight or in the shade at the moment of data acquisition. Shaded pixels were 285 masked in the final hyperspectral reflectance orthomosaic. Hyperspectral images are 286 orthorectified onto the lidar derived digital surface models using a custom ray tracing workflow 287 (Broadbent et al. 2021). The spatial resolution of the final HSI image was 0.20 m. We 288 performed additional filtering on the hyperspectral data using a 0.20 m moving window filter across the CHM to remove pixels with a height below four meters. This filtering enabled us to 289 290 restrict the spectral data to vegetation targets when estimating tree species compositional values 291 versus being dominated by the ground level exposed soil spectra which greatly differ from 292 vegetation.

The bidirectional reflectance distribution function (BRDF) describes the variations in reflectance or radiance intensity measured by a sensor as a function of (1) the angle of separation of two vectors - view and illumination - and of (2) forward-scatter (viewing toward the sun) and backscatter (sun behind the viewer). In remotely sensed imagery, BRDF significantly impacts the retrieval of biophysical surface properties (Wanner et al. 1995). We corrected the HSI orthomosaic for BRDF effects using a kernel-driven approach. More details can be found in the Supplementary Material.

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2.3. Data processing and analysis

Post-deliverables data processing was performed in the R environment (R Core Team 2020). Three structural attributes were derived from lidar data: canopy height, leaf area index - LAI, and leaf area index in the understory - LAI.under. (Table 1). At the plot level, we calculated the mean canopy height and its heterogeneity (standard deviation). The canopy height was obtained directly from the CHM (0.20 m resolution). To calculate canopy height, the cloud pulse density was not filtered to a standard density, ensuring the highest accuracy. Nonetheless, Silva et al. (2017) have shown that the accuracy of canopy height estimate in 311 Amazon forests stabilizes when pulse density reaches 4 ppm². The LAI (1m resolution) was 312 calculated from the leaf area density (LAD) estimated using the lad.voxels function from the 313 "leafR" package (Almeida et al. 2019d). The LAI is the sum of the entire LAD vertical profile, 314 and the LAI understory is the sum of the LAD vertical profile between 1-5 meters in height. 315 To improve the accuracy of the LAD estimates and remove lidar pulse density bias, the 316 normalized lidar cloud was filtered to first returns only and then homogenized to 30 ppm² 317 before the LAD calculation. Almeida et al. (2019c) found that higher pulse densities result in 318 higher LAI estimates in tropical forests. While this bias is small when pulse densities exceed 319 20 ppm², for all LAI and LAD estimates we elected to standardize to 30 ppm² using a 320 homogenizing filter. The method used to estimate the LAD uses the MacArthur-Horn equation 321 (MacArthur and Horn 1969) and is based on the Beer-Lambert law, i.e., the attenuation of the 322 energy transmission rate (lidar pulses) between the canopy vertical strata. See Almeida et al. 323 (2019c) for more details.

A total of 18 variables derived from HSI data were calculated (Table 1): 15 vegetation indices (VIs), the first two components of the minimum noise fraction (MNF) transformation (related to spectral composition), and the spectral angle (related to spectral variability). VIs were divided into four categories: (i) Structural, (ii) Chlorophyll, (iii) Anthocyanin / Carotenoid, and (iv) Physiology. MNF is a linear transformation of the original HSI data that applies two cascaded PCA and maximizes the signal/noise ratio (Green et al. 1988). We performed MNF using ENVI software version 5.3.

To assess if species diversity is related to canopy spectral diversity, we computed the spectral angle between all pairwise combinations of the pixels of each treatment. The spectral angle (θ) is a suitable measure of the spectral variability (Richer et al. 2016; Ferreira et al. 2018), and was computed as follows, according to Price (1994):

$$\theta = \cos^{-1} \left(\frac{\int_{\lambda_a}^{\lambda_b} X(\lambda) Y(\lambda) d\lambda}{\left[\int_{\lambda_a}^{\lambda_b} X(\lambda)^2 d\lambda \right]^{1/2} \left[\int_{\lambda_a}^{\lambda_b} Y(\lambda)^2 d\lambda \right]^{1/2}} \right)$$
(2)

where θ is the spectral angle, measured in radians, between the spectral reflectance of the pixel X and the pixel Y in the spectral interval λ_a to λ_b , i.e., 400 to 1000 nm. The spectral angle was computed with sunlit foliated canopy pixels that were selected using NDVI >0.8 and canopy height >4m. We used sunlit foliated canopy pixels to avoid the influence of non-photosynthetic canopy elements (e.g., branches) in the quantification of spectral diversity. Non-photosynthetic vegetation causes variations in the spectral amplitude, that is, brightness differences that may increase the spectral variability even if the spectral shapes were the same.

Table 1. Variables and their respective descriptions and references. "ρ" indicates reflectance
 of a hyperspectral band, followed by its wavelength center in nanometers.

	Variable	Description	Reference
Field-derived	Aboveground biomass - AGB (Kg)	Equation 1	Ferez et al. 2015
ved	Canopy structural attribute		
eri	Canopy height - CH (m)	Mean of canopy height model	Almeida et al. 2019b
ar-c	Leaf area index - LAI	Sum of leaf area density profile	Almeida et al. 2019c
Lida	LAI understory - LAI.under	Sum of leaf area density profile (1-5 m)	Almeida et al. 2019b
	Structural VIs		
	Vegetation Atmospherically Resistant Index (VARI)	ρ (ρ557 - ρ643) / (ρ557 + ρ643 - ρ465)	Gitelson et al. 2002a
	Simple Ratio (SR)	ρ865 / ρ672	Jordan et al. 1969
	Normalized Difference Vegetation Index (NDVI)	(ρ865 - ρ672) / (ρ865 + ρ672)	Rouse et al. 1974
	Enhanced Vegetation Index (EVI)	$2.5\times((\rho865$ - $\rho672)/(\rho865$ + $6\times\rho672$ - $7.5\times\rho464$ +	1 Huete et al. 2002
	Chorophyll VIs		
	Structurally Insensitive Pigment Index (SIPI)	(p800 - p445) / (p800 + p680)	Peñuelas 1995
	Chlorophyll Absorption in Reflectance Index (CARI)(ρ700 - ρ670) - 0.2 × (ρ700 - ρ550)	Kim (1994)
	Chlorophyll Red-Edge Index (CI.rededge)	ρ851 / ρ730 - 1	Gitelson et al. 2006
	Chlorophyll Green Index (CI.green)	ρ730 / ρ531 - 1	Gitelson et al. 2006
	Anthocyanin VIs		
HSI-derived	Modified Anthocynanin Reflectance Index (mARI)	(1 / ρ551) - (1 / ρ701)	Gitelson et al. 2006
	Anthocyanin Content Index (ACI)	ρ531 / ρ941	van den Berg and Perkins 2005
	Carotenoid VI		
	Carotenoid Reflectance Index (CRI)	(1 / ρ511) - (1 / ρ551)	Gitelson et al. 2007
	Physiology VIs		
	Photochemical Reflectance Index (PRI)	(ρ531 - ρ571) / (ρ531 + ρ571))	Gamon et al. 1997
	Red-edge Vegetation Stress Index (RVSI)	(p712 + p753) / 2 - p733)	Merton et al. 1999
	Red edge position (REP)	Max first derivative: 680-750 nm	Horler et al. 1983
	Water Band index (WBI)	ρ900 / ρΧ970)	Peñuelas et al. 1997
	Spectral composition		
	MNF.1	First component of minimal noise fraction	Green et al. 1988
	MNF.2	Second component of minimal noise fraction	Green et al. 1988
	Spectral heterogeneity		
	Spectral angle	Equation 2	Price 1994

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We used Spearman's correlation diagram to assess the relationship between the VIs 351 (HSI-derived) and the canopy structural variables (lidar-derived). This analysis was performed 352 at the pixel level (0.20 m resolution). The variables AGB (field-derived) and spectral angle 353 (HSI-derived) were evaluated at the plot level. For comparing the spectral angle, only the 354 highest spectral angles of each plot (percentile 90%) were considered. This ensures that the test 355 assesses the most significant differences within the plots. To determine the relationship of the variables with the tree species richness levels (treatments), we performed ANOVA and post-356 357 hoc Tukey tests (plot-level analysis). For these analyses, we considered the variables' mean 358 value and standard deviation within the plots, and the latter was used to describe the 359 heterogeneity of each variable within plots. Finally, the predictive power of AGB from lidar 360 and HSI variables was evaluated using simple and multiple ordinary least square regressions. 361 To identify and eliminate outliers, we used t tests based on studentized residuals implemented 362 using the function outlier.test in R package "car" (Fox & Weisberg, 2019). The assessment of 363 model accuracy was performed by a leave-one-out cross-validation (LOOCV) procedure 364 (Almeida et al. 2020a). The relationship between the observed and predicted (via LOOCV) 365 values were evaluated by testing their 1:1 correspondence under the null hypothesis that their regression intercept and slope were 0 and 1, respectively (Valbuena et al. 2017). 366

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3. **RESULTS**

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3.1. Variables derived from lidar and HSI

373 Lidar-derived LAI was significantly correlated with almost all HSI-derived variables at 374 the pixel level (Fig. 2). The structural VIs (HSI-derived) had the highest correlations with LAI 375 (r > 0.50, p-values < 0.05). In general, structural VIs increased between LAI values ranging from 376 0 to 2, but then saturated (Fig. 3). The canopy height attribute CH (lidar-derived) was 377 significantly correlated with seven HSI-derived variables (Fig. 2), with EVI being the VI 378 variable with the highest correlation (r = 0.22, p-value = 0.006). The EVI and the other 379 structural VIs all showed a positive correlation with CH for values ranging from 5 to 15 m, but 380 they stabilized or decreased for CH values within 15-20 m (Fig. 3). The lidar-derived 381 understory LAI (LAI.under) showed no significant correlation with any of the HSI-derived 382 variables.

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Figure 2 - Spearman's correlation diagram among the lidar- and hyperspectral-derived variables. The correlation values are ranked using a color gradient from -1 to 1, where 0 means no correlation, -1 a strong negative correlation (red color), and one a strong positive correlation (blue color). The *p*-value significance levels are "*" 0.05, "**" 0.01, and "***" 0.001. Acronyms of variables are described in Table 1.

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Figure 3 - Standardized hyperspectral-derived structural vegetation indices (Vegetation Atmospherically Resistant Index - VARI, Simple Ratio - SR, Normalized Difference
Vegetation Index - NDVI, and Enhanced Vegetation Index - EVI) as a function of lidar-derived
leaf area index (LAI) (left) and lidar-derived canopy height (CH) (right). Lines are the
smoothed mean of the observations (pixels of 0.20 m resolution).

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3.2. Distinguishing tree species richness levels

The 20 sp. treatment had lower field-derived AGB (mean \pm *SE*, 69.5 \pm 10.4 Mg/ha) than the 60 sp. treatment (94.3 \pm 9.8 Mg/ha), whereas the 120 sp. treatment had intermediate (88.7 \pm 15.6 Mg/ha) AGB and did not differ statistically from the other two treatments (Table 2). However, when changing the significance level to 0.1 (instead of 0.05), the two treatments with the highest species richness (60 and 120 sp.) showed higher AGB than the treatment with the lowest species richness (20 sp.).

The CH (lidar-derived) was higher in the two species-richer treatments (60 and 120 sp.) (Table 2). However, the CH heterogeneity did not significantly differ between richness levels (Table S1, p-value = 0.59). The richest treatment had the highest LAI value, and when considering the significance level at 0.1, a significant increase in LAI was verified with the increase in species richness class. The LAI heterogeneity was higher in the two richest treatments (Table S1, p-value < 0.001). LAI.under showed no difference among richness levels (Table 2 and Fig. 5). The vertical distribution of the LAD was mono-modal, with a higher 417 concentration of vegetation in the middle layer of the canopy for all three treatments (Figure418 4).

419 For the HSI-derived VIs, the structural VIs (VARI, SR, NDVI, and EVI) increased with 420 increasing richness (Table 2), and in some of them (VARI and NDVI), the heterogeneity was 421 lower in the 120 sp. treatment (Table S1, p-values <0.05). For the VIs related to chlorophyll 422 concentration, SIPI decreased with increasing richness (SIPI is inversely proportional to 423 chlorophyll concentration), while CI.rededge and CI.green increased with increasing species richness. The CARI VI showed no significant difference among richness treatments. For the 424 425 VIs related to the anthocyanin concentration, the mARI has no significant difference, although 426 its heterogeneity was greater in the richest treatment. ACI was lower in the lowest richness 427 treatment. The VI related to carotenoid concentration, CRI, was higher in the richest treatment 428 (with a significant gradual increase at the 0.1 significance level).

429 For the physiological VIs, RVSI decreased with the increase in richness, while the REP 430 showed a directly proportional relationship with the increase in richness. WBI presented no 431 significant difference, and PRI did not show a clear relationship with richness levels. The 432 composition variable MNF.1 increased its mean and heterogeneity proportionally with richness 433 (Table 2 and Table S1). The MNF.2 did not show any significant difference between 434 treatments. Spectral variation increases with increasing richness (Fig. 5). The spectral angle, a 435 proxy for the spectral diversity, showed a significant difference with richness levels only when 436 the significance of 0.1 was considered (p-value = 0.09).

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439**Table 2** - Statistical analysis (mean \pm SE; ANOVA post hoc Tukey) of field, lidar, and440hyperspectral (HSI) variables by plot comparing diversity level treatments (20, 60, and 120441sp.). Lidar and hyperspectral variables were summarized by the mean of the pixels (0.20 m442resolution). The significant variables were colored green ranging from the lowest (light green)443to the highest (dark green) values.

Туре	Variable	20sp	60sp	120sp	p-value
Field	AGB	$69.459\pm10.409~\textbf{b}$	94.253 ± 9.736 a	$88.698 \pm 15.55 \text{ ab}$	0.043
	СН	$10.331\pm1.029~\textbf{b}$	12.77 ± 1.098 a	12.993 ± 0.973 a	0.01
Lidar	LAI	$1.063\pm0.149~\textbf{b}$	$1.711\pm0.139~\textbf{b}$	$2.639\pm0.589~\text{a}$	0.001
	LAI.under	0.074 ± 0.007	0.092 ± 0.017	0.08 ± 0.014	0.223
	VARI	0.11 ± 0.023 c	$0.167\pm0.016~\textbf{b}$	0.248 ± 0.003 a	< 0.001
	SR	7.728 ± 0.882 c	$9.931\pm0.94~\textbf{b}$	12.987 ± 0.395 a	< 0.001
Structural	NDVI	0.722 ± 0.024 c	$0.776\pm0.02~\mathbf{b}$	0.835 ± 0.007 a	< 0.001
	EVI	$0.436\pm0.009~\boldsymbol{b}$	$0.496 \pm 0.03 \ \textbf{ab}$	$0.534\pm0.048~\textbf{a}$	0.008
	SIPI	1.118 ± 0.017 a	$1.078\pm0.012~\textbf{b}$	1.042 ± 0.004 c	< 0.001
	CARI	0.027 ± 0.001	0.028 ± 0.002	0.027 ± 0.005	0.612
Chlorophyll	CI.rededge	$0.504\pm0.038~\textbf{b}$	$0.556\pm0.023~ab$	$0.622\pm0.038~a$	0.005
	CI.green	$3.226\pm0.179~\textbf{c}$	$3.719\pm0.239~\textbf{b}$	4.313 ± 0.082 a	< 0.001
	mARI	1.691 ± 0.079	1.78 ± 0.143	1.798 ± 0.071	0.381
Anth/Caro	ACI	0.193 ± 0.014 a	$0.166\pm0.011~\textbf{b}$	$0.143\pm0.004~\textbf{b}$	0.001
	CRI	$12.574\pm1.672~\textbf{b}$	$15.327\pm1.834~\textbf{b}$	19.802 ± 2.527 a	0.004
	PRI	-0.084 ± 0.002 ab	-0.086 ± 0.006 b	-0.071 ± 0.009 a	0.021
DI	RVSI	-0.009 ± 0.001 a	-0.01 ± 0.001 ab	-0.012 ± 0.001 b	0.032
Physiology	REP	$715.857\pm2.854~\textbf{b}$	719.913 ± 2.389 ab	723.277 ± 2.091 a	0.014
	WBI	1.232 ± 0.014	1.233 ± 0.015	1.251 ± 0.008	0.169
	MNF.1	-1.568 ± 0.431 b	-0.989 ± 0.187 b	1.125 ± 0.657 a	< 0.001
Hyperspectral	MNF.2	-0.608 ± 0.322	0.118 ± 0.82	-0.079 ± 0.972	0.391
variability	Spectral angle	0.111 ± 0.008	0.122 ± 0.011	0.127 ± 0.004	0.09





Figure 4 - Mean leaf area density (LAD) profiles (left) and cumulative leaf area (LAI) (right) for the three tree diversity level treatments (20, 60, and 120 sp.). Lines are the plots' mean, and the dashed polygons represent the standard error amplitude.



Figure 5 - Mean (left) and standard deviation (SD) (right) of reflectance for the three tree richness level treatments (20, 60, and 120 sp.).

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3.3. Predicting aboveground biomass

The AGB were significantly correlated (p < 0.001) with one lidar-derived variable (CH, r2 = 0.81), and three HIS-derived VIs (RVSI, r2 = 0.78; EVI, r2 = 0.76; and CARI, r2 = 0.77) (Figure S2). However, after eliminating an outlier observation, the best AGB predictors were CH (r2 = 0.82, RMSE = 7.62, relative RMSE = 9.0%), followed by the RVSI (r2 = 0.75, RMSE = 8.98, relative RMSE = 10.1%) (Figure 6). Multiple regression models did not provide significant improvements.





474 Figure 6 - Aboveground biomass of plots as a function of (A) lidar-derived canopy height (CH); and (C) hyperspectral-derived RVSI. The "*" purple point is an outlier plot not included 475 in these regressions. Numbers in parentheses are the standard errors for each coefficient. (B) 476 and (D) are Leave-one-out cross-validations (LOOCV) of aboveground biomass as a function 477 of CH and RVSI, respectively. The dashed line represents a 1:1 correspondence, and the solid 478 line is the linear regression fit between observed and leave-one-out predicted values ($obs_i = \alpha$) 479 480 + β ·pred_i). The values of α and β showed no significant difference from 0 and 1, respectively. in both cases. Point color represents the treatments of 20, 60, and 120 species (green, blue and 481 482 purple, respectively).

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4. **DISCUSSION**

487 Our UAV-lidar-HSI system showed a strong potential to assess canopy structure, AGB, 488 and tree diversity in tropical forest restoration plots, combining lidar and the VIs derived from 489 HSI. It also helped reveal a suite of canopy differences related to forest structure and ecosystem 490 function over an experimental biodiversity gradient. This included both bulk properties like 491 height and LAI (from lidar) and physiologically-linked community traits such as EVI 'greeness' (from hyperspectral), consistent with theories about the advantages of higher 492 493 biodiversity in restoration. To our knowledge, this is the first study to use both lidar and HSI onboard a UAV to monitor tropical forest restoration (but see Vaglio Laurin et al. 2014 for a 494 495 pioneer attempt in a mature tropical forest).

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4.1. Variables derived from lidar and HSI

499 Almost all HSI variables were significantly correlated with the LAI. In general, VIs 500 including information from the NIR domain (750-850 nm, a spectral region characterized by 501 multiple scattering of foliar tissues) show sensitivity to LAI. However, the VIs tend to saturate 502 for LAI values higher than 2. Only mARI and PRI (which do not use NIR information) did not 503 correlate with LAI. VARI and CRI do not have NIR bands in their equation but nonetheless 504 showed a saturating correlation with LAI. These VIs are related to the photosynthetically active 505 leaf area, with VARI using the ratios between the green (~ 550 nm) and red (~ 650 nm) bands 506 and the CRI using two different green bands (~ 500nm) (Gitelson et al. 2002 and 2007). VARI 507 has been proposed as a substitute for NDVI to measure canopy structure using ordinary RGB 508 images (Fuentes-Peailillo et al. 2018; Gitelson et al. 2002). Among the structural VIs, EVI is 509 known to have lesser degree of saturation with increasing LAI due to its higher sensitivity to 510 NIR reflectance (non-saturated) than red reflectance, making it more responsive to canopy 511 structural variations than indices such as NDVI (e.g. Huete et al. 2002). However, in our study 512 EVI showed saturation at LAI=2.0. Our analysis was conducted on an unprecedented fine 513 spatial scale, allowing a better understanding of the relationship between the LAI and the VIs 514 derived from high-spatial-resolution optical sensors, without the confounding effects of leaf 515 age or sub-pixel shade fraction. Nevertheless, relationships (including VIs saturation) may be 516 dependent on season and spatial resolution, an important question for future UAV-based high-517 resolution analysis that must be answered to connect UAV observations to those from coarser 518 grain airborne and orbital sensors. We also note that the lidar-derived LAI represents a proxy 519 for the actual LAI (Almeida et al. 2019c) and includes surface area contributions from other 520 canopy components such as branches.

As expected, no HSI-derived variable was correlated to the understory LAI since HSI data are limited to the canopy surface, as is usual for optical sensors. On the other hand, lidar can record understory vegetation, providing information for forest restoration monitoring. The understory LAI showed potential to distinguish forest succession stages and forest types (Almeida et al. 2019a and 2020). Almeida et al. (2020), using a UAV-lidar system, showed that forest age was negatively correlated with understory LAI.

527 Some structural VIs were less spatially heterogeneous in the plots with higher LAI 528 values (and higher richness levels). The saturation effect, in those cases, decreased their spatial 529 heterogeneity, limiting the effectiveness of methods based on the spatial variation of VIs for 530 estimating tree species diversity or the separation of forest types. VIs are limited in 531 distinguishing between secondary and primary growth forests. However, using multiangular, off-nadir viewing hyperspectral data can improve forest successional stage discrimination
(Galvão et al. 2009; Garcia Millan and Sanchez-Azofeifa 2018). Combining temporal VIs
analyses of land cover (vegetation or exposed soil) allows the determination of cover classes
such as forest regeneration (including forest age) or short-term agricultural crop (Silva Junior
et al. 2020).

537 The restoration plantations that we studied have a more homogenous canopy structure 538 when compared with sites under natural regeneration, likely related to the even-aged cohort 539 that comprises the canopy layer. We expect heterogeneity to increase with time through stand 540 development competitive thinning dynamics, enhanced potentially by the years-to-decades that 541 some slow-growing tropical trees require to express their unique structural characteristics and 542 profile in the canopy. We believe that the ability of lidar technology to differentiate tree 543 diversity levels may improve along with the structural development of forest stands. 544 Conversely, the HSI spatial patterns were relevant proxies for distinguishing tree diversity 545 levels even in 13-year-old restoration, highlighting the potential of this technology to monitor 546 broad-scale restoration programs.

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4.2. Distinguishing tree species richness levels

550 Several lidar-derived variables were more sensitive to differences in diversity than 551 AGB. While we detected differences in AGB only between the treatments with 20 and 60 sp., 552 LAI differed among all three diversity treatments and increased with each increasing species 553 richness level. For the same study site, Duarte et al. (2021) found that AGB saturated from 60 554 sp. to 120 sp. while LAI and light interception (both derived from LAI-2200C equipment) were 555 positively correlated to diversity even at very high richness levels. However, both our and 556 Duarte et al. study evaluated only stem AGB and did not consider branches and leaves. Our 557 results also showed that canopy height was positively associated with species richness. 558 Previous studies have shown that enhanced light interception and LAI in diverse tropical forests 559 result from enhanced complementarity among crowns in canopy space, promoted by a high 560 diversity of crown shapes and heights among species and neighborhood-driven plasticity in 561 crowns (Guillemot et al. 2020, Duarte et al. 2021, Williams et al. 2017). We showed that the 562 diversity effects on stand structure and AGB were efficiently captured by lidar-derived 563 variables, which open promising perspectives for the large-scale monitoring of hyper-diverse 564 tropical forest functioning. Canopy height heterogeneity and the LAI under the canopy did not 565 significantly vary among treatments, which may be explained by the forest's low maturity and 566 structural homogeneity. Increasing diversity and associated LAI in the upper canopy do not 567 appear to impact understory LAI. A potential explanation for this surprising result is that light 568 use efficiency increases with diversity—an expectation of higher crown type diversity—such 569 that understory light availability changes little over this diversity gradient.

570 Structural VIs were positively associated with species richness. The capacity of VIs to 571 discriminate among richness levels can be explained by the relatively low LAI compared with 572 natural regeneration and mature forests (Almeida et al. 2019a). However, increasing LAI may 573 result in saturation of the structural VIs and reduced ability to differentiate among richness 574 levels. In general, the VIs that showed a significant difference among the treatments also 575 showed an association with the canopy structure (i.e., significant correlation with LAI). It is 576 important to note that many of the biochemical VIs were developed from laboratory 577 spectrometers characterized by a higher signal-to-noise ratio (Meneses et al. 2019). The aerial 578 collection of hyperspectral images (e.g. from drones) is subject to interference from the 579 conditions of acquisition (atmospheric properties, geometry of acquisition) and canopy 580 structure. However, some studies have shown promising results from VIs for tropical tree 581 species classification (Ferreira et al. 2016).

582 One of the most interesting results concerning HSI data was that spectral diversity 583 appeared to increase with richness treatments. The spectral angle was significantly different

584 across categorical classes of species richness at p < 0.1 (Tukey test) and at p < 0.05 when 585 species richness was treated as a continuous predictor in a simple linear regression (Table S2). 586 The hyperspectral composition variable (MNF.1) differed among treatments in both mean and 587 variance, and the spectral response showed higher variability in treatments with greater 588 diversity (Fig. 5). By computing the spectral angle among the treatments, we showed that the 589 spectral variability increased with diversity, which broadly agrees with the spectral variation 590 hypothesis (Palmer et al. 2002). This hypothesis states that the spectral heterogeneity is induced 591 by variations in habitat and has been used to assess forest canopy diversity with hyperspectral 592 data (Féret and Asner, 2014). Our results suggested that tree diversity itself impacts spectral 593 heterogeneity.

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4.3. Predicting aboveground biomass

598 Some lidar and HSI variables demonstrated a remarkable capacity to estimate AGB 599 accurately. This prediction represents a well-known potential of lidar structural data but is a 600 less-universal finding for HSI variables. While VIs are known to saturate at high biomass and 601 LAI values, the low plot-level density of vegetation (LAI ~ 2) in our study maintained VIs in 602 an unsaturated range, where there is a strong correlation with AGB. This non-saturated stage 603 behavior was also found in another study focusing on young, low diversity plantations 604 established in a temperate forest ecosystem (Williams et al. 2021). The RVSI (Red-edge 605 Vegetation Stress Index) was the most accurate predictor for biomass, which can be explained 606 by the high positive correlation between the red-edge region (680–750 nm), the chlorophyll 607 content, and the canopy LAI (Fillela & Penuelas, 1994). The increase in the chlorophyll content 608 tends to move the red-edge position to longer wavelengths, while the increase in LAI increases 609 the difference between NIR and red reflectance. As the RVSI uses bands near the end of the red edge (>730 nm), it may be sensitive to AGB variations induced by LAI and chlorophyllcontent.

612 The AGB predictions performed by the structural attribute derived from lidar (canopy 613 height) did better than that of HSI-derived VIs. Lidar sensors have been shown to be the best 614 tool for AGB estimates, especially in dense tropical rainforests (Wulder et al. 2012). Adding 615 more variables to the model (multiple regression models) did not improve the prediction, 616 probably due to the low structural complexity and low age of the vegetation. In a previous 617 study performed in the same region but based on a greater number of forest types and more 618 structurally complex forests, the addition of more variables improved AGB models (Almeida 619 et al. 2019a). The utility of fusing lidar and hyperspectral data for AGB prediction per se 620 remains an unresolved problem in the literature. Some studies have shown slight improvement 621 with the addition of hyperspectral metrics in the AGB estimation models when they already 622 have included lidar metrics (e.g. Clark et al. 2011; Fassnacht et al. 2014), while others have 623 found better performance mixing lidar and HSI variables (e.g. de Almeida et al. 2019; Vaglio 624 Laurin et al. 2014).

625 The use of lidar data as an intermediary layer between field and spectral satellite data 626 ("upscaling" technique) is critical to generate large samples of AGB with high accuracy and 627 thus generate more robust maps using satellite images for more extensive areas. Csillik et al. 628 (2019) combined lidar and high-resolution satellite images to generate a biomass map for the 629 entire country of Peru. New orbital lidar sensors are expected to generate more accurate maps 630 of tropical forest AGB and stand structure attributes. One of them is the "Global Ecosystem 631 Dynamics Investigation" (GEDI) orbital lidar sensor; however, its information is not spatially 632 continuous and has much lower precision and accuracy compared with lidar sensors onboard 633 aircraft and UAVs (Dubayah et al. 2020).

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4.4. Monitoring tropical forest restoration

637 Given the high cost of field inventories, restoration programs have often used an 638 insufficient number of plots, which have ultimately compromised the reliability of restoration 639 field assessments (Viani et al. 2018). Upscaling restoration monitoring requires more than the 640 replication over space of traditional forest inventory approaches because of the costs and scales 641 involved (Brancalion et al. 2017). At the other extreme, satellite images and novel analytical approaches are still incapable of measuring restoration quality (Rosa et al. 2021). A successful 642 643 monitoring program must consider the gap between detailed and costly information from field 644 plots and the million hectares of information generated by satellites with low capacity to detect 645 restoration success.

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646 We believe that the novel UAV-borne lidar and hyperspectral system described here 647 can fill this technological gap, offering data streams that can be connected with plot-based 648 monitoring and broad-scale remote sensing alike to improve upscaling and forest restoration 649 monitoring. Particularly by blending lidar and HSI data, it is possible to assess biomass 650 structural, functional, and diversity linked restoration outcomes simultaneously, a great 651 advantage over methods based solely on either lidar or HSI. Further, it may represent a 652 revolution in tracking restoration success globally. The development of new remote sensing 653 approaches and their application to a restoration context would help expand our capacity to 654 assess restoration over unprecedented spatial and temporal scales (White et al. 2019). Lidar-655 HSI upscaling has recently become possible due to the new generation of orbital sensors. In 656 addition to the abovementioned spaceborne GEDI lidar mission, the DESIS (Krutz et al., 2019) 657 and PRISMA (Vangi et al., 2019) hyperspectral sensors provide data with fine sampling using 658 narrow bands (lower than 10 nm) and 30 m of spatial resolution. Together GEDI and DESIS 659 or PRISMA data can provide unprecedented results on the structure and diversity of forest 660 restoration at broader spatial scales. UAV-lidar-HSI systems are still relatively expensive and potentially unaffordable by some decision-making organizations such as governments, NGOs,small landowners, and companies.

663 In addition to acquisition costs, a high level of technical knowledge is required to operate drone-based systems and process and analyze the data. Thus, their use is still 664 constrained to a minority of research groups. In tropical countries, particularly, the use of these 665 systems is considerably limited due to high import tariffs and a lack of local technical 666 667 assistance. However, these initial constraints are precisely the same faced by other technological innovations of the past, which are now broadly present in modern societies 668 669 worldwide. Despite the constraints, efficient and relatively inexpensive UAV-lidar systems 670 have been developed (Hu et al. 2021), which may facilitate their broader use in diverse sectors, 671 particularly in forest restoration. Institutions in tropical countries should encourage the 672 development of these technologies through investing in research, eliminating import taxes, 673 encouraging open hardware development (Tsanni 2020) and facilitating the arrival of 674 specialized companies.

675 There are many benefits that UAV-lidar-HSI systems bring to forest restoration 676 monitoring, including the potential to monitor small areas with very high accuracy, reduced 677 field sampling effort (Papa et al. 2020), and the increase of remote sampling for upscaling and 678 generation of global models. Standardized monitoring protocols would help to evaluate 679 restoration strategies' efficacy and compare results across projects to learn from the past and 680 inform future restoration efforts (Viani et al. 2017). The unprecedented scale of global forest 681 restoration targets will need to be accompanied by the evolution of restoration monitoring 682 approaches and delivering, at much-reduced costs and higher spatial and temporal scales, 683 critical information for tracking restoration success and guiding adaptive management. This 684 constitutes an enormous scientific and technological challenge that has just started to be 685 addressed by a joint effort of restoration, policymakers, and remote sensing experts. The

- 686 positive results obtained by the UAV-lidar-HSI system described here are very encouraging
- 687 and may hopefully foster the ongoing development and application of remote sensing
- 688 innovations in ecosystem restoration.
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