

Communication

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A protocol for canopy cover monitoring on forest restoration projects using low-cost drones

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Abstract: Remotely piloted aircrafts (RPAs) are becoming well-known for monitoring forest restoration (FR). Canopy cover percentage on a restoration site is a major indicator for the early phases of FR. We present a protocol to evaluate canopy cover using low-cost RPA and a friendly computational environment. We tested the protocol in six FR projects in the Brazilian Atlantic Forest. After processing the images automatically to generate the digital surface model and the digital terrain model, the canopy cover is measured in QGIS by considering height thresholds in the canopy height model. The results had *F1* values higher than 0.9, which confirms a robust methodology that does not require specific computer science or remote sensing skills. Thus, low-cost RPA proved to be accurate and user-friendly in measuring the canopy cover, which improves monitoring during most FR stages. Such finding plays an important role

in FR policies and future works must study a user-friendly protocol for measuring tree height via low-cost drones.

Keywords: remotely piloted aircraft, tree cover, forest restoration, protocol, unmanned aerial vehicles

1 Introduction

Forest restoration (FR) monitoring is critical to ensure the estimation of the restoration outcomes [1–3]. FR is the process of recreating the ecological function of forests that have been degraded due to timber harvest and fire suppression [1].

FR monitoring consists of a set of indicators where each indicator evaluates a specific forest attribute. A major ecological indicator of early FR success is canopy cover, which is the percentage of soil covered by tree crowns. During early FR, canopy cover must reach at least 70–80% [4]. When a site closes the canopy, a restored forest shades out invasive grasses, attracts seed dispersers, and modifies the microclimate and soil for tree seedling establishment [4,5]. After closing the canopy, the next phase is the density and diversity of recruits that will replace canopy trees in the next years, guaranteeing a long-term forest structure and species diversity [4,5].

Remotely piloted aircraft (RPA), popularly known as drones, have a high potential to monitor FR [6,7]. RPA can register whole areas of interest with a georeferenced panoramic high spatial resolution image and point cloud data [8–10]. In FR projects, this technology could assess relevant information on areas not covered by traditional field plots [7,11].

RPA has accurately measured canopy cover in open canopy conditions [7,12–14], but assessing and publishing its accuracy on a wider spectrum of open and closed canopy conditions is timely given. Thus, considering the RPA potential for FR monitoring, it is worth publicizing a friendly protocol for measuring canopy in a wide variety of FR situations. In such a protocol, society should be able to monitor canopy cover accurately and

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without specific knowledge requirements, as Mohan *et al.* [15] did, but for individual tree detection. For canopy cover in FR projects, machine learning processes accurately measured it [16], but a remote sensing specialist is required to conduct this kind of methodology.

This study aims to present a low-cost RPA canopy cover monitoring protocol where neither specific field of knowledge is required, nor any remote sensing samples. To test and illustrate the protocol, we evaluated its effectiveness in six different FR situations.

2 Materials and methods

2.1 Materials

The RPA must couple RGB sensors that have at least 1/2.3" and 12MP CMOS. Within such sensor specs, the RPA takes pictures that will be processed by structure from motion – multi view stereo (SfM-MVS) [17,18] to generate cartographic information. For the case studies of this work, we used a Phantom 4 Pro (a rotary wing RPA), which is coupled with a RGB 1" and 20 MP CMOS. For more information about this model, see [19].

Regarding software, we mentioned the ones that we applied in the case studies of this work, but other software with similar functions can be used. Thus, in the case studies, we drafted the flight plan using the Map Pilot software [20], while we obtained the digital surface model (DSM), digital terrain model (DTM), and orthorectified mosaics using the Agisoft Metashape [21] software. We used the QGIS [22] software version 3.12 to perform the image processing workflow and map layouts.

2.2 Methods

2.2.1 Flight patterns

All flights must comply with the local authority's laws, and thus the heights of the flights are recommended to be

less than 120 m in general. The RPA pilot must choose the flight height according to: the desired ground sampling distance (GSD); and the height of the surface objects (mainly trees) to avoid RPA collisions.

The flights must be planned according to the RPA characteristics. Since this protocol considers low-cost RPA, the battery of this kind of equipment usually enables 15 min flights. Low-cost RPA can thus be recommended for areas smaller than 100 ha [23], but it is possible to use more than one RPA during the fieldwork for mapping large sites. Despite this battery limitation, RPA engines fed by solar energy may solve this flight time limitation in the near future [24].

In the RPA flight missions, the camera angle must be equal to zero degrees (Nadir), and the minimum front and side overlap between photos must be equal to 90 and 80%, respectively. Although these overlapping values increase the SfM-MVS processing time for generating the cartographic data, it provides enough details that are required for processing the point cloud data to FR projects [25].

2.2.2 Canopy cover measured by RPA

Figure 1 synthesizes the canopy cover measurement method via low-cost RPA.

Ground control points (GCPs) are not mandatory for the canopy cover measurement, and thus the cartographic precision of the RPA data gets close to 3 m in these situations [26]. If each RPA image without GCP accurately provides canopy cover, it is possible to monitor this indicator's evolution through time. However, the lack of GCP makes it not possible to overlap the images or the canopy cover maps between them (cartographic precision is not enough to overlap maps in this case). Therefore, if the objective is to measure canopy cover, which is a number in percentage (%), and not to overlap maps, GCP is not mandatory. The lack of GCP is an advantage because it reduces costs due to a shorter time spent in fieldworks [27] and the considerable price of precise global navigation satellite system (GNSS) equipment [28]. If one needs to overlap maps, GCPs have to be measured at least in the first flight, as Albuquerque *et al.* [7] recommends.

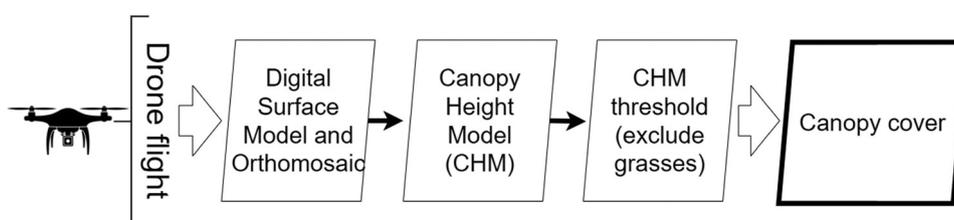


Figure 1: Methods for the canopy cover measurement via low-cost RPA.

After flying the RPA and generating the orthomosaic and the DSM via SfM-MVS, canopy cover is measured using the canopy height model (CHM) data, which is the difference between DSM and DTM [29]. Then, each FR site must have the values of the algorithm parameters for DTM generation calibrated according to its characteristics and to the experience of the analyst. To illustrate some examples of values that can be used on the DTM algorithm parameters, Table 1 gives the “classify ground points” tool parameters (which are maximum angle, maximum distance, and cell size in Agisoft Metashape) that we used in the case studies of this work.

After generating the DTM, the CHM is obtained by the difference between the DSM layer and the DTM layer. In the case studies of this work, we performed this operation using the “Raster Calculator” tool in QGIS. Then, after the CHM acquisition, a height value threshold has to be defined in the CHM layer to avoid confusions with bulky grass. According to Viani et al. [4], canopy cover in the Atlantic Forest biome must separate trees (woody vegetation) from grasses (herbaceous vegetation). Since some sites may present conditions that favor grass development, it is relevant to check how much tall the grass is at each site. A CHM threshold may perform such a task by involving only trees when they are taller than grasses. In QGIS, this CHM threshold can be applied using the “Raster Calculator” tool by entering, for instance, “CHM_layer > 0.5,” where “CHM_layer” is the CHM raster layer and the grass height is 0.5 m tall. The grass height varies in each FR project, and thus the user must check which threshold value generates feasible results. In the case studies of this work, the grass height ranged from 0 to 1 m along with the FR sites.

After choosing the threshold value that includes only woody cover, the “Raster Calculator” tool in QGIS generates a binary mask where tree pixels have value 1, and non-tree pixels have value 0. To check the area (in square meters) covered by tree and non-tree pixels, the “Raster layer unique values report” tool in QGIS can be used. Canopy Cover is then calculated according to equation (1).

$$CC = \frac{ATP}{ATP + ANTP}, \tag{1}$$

where CC = canopy cover (ranges from 0 to 1), ATP = area of tree pixels, and ANTP = area of non-tree pixels.

2.2.3 Case studies

We evaluated six FR sites in the Brazilian Atlantic Forest biome. Three sites are located in the municipality of Extrema in the state of Minas Gerais (MG) – Brazil and

Table 1: Values of the “Classify ground points” algorithm parameters that were used and the canopy cover accuracy of the case studies

FR site	“Classify ground points” algorithm parameters			Canopy cover accuracy				
	Max angle (°)	Max distance (m)	Cell size (m)	Canopy cover	Overall accuracy	Precision	Recall	F1
6 years old active FR with a 1 year active FR patch	11	0.6	35	0.417	0.935	0.892	0.99	0.938
4–16 years-old active FR varying in different patches	2.5	0.5	10	0.735	0.97	0.99	0.95	0.969
1 year active and passive FR with some mature forest patches	1	0.1	3	0.353	0.965	1	0.93	0.964
40 years old active FR with grass patches	5	0.2	20	0.698	0.985	0.98	0.99	0.985
Mature forest with grass patches	11	0.6	35	0.646	0.985	0.971	1	0.985
Mature forest with 1 year old active FR patches	15	1	50	0.518	0.975	0.952	1	0.976

are part of the Fernão Dias Environmental Protection Area. The other three sites are in the municipality of São José dos Campos in the state of São Paulo (SP) – Brazil and inside the Paraíba do Sul Basin Environmental Protection Area (Figure 2).

The case studies were active and passive restoration [30,31] sites. Site 1 (Figure 3a) has a 6 years old active restoration patch and a 1 year old active restoration patch in a hilltop area. Site 2 (Figure 3b) has active restoration patches varying from 4 to 16 years old. Site 3 (Figure 3c) has a 1 year old active and passive restoration patch and some mature forest patches. Site 4 (Figure 3d) is a 40 year old active restoration site with some grass patches. Site 5 (Figure 3e) is a mature forest with grass patches. Site 6 (Figure 3f) is a mature forest with patches of 1 year old active restoration.

The flights over the study areas in Extrema Municipality happened in January 2019, while in São José dos Campos in June 2019. All flights complied with Brazil's RPAs laws [32] at 100 m height, generating approximately 3 cm GSD with front and side overlap equal to 90% and 80%, respectively.

When evaluating canopy cover accuracy, each site had 200 test samples collected by photointerpretation for the binary classification of trees (100 samples) and non-trees (100 samples). Each sample consisted of a pixel because it is considered more flexible than blocks of pixels [33] and can be applied when there is no segmentation process to detect objects [34]. After all, measuring canopy cover is not the same as detecting each tree crown via Object-based image analysis (OBIA) classification [35] or

instance segmentation [36]. The amount of 200 test samples was enough because each hectare must contain at least 10 test samples [37], and the largest study area of the manuscript has 17.5 ha.

After collecting 200 test samples via photointerpretation of the RPA orthomosaic of each site, we then calculated the overall accuracy [38], recall, precision, and $F1$ indexes [39] according to equations (2)–(5), respectively.

$$OA = \frac{TP + TN}{(TP + TN + FP + FN)}, \quad (2)$$

$$r = \frac{TP}{(TP + FN)}, \quad (3)$$

$$p = \frac{TP}{(TP + FP)}, \quad (4)$$

$$F1 = 2 * \frac{(r * p)}{r + p}, \quad (5)$$

where OA = overall accuracy, TP = true positive, FN = false negative, FP = false positive, r = recall, and p = precision.

3 Results

Figure 4 shows the canopy cover mapping results of all the case studies. By looking at Figure 4, the canopy cover results seem to be very accurate when assessed qualitatively.

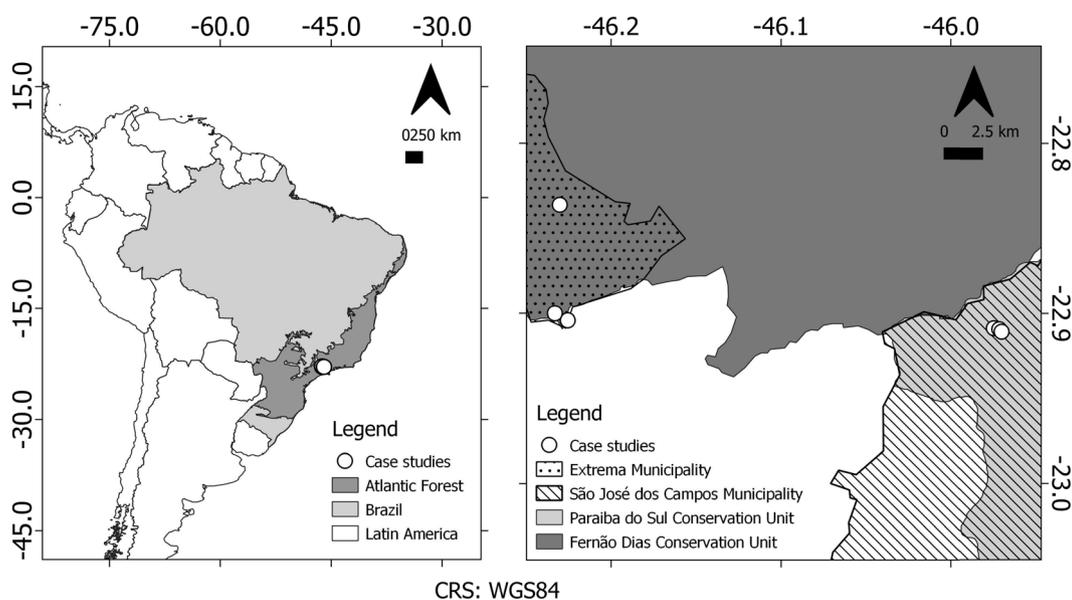


Figure 2: Location of the FR case studies on Brazilian Atlantic Forest.

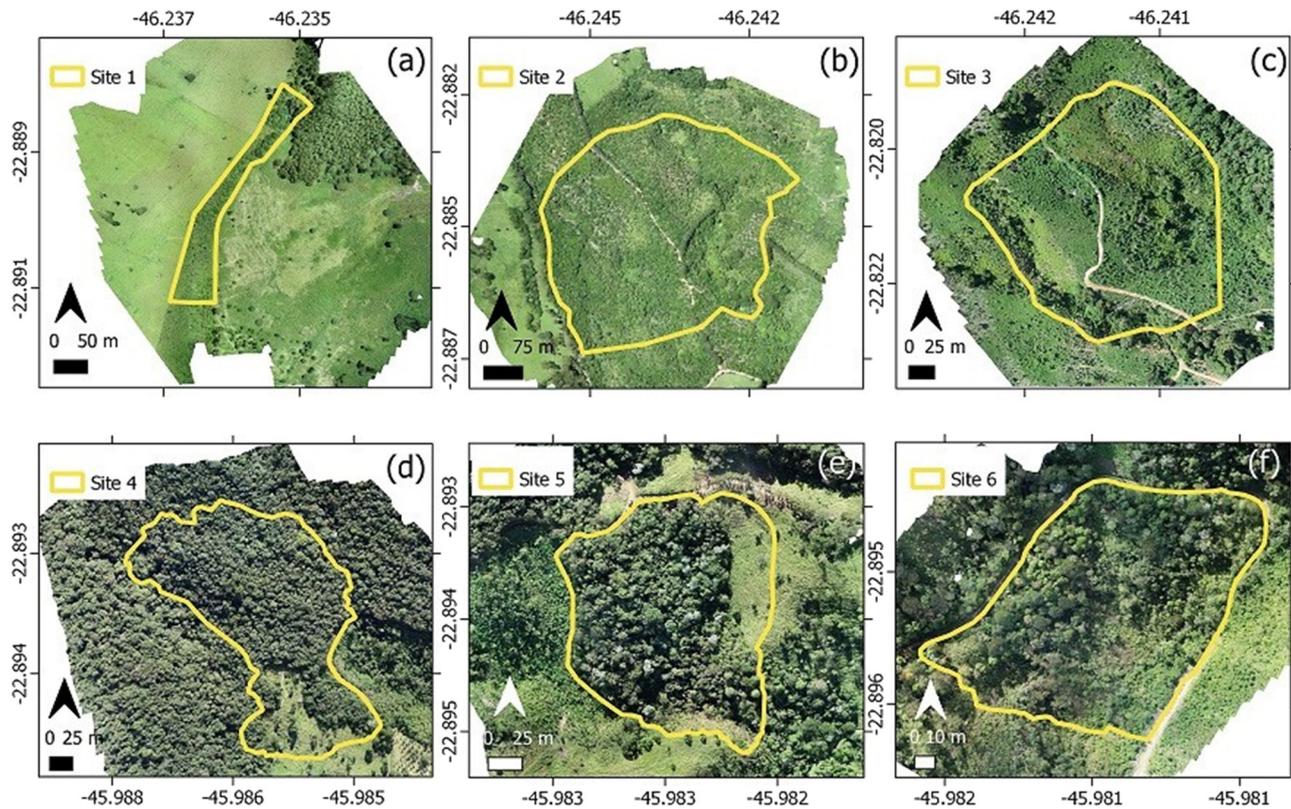


Figure 3: RPA orthomosaics of the 6 FR sites: 6 years old active restoration patch and a 1 year old active restoration patch in a hilltop area (a); active restoration patches varying from 4 to 16 years old (b); 1 year old active and passive restoration patch and some mature forest patches (c); 40 years old active restoration with grass patches (d); mature forest with grass patches (e); and mature forest with patches of 1 year old active restoration (f).

Table 1 shows the parameter values used by the “Classify ground points” algorithm in Agisoft Metashape to generate the DTM of each case study site. Table 1 also shows the canopy cover result’s quantitative accuracy, which proves that the low-cost RPA accurately mapped it in all case studies. All $F1$ values are higher than 0.9, while the mean overall accuracy, precision, recall, and $F1$ of all the case studies were equal to 0.97, 0.96, 0.98, and 0.97, which shows the robustness of the method. Some grass patches were included in some of the FR surrounding areas (Figures 3 and 4) to assess the proposed method’s capability of separating woody and herbaceous vegetation.

4 Discussion

The low-cost RPA canopy cover monitoring protocol accurately mapped the canopy cover by using a friendly computational environment. No advanced skills are required to run the proposed method, so one must know how to fly

an RPA, generate an orthomosaic, a DSM, a DTM, and a CHM. These are widespread automatic procedures that can be learned after a few days of proper training without specific background as a pre-requisite.

GCP are not mandatory. This is relevant because GCP increases operational costs due to the amount of time spent in fieldwork [27] along with the high price of precise geodetic GNSS equipment [28]. Besides increasing the costs, managing geodetic GNSS equipment is a specific field of knowledge that requires intensive training for proper operation.

Moreover, no machine learning processes are involved, no coding abilities are required and the canopy cover calculation can be done in a free and open-source software. Other solutions mentioned in the literature require costly hardware (multispectral sensor and LiDAR – light detection and ranging) and supervised classification of land cover classes [7,16,40–43]. However, this work demonstrated a low-cost RPA methodology that does not require land cover samples, which is relevant because these methods (where samples are not mandatory) are more automated than the supervised classification ones [44,45].

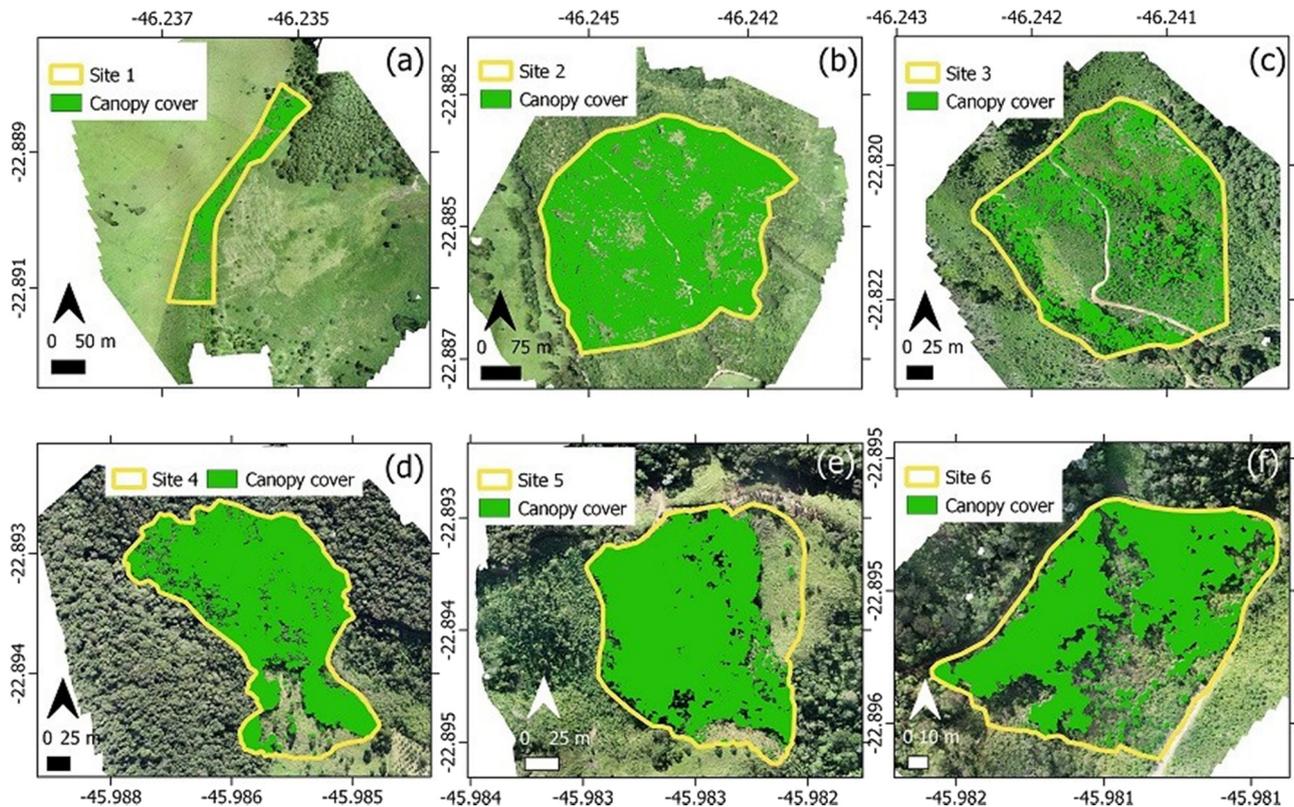


Figure 4: Canopy cover results on the RPA orthomosaics of the 6 FR sites: 6 years old active restoration patch and a 1 year old active restoration patch in a hilltop area (a); active restoration patches varying from 4 to 16 years old (b); 1 year old active and passive restoration patch and some mature forest patches (c); 40 years old active restoration with grass patches (d); mature forest with grass patches (e); and mature forest with patches of 1 year old active restoration (f).

Another advantage of the protocol described in this work is that it uses the point cloud data of a single flight. This flight generates a single image that does not depend on sunlight conditions, and thus it does not require domain adaptation [46], which is a remote sensing disadvantage when involving machine learning processes [47]. Also, in this work, the closed canopy conditions did not degrade the canopy cover accuracy, as it does to SfM-MVS tree height measurement, as stated in the literature [12–14].

We generated the orthomosaic and the CHM using commercial software in this study, but open-source software is more democratic [48]. If open license initiatives, like OpenDroneMap [49], prove to be capable of accurately generating these cartographic data, RPA usage in FR monitoring would become even more accessible. In this case, only the acquisition of the hardware (RPA and computer with processing capacity) would be necessary. Also, it is relevant to highlight that some initiatives, like OpenDroneMap, also offer processing data in the cloud and, therefore, could avoid the high processing computer requirement.

Despite using a user-friendly hardware and software environment, the canopy cover method applied in this study works only after the tree height becomes higher than grass height. Albuquerque *et al.* [7] used a non-user-friendly method to map canopy cover in patches where trees were a bit taller than grasses, which means that, in FR areas in biomes such as the Brazilian Cerrado, where invasive grass significantly jeopardizes trees' growth [50], our methodology may not work during the first years of restoration. However, other relevant Biomes, such as the Amazon and the Brazilian Atlantic Forest, benefit from our RPA remote sensing methodology.

Besides 90% of the front and side overlap between photos, Swayze *et al.* [51] recommends crosshatch flights for a more refined point cloud data of vegetated areas. The authors stated that crosshatch flights improve the accuracy of relevant parameters measured by RPA, such as diameter breast height (DBH) and tree height. However, this study evaluated the canopy cover only. In closed-canopy conditions, although canopy gaps are a relevant biodiversity metric [52] that can be assessed by canopy cover measurements, tree height also becomes a

relevant structural parameter for FR monitoring because it estimates the community ecology sustainability [53] and the forest biomass/carbon [54], which is related to species diversity [55]. However, the canopy height measurement via low-cost RPA requires GCP [7]. Thus, future works must evaluate user-friendly protocols for tree height measurements using low-cost RPA in the FR context.

5 Conclusion

This study shows a canopy cover monitoring protocol for FR projects using low-cost RPA and a user-friendly computational environment. The method was accurate in all the six case studies, which involved the whole range of canopy cover. Thus, the low-cost RPA protocol presented in this work can improve the monitoring policies such as the ones of the Atlantic FR Pact. Since no specific field of knowledge is required, restoration technicians can use this protocol for canopy cover monitoring of FR projects without intense training requirements, as hardware acquisition, flights, and time for processing the RPA data are the main issues to be planned. The protocol can be useful in the initial FR stage, when canopy cover is less than 70%, and in the advanced stage, when canopy gaps play a relevant role.

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