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ARTICLE

Applying unmanned aerial vehicles (UAVs) to map shrubland structural attributes in northern Patagonia, Argentina[1]

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Abstract: Unmanned aerial vehicles (UAVs) have gained attention for forestry applications in recent years. These technologies provide ultrahigh-resolution spatial data for detailed mapping of forest structure, among other forestry applications. UAVs have mainly been tested in high-value timber stands, but little is known about their performance in other woody ecosystems such as shrublands that also provide key ecosystem services. Field measurements in shrublands are time-consuming, so UAVs could be used instead to provide data for shrubland management and conservation. We tested whether UAVs could map common structural attributes in shrublands of northern Patagonia. We specifically evaluated the capability of UAV point clouds for mapping (*i*) canopy height, (*ii*) stand density, (*iii*) basal area, and (*iv*) volume. The agreement with the field measurements was satisfactory (R^2 was up to 0.95 and relative root mean square error (rRMSE) ranged between 12% and 39%) and comparable with those found for coniferous forests in similar studies. This study is a first attempt to characterize the structure of Patagonian shrublands using UAV data. Despite the challenges and methodological aspects that need to be solved, our results encourage the use of UAVs in these types of ecosystems.

Key words: UAV, shrublands, structural attributes, photogrammetric point cloud.

Résumé : Les drones ont suscité de l'intérêt pour des usages en foresterie ces dernières années. Entre autres applications forestières, ces technologies fournissent des données spatiales à très haute résolution pour une cartographie détaillée de la structure forestière. Les drones ont été principalement testés dans des peuplements où le bois a une grande valeur, mais on sait peu de choses sur leur performance dans d'autres écosystèmes ligneux comme les arbustaies, qui fournissent également des services écosystémiques clés. Les mesures sur le terrain dans les zones arbustives prennent du temps, de sorte que les drones pourraient fournir des données pour la gestion et la conservation des zones arbustives. Nous avons testé si les drones pouvaient cartographier les attributs de structure habituels dans les arbustaies du nord de la Patagonie. Nous avons spécifiquement évalué la capacité des nuages de points acquis au moyen d'un drone à cartographier (*i*) la hauteur du couvert forestier, (*ii*) la densité du peuplement, (*iii*) la surface terrière et (*iv*) le volume. La concordance avec les mesures prises sur le terrain était satisfaisante (R^2 allant jusqu'à 0,95 ainsi qu'une erreur quadratique moyenne relative variant de 12 à 39 %) et comparable à ce qui a été obtenu pour des forêts de conifères dans des études similaires. Cette étude est une première tentative pour caractériser la structure des arbustaies de la Patagonie à l'aide de données provenant d'un drone. Malgré les défis et les aspects méthodologiques qui doivent être résolus, nos résultats encouragent l'utilisation de drones dans ces types d'écosystèmes. [Traduit par la Rédaction]

Mots-clés : drone, arbustaies, attributs de structure, nuage de points photogrammétriques.

1. Introduction

Unmanned aerial vehicles (UAVs) have gained increased attention for forestry applications in recent years (Tang and Shao 2015). These technologies allow users to acquire ultrahigh-resolution spatial data for detailed mapping of forest structural attributes and parameters (Zhang et al. 2016), species composition (Baena et al. 2017), forest gap detection (Getzin et al. 2014), and diseases (Waite et al. 2019), among other forestry applications (Torresan et al. 2017). UAV data acquisition provides flexibility; it can be applied to cases in which spaceborne technologies and manned aircraft are not efficient (Shahbazi et al. 2014). These features have made UAVs especially useful for overcoming the spatiotemporal scale mismatch between field data and satellite images (Shahbazi et al. 2014). UAVs are becoming cost-efficient for end users (Anderson and Gaston 2013), and the potential for operational applications in forestry is increasing (Tang and Shao 2015).

Unlike the use of satellites and aircraft, the use of UAVs as a remote sensing tool is still being developed, and forestry applications should be considered a main research issue (Getzin et al. 2012). A considerable body of research is being developed with visible light (RGB) and near-infrared (NIR) sensors as the most commonly used sensors on UAV platforms. Although light detection and ranging (LiDAR) is considered the most accurate sensor for estimating structural attributes at the stand level (White et al. 2016), the high costs of acquisition make it difficult to access this kind of information. UAV-derived photogrammetric point clouds (PPCs) are analogous to those obtained by LiDAR and therefore represent an alternative to characterize forest structure (Puliti

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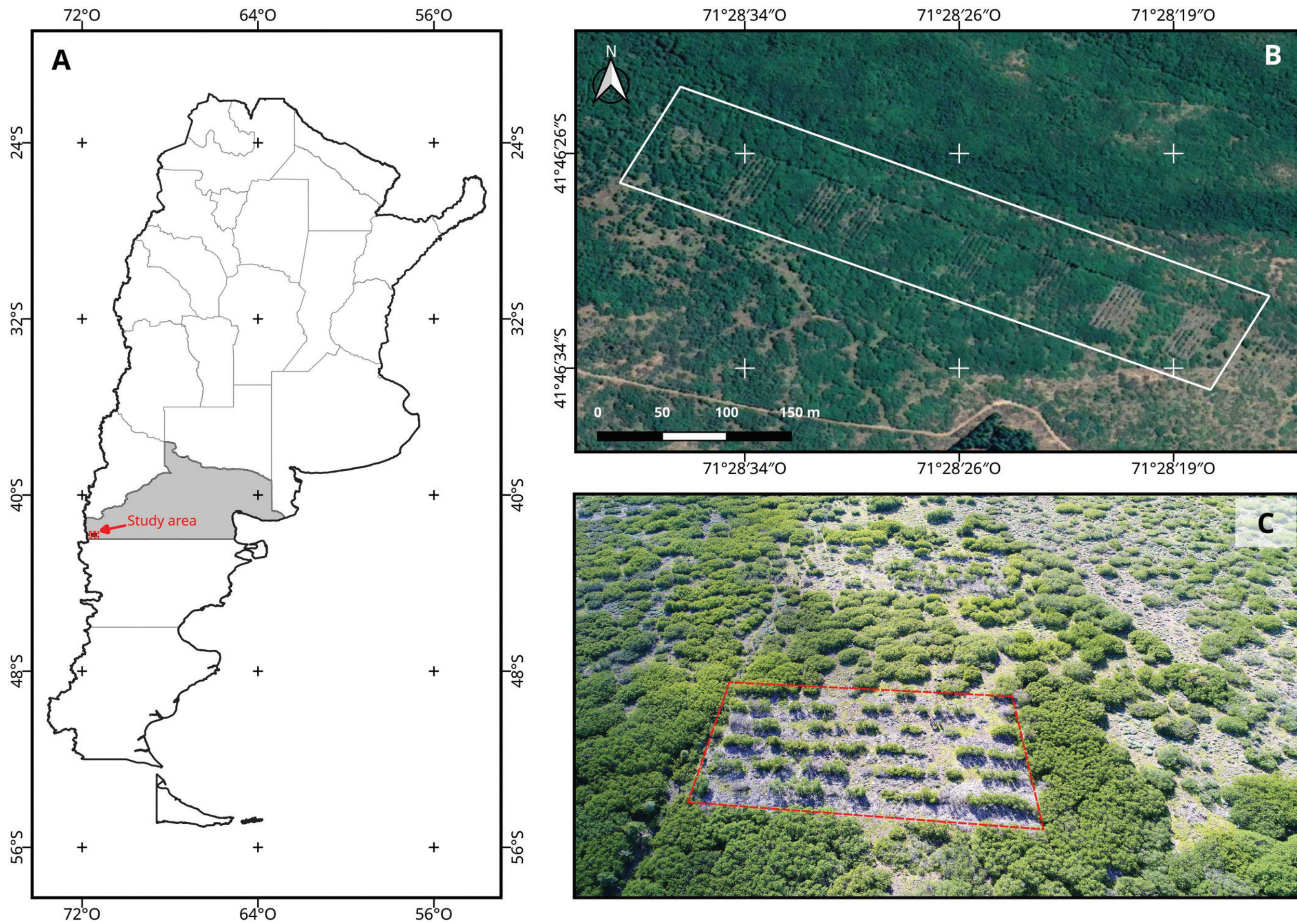
Fig. 1. Study area and experimental stand. (A) Location of study area in Argentina. (B) Boundaries of the long-term monitoring experiment (white lines). (C) Aerial view of *N. antarctica* shrublands (red lines outline one of the harvested plots in the experimental stand). The map was created using QGIS version 3.10 (QGIS Development Team 2019). Base map from Google Earth, courtesy of Google and Maxar Technologies. [Color online.]



et al. 2015). These point clouds and other image-based applications of UAVs have been tested in high-value timber stands, but little is known about their performance in other woody ecosystems such as shrublands. Although there are some examples of using UAV for shrubland monitoring (Easterday et al. 2019), to date, only Prošek and Šímová (2019) have applied PPCs to classifying shrubland vegetation.

Shrublands provide key ecosystem services such as carbon sequestration (Peri 2011). Historically, they have been degraded by grazing or converted to other land uses (Naveh 2007). Sustainable management efforts are required to maintain or enhance the ecosystem services that shrublands provide (Goldenberg et al. 2019). Monitoring of management requires the characterization of shrubland structure, which is difficult because shrubland structure is often complex (high density, multiple stems per individual, and high diversity of species). Consequently, field measurements are expensive and logistically difficult. In addition, shrublands are usually fast growing, and monitoring after silvicultural interventions or disturbances requires information to be updated over relatively short periods. Therefore, UAVs could become key instruments for the management and conservation of shrublands, as long as the information they provide is accurate enough.

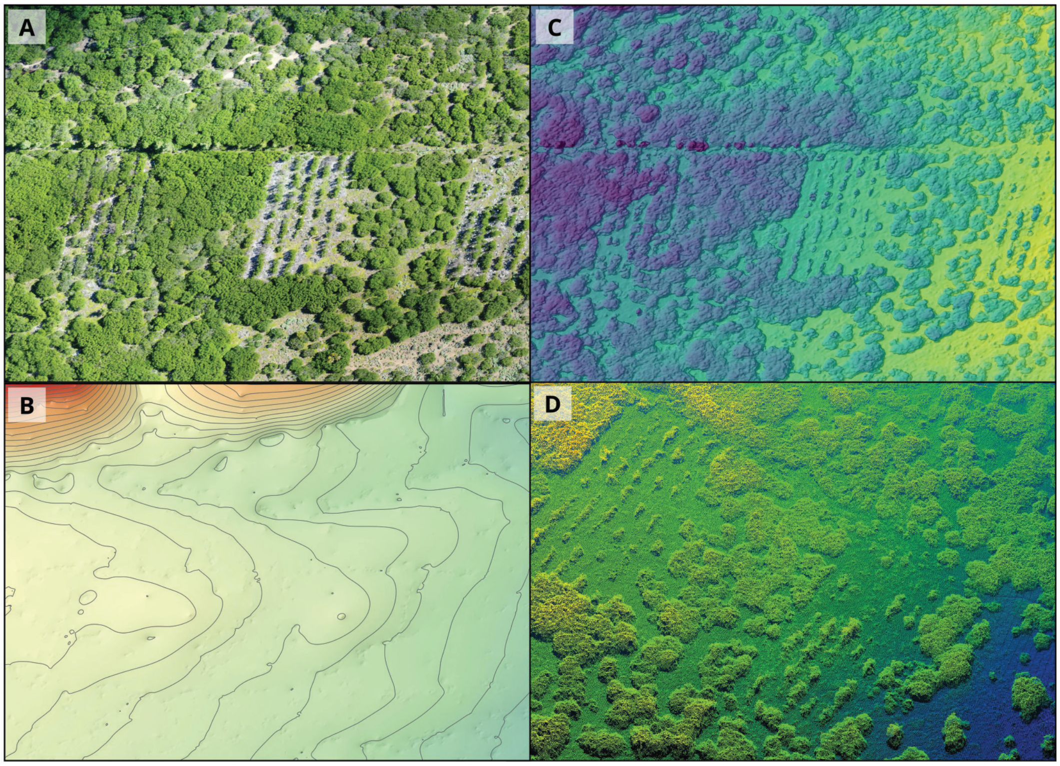
Nothofagus antarctica (G. Forst.) Oerst. (in Spanish, "ñire") shrublands are one of the most common ecosystems of northern Patagonia. However, information about silvicultural practices is sparse, and there are not enough sustainable management schemes for these communities in this region (Grosfeld et al. 2019). Considering that new legislation in Argentina (National Law 26331) demands sustainable management, UAV technology would have straightforward applications in these ecosystems. Irrespective of the regional relevance, evaluation of UAV performance in shrublands for obtaining structural attributes from PPCs has not yet been deeply explored in remote sensing research. However, based on the results achieved by Prošek and Šímová (2019), PPCs will likely allow stand structure to be mapped in shrublands. Our general objective was to test the performance of UAV data in mapping structural attributes in shrublands of northern Patagonia. We specifically evaluated the capability of PPCs for mapping (*i*) canopy height, (*ii*) stand density, (*iii*) basal area, and (*iv*) volume.

2. Materials and methods

2.1. Study area

The study was carried out in northern Patagonia, near the rural area known as Los Repollos (41°46′S, 71°28′W) in Río Negro, Argentina (Fig. 1A). This region is characterized by a Mediterranean-type climate, with annual precipitation ranging from 920 to 1300 mm and mean temperatures between 8 and 9 °C (Gallopin 1978; Reque et al. 2007). Landscapes are covered by extensive broadleaf shrublands dominated by *N. antarctica*. UAV flights were performed on a monospecific *N. antarctica* stand of heavily branched,

Fig. 2. Unmanned aerial vehicle (UAV) spatial products derived from photogrammetric processing: (A) georeferenced orthomosaic, (B) digital terrain model (DTM) and contour lines, (C) digital surface model (DSM), and (D) dense point cloud. [Color online.]



medium-sized shrubs (up to 3 m high) with diameter at breast height (DBH; breast height = 1.30 m) no greater than 10 cm. This stand is located in a relatively flat valley, where soils are shallow and dominated by Udivitrants. In 2013, Instituto de Investigaciones en Recursos Naturales, Agroecología y Desarrollo Rural (IRNAD) from Universidad Nacional de Río Negro (UNRN) started a long-term monitoring experiment (Fig. 1B), in which several plots were harvested by applying a clear-cutting strip system (strips were 2.5 m wide, on average; Fig. 1C) (Coulin et al. 2019). Therefore, the study system represents a typical situation in which foresters would require stand-level information for management decision-making.

2.2. Remotely sensed data

UAV data were acquired in early December 2017 (i.e., late spring and early summer in the Southern Hemisphere), under sunny and moderately windy conditions (mean wind speed of 25 km·h^{-1}). A DJI Phantom 4 Pro quadcopter (1.4 kg and ≈30 min of flight autonomy; DJI, Shenzhen, China) equipped with a 20-megapixel RGB sensor was used to take the photographs. The camera, which has a mechanical shutter and adjustable aperture range, provides a 24 mm equivalent focal length. DroneDeploy software (https://www.dronedeploy.com) was used to program the flight mission over the experimental stand, setting an overlap of 75% (both front and side lap). The operation was carried out in compliance with Argentinian laws and regulations (Autoridad Nacional de Aviación Civil (ANAC) 2015). The flying altitude was between 90 and 100 m above ground level, and the flying speed was approximately 10 m·s^{-1}. The whole study area was covered with one flight mission, and 75 images were acquired.

2.3. Data processing

The photographs were processed using the Aerial Insights online processing platform (https://www.aerial-insights.co). Most of the workflow process in Aerial Insights is supported by Pix4D photogrammetric software (https://www.pix4d.com), which applies the structure from motion (SfM) algorithm (Frey et al. 2018) to align the set of overlapping photographs and generate a three-dimensional (3-D) reconstruction. As a result, the software generates a georeferenced PPC, as well as a high-resolution orthomosaic, digital surface model (DSM), and digital terrain model (DTM). The spatial products covered 7.3 ha with 3 cm·pixel^{-1} of spatial resolution (Fig. 2).

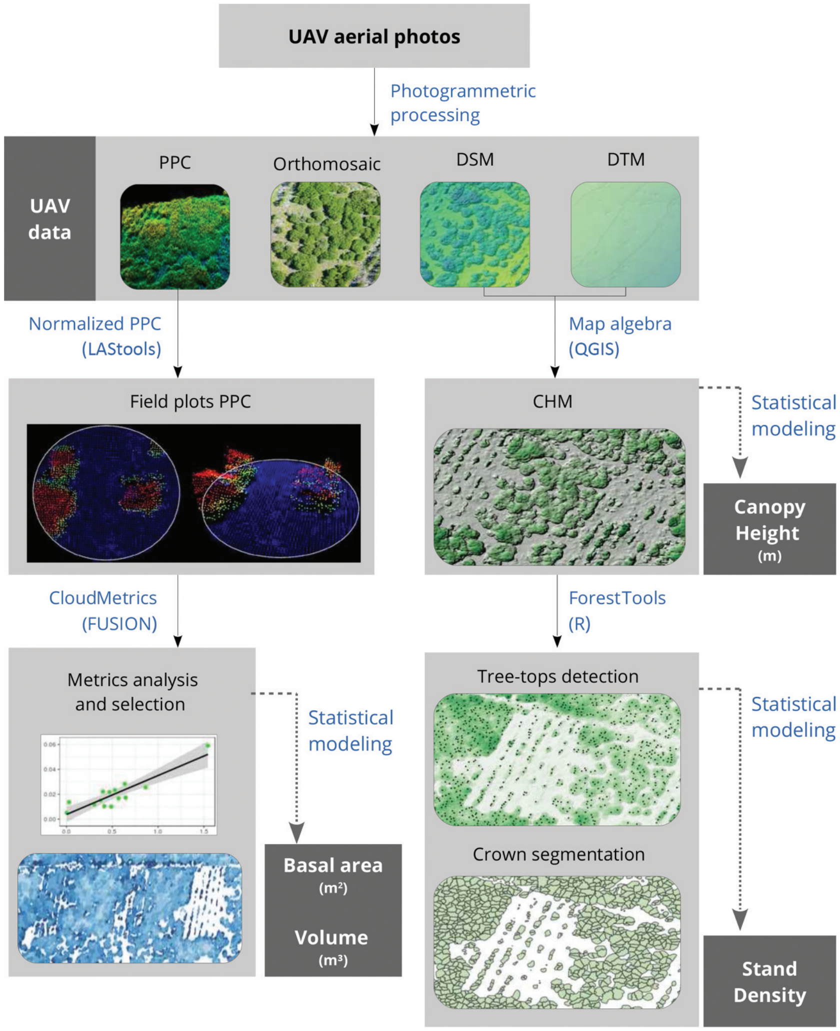
2.3.1. Canopy height model (CHM)

A canopy height model (CHM) is a spatial layer representing the vegetation height above the ground surface (Zhao and Popescu 2007). One of the methodological approaches to obtaining a CHM is to compute the difference between a DSM (earth height including plant canopy) and a DTM (bare-earth height) (Panagiotidis et al. 2017). This methodology was followed in the present study; the CHM of the shrubland stand was obtained by subtracting the DSM from the DTM. Both the DSM and the DTM layers were derived from the photogrammetry process (Fig. 3).

2.3.2. Individual tree crown segmentation

The CHM obtained from the UAV data can be used to identify tree crowns in forest stands (Grznárová et al. 2019). Treetops were identified, and crowns were delineated using the CHM, allowing us to estimate stand density (in number of plants per hectare). The workflow (Fig. 3) was performed using the ForestTools package (Plowright 2018) in R software (R Core Team 2019). The vwf() function was applied to the CHM (Popescu and Wynne 2004) to identify treetops, with suitable settings for this kind of shrub. The variable window filter of the function was set with a minimum height of 55 cm to mask vegetation that was not of interest (e.g., small bushes). Once treetops were detected, individual tree crown segmentation was performed using marker-controlled segmentation (Beucher and Mayer 1993), which is a modification of the watershed algorithm.

Fig. 3. Methodological flowchart for obtaining the stand structural attribute spatial layers. PPC, photogrammetric point cloud; CHM, canopy height model. [Color online.]



2.3.3. Point cloud metrics

Point cloud metrics are descriptive statistical summaries of the point cloud structure such as measures of central tendency (mean, median, and mode), position (percentiles), and variability (variance and standard deviation). Metrics for each field plot were computed using the CloudMetrics command of FUSION/LDV (McGaughey 2018) on the PPC that was normalized with LAStools (Isenburg 2018) (Fig. 3). Once extracted, we evaluated the capacity of these metrics to predict the forest attributes of the shrubland stand (Table 1).

2.4. Field data

Field data were collected to spatially model structural attributes of the stand and validate the UAV products. Data collection included measuring the height of individuals, counting the number of plants along transects, and recording the diameter of stems in fixed-size circular plots (Table 2).

Height measurements were made after the UAV flight. Twenty-eight individuals of different heights (0.9–4 m) were measured to capture the variability of the stand. These sample shrubs were selected on the UAV high-resolution orthomosaic because they were easy to identify in the field. Navigation was done using a Global Positioning System (GPS) and a mobile geographic information system (GIS) software running on a tablet. The software used for this task was QField (https://qfield.org), which can display the UAV orthomosaic as a base map during navigation, allowing accurate identification of the selected individuals. Individuals over 4 m in height were measured using a Nikon Forestry Pro 550 hypsometer (Nikon, Tokyo, Japan), and smaller ones were measured with a height pole.

Eleven transects were established within the shrubland stand, and we counted the number of plants in each transect. Stand density (in number of plants per hectare) was estimated using the transect size of 100 m^2 (50 m × 2 m).

Fourteen fixed-size circular plots of 3 m radius were established. The diameters of all stems were measured using a forestry caliper (Haglöf Mantax Blue, Haglöf Sweden, Långsele, Sweden). DBH was smaller than 1 cm in most of the shrubs, so we measured basal diameter instead because it is a good predictor of stem volume in *N. antarctica* (Gyenge et al. 2009). Basal diameter of stems was used as an input to calculate basal area and estimate volume at the plot level. Volume equations available for this species were developed using DBH greater than 8 cm (Lencinas et al. 2002; Gyenge et al. 2009). Therefore, a local equation was developed (n = 20) to estimate the volume of stems, based on the range of basal diameters found in the study site. The fitted equation was

$$\text{(1)} \qquad SV = 2.84 - 27.15 \times BD + 74.46BD^2$$

Table 1. Photogrammetric point cloud (PPC) metrics (using elevation values) and type of statistic that each metric represents.

		R^2	
Type of statistic measure	PPC metric	Basal area	Volume
Central tendency	Mean	0.40	0.41
	Mode	0.24	0.24
Dispersion	Standard deviation	0.67	0.70
	Variance	0.71	0.75
	Coefficient of variation	0.12	0.10
	Interquartile distance	0.13	0.70
	AAD	0.71	0.72
	MAD Median	**0.81**	**0.81**
	MAD Mode	0.24	0.24
Position	Percentiles (40th, 50th, 60th, 70th, 80th, 90th, and 95th)	0.50 (mean)	0.51 (mean)
	Maximum	0.51	0.54
Shape	Skewness	0.12	0.10
	Kurtosis	0.13	0.10
Frequency	Percentage of all returns above a specified height	0.31	0.34
	Percentage of all returns above the mean height	0.03	0.02
	Percentage of all returns above the mode height	0.03	0.02
	Canopy relief ration	0.15	0.14

Note: Metrics were derived from the CloudMetrics command of FUSION/LDV (McGaughey 2018) and were used for modelling basal area and volume. Boldface type indicates the best metric. R^2, coefficient of determination; AAD, average absolute deviation; MAD Median, median of the absolute deviations from the overall median; MAD Mode, median of the absolute deviations from the overall mode.

Table 2. Summary statistics of the field data.

Forest attribute	Range	Mean
Height (m)	0.90–3.80	2.4
Stand density (plants·ha^{-1})	1300–4600	2500
Basal area (m^2·ha^{-1})	4.2–23.4	9.9
Volume (m^3·ha^{-1})	1.8–20.0	7.1

where SV is the stem volume (in cubic centimetres) and BD is basal diameter (in centimetres).

Plot centers and the starting points of the counting transects were marked with visible color objects (Fig. 4). These marks were captured in the UAV aerial images and later identified in the orthomosaic to allow the field information to be collocated with the UAV processed data.

2.5. Data analysis: modelling stand attributes

2.5.1. Height and number of plants

Linear models were fitted to evaluate the agreement between field measurements of height and number of plants and measurements obtained by the photogrammetric processing products (CHM and crown segmentation):

(2) $$y_i \sim N(\mu_i; \sigma^2)_{\text{indep.}} \qquad \mu_i = \beta_0 + \beta_1 x_i$$

where y is the attribute (height or number of plants), x is the UAV information, and i is the experimental unit (plant or transect, respectively). Normality (N) and homogeneous variances (σ) are assumed. The agreement between field data and UAV predictions was assessed based on the coefficient of determination R^2. In addition, the possible bias of the UAV data was assessed from the parameter estimates; the UAV predictions would be unbiased if β_0 and β_1 were 0 and 1, respectively (i.e., a one-to-one relationship). Otherwise, they should be corrected by applying the fitted model equation.

2.5.2. Basal area and volume

Twenty-seven point cloud metrics (Table 1) were evaluated for their ability to predict the basal area and volume (y) recorded in the field plots (i). Hence, one linear model per metric (m) was fitted:

(3) $$y_i \sim N(\mu_i; \sigma^2)_{\text{indep.}} \qquad \mu_i = \beta_0 + \beta_1 m_i$$

Metrics were ordered according to their goodness of fit. In both analyses (basal area and volume), the metric with the higher R^2 was selected to map the attribute in the stand. That is, both basal area and volume were regressed by applying the fitted equations to the spatial layer. Before the metric was used for mapping, the model's assumptions (linearity, normality, and homoscedasticity) were visually checked.

2.5.3. Model validation

As in similar studies (Puliti et al. 2015), the accuracy of model predictions of each structural attribute (height, density, basal area, and volume) was validated using leave-one-out cross-validation (Harrell 2001). Models were fitted iteratively leaving out one observation at a time, and at each iteration, the estimated parameters were used to predict that observation. Both the absolute and relative root mean square error (RMSE and rRMSE, respectively) were used as prediction accuracy indicators:

(4) $$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n}}$$

(5) $$\text{rRMSE} = \sqrt{\frac{\sum_{i=1}^{n}[(y_i - \hat{y}_i)/\hat{y}_i]^2}{n}}$$

where n is sample size.

2.5.4. Mapping structural attributes

Height, basal area, and volume were mapped by applying the fitted statistical models to the UAV-derived products. As a result, spatial raster layers were generated in which each pixel represented a value of the structural attribute. To obtain a more realistic visualization and estimate inventory attributes at an individual tree scale, we applied zonal statistics to compute the mean value of the pixels within each polygon of the segmented crown. This process allowed ground, shadows, and areas with no vegetation to be masked. Stand density was mapped as a heat map derived from the treetops vector layer, transforming points into a regular grid

Fig. 4. Collocation marks: (A) general view of the orthomosaic, (B) amplified view of the orthomosaic showing one of the marks, and (C) fixed plot center mark used during the field sampling. [Color online.]

in which areas with greater or fewer dots were shown in a contrasting color ramp.

3. Results

3.1. Evaluation of stand attribute models

The CHM predicted shrub heights accurately (R^2 = 0.95), and the model validation showed an RMSE of 0.27 m and an rRMSE of 12%. However, the estimate of β_1 was greater than 1 (the confidence interval did not contain 1) because height predictions were consistently low. Consequently, it was necessary to correct the CHM using the fitted equation model (Table 3). Estimation of stand density by treetop identification and crown segmentation showed a similar result to that of CHM. It was accurate (R^2 = 0.93), with a relative error of 13% (RMSE = 3 plants), but β_1 was no different from 1 (Table 3), so correction was not necessary for mapping. The observed and predicted stand densities were 2500 and 2300 plants·ha^{-1}, respectively.

Point cloud metrics with higher predictive capacity estimated basal area and volume with R^2 values up to 0.81. The better metrics, according to this criterion, were dispersion metrics: median of the absolute deviations from the overall median (MAD Median), variance, and average absolute deviation (AAD). Model validation using MAD Median, the best metric for both variables, ranged between 33% (basal area) and 39% (volume) of relative error (rRMSE) (Table 3). Figure 5 shows field measurements predicted from UAV information, and Fig. 6 shows the resulting maps for each attribute.

4. Discussion

UAV technology is increasingly considered a key tool for forest management because it performs well in high-elevation forests under silvicultural management (Banu et al. 2016; Torresan et al. 2017). However, there is little information about uses for UAVs in shrublands. Shrubland volume and biomass are difficult to estimate with field data collection. For example, in northern Patagonia, where *N. antarctica* shrublands cover large areas and display great morphological variation (Veblen et al. 1996), few specific allometric equations have been developed for this species (Lencinas et al. 2002; Gyenge et al. 2009). Furthermore, the ranges of application of these equations (DBH and plant heights) are not suitable for all morphotypes, as was the case of the stand studied in the present paper. For this reason, it is important to explore alternatives and new survey methods such as UAVs that could provide reasonably accurate measurements of shrublands.

This study shows that structural attributes estimated from UAVs are reliable for shrubland ecosystems (models with R^2 up to 0.95; Table 3). In particular, the best results were obtained for height estimation and treetop detection (stand density), followed by basal area and volume. However, UAV-based estimates were slightly biased, and the bias increased with shrub size and shrubland density (estimates of β_1 greater than 1). Therefore, UAV performance may decrease in more productive sites with taller individuals and denser stands. Basal area and volume were best predicted by the same UAV-derived metrics. This result was to be expected because of the direct relationship between these two forest attributes (Francis 1988). During validation of the models, errors ranged between 12% and 39%, similar to the values reported in other studies (most of them carried out in coniferous forests), which ranged from 12% to 46% (Puliti et al. 2015; Kachamba et al. 2016; Ota et al. 2017; Shin et al. 2018; Alonzo et al. 2018). As in those studies, volume was predicted with less precision than height, which is the variable for which the best results are usually observed. Analyzing the performance of PPCs in mapping structural attributes of shrublands is important because most studies have evaluated its potential in conifers. For instance, a recent review of the applications of aerial images for updating forest inventories included 20 studies, which were all in coniferous forests (Goodbody et al. 2019). On the contrary, most studies that apply UAV technologies in deciduous forests are not specifically focused on the potential of PPCs for forest inventories (Baena et al. 2017; Grznárová et al. 2019; Prošek and Šímová 2019; Rossi et al. 2018). In deciduous species like *N. antarctica*, results may depend on the timing of the flight. In the present study, the UAV flight was made in late spring when plant vigor is greatest; UAV performance could differ if data were generated in winter when plants are leafless.

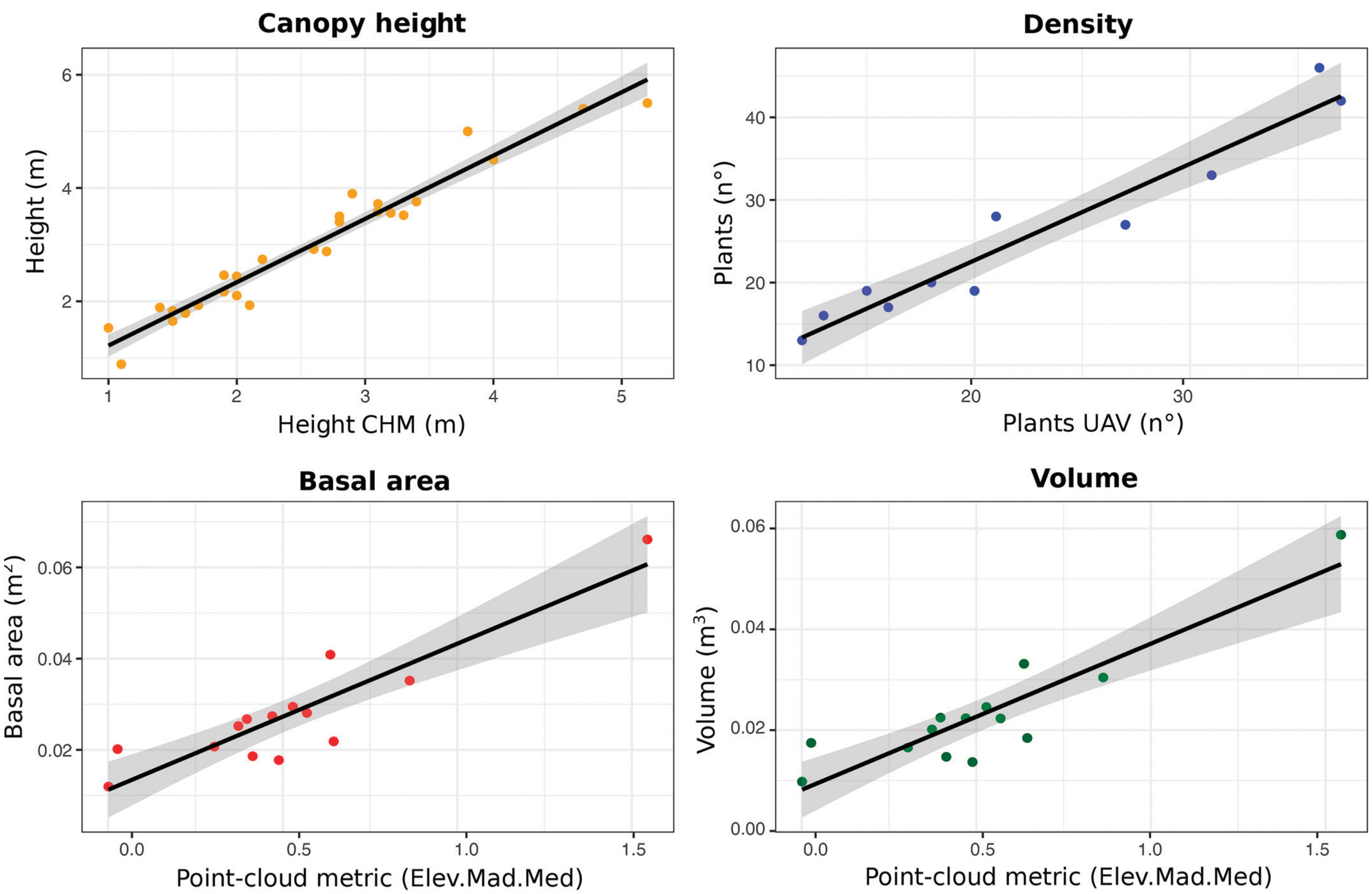
Although the differences in measurements derived from field data and UAV imagery were small, collecting UAV data required much less time. In the study stand, traditional field sampling requires two people (one technician and one field assistant) working 5–6 days (i.e., 10–12 workdays), plus 1 day in the laboratory for

Table 3. Summary of the fitted linear models for structural attributes, including height, stand density, basal area, and volume, and sampling size (*n*).

	Model adjustment					Validation	
Attribute	*n*	$\hat{\beta}_0$	$\hat{\beta}_1$	Equation	R^2	RMSE	rRMSE
Height (m)	28	0.099 [−0.186; 0.385]	1.118 [1.014; 1.222]	$H = 0.10 + 1.12 \times \text{CHM}$	0.95	0.9	12%
Stand density (plants·ha^{-1})	11	−0.669 [−6.406; 5.066]	1.168 [0.928; 1.407]	$N = -0.67 + 1.17 \times N_{\text{UAV}}$	0.93	3.3	13%
Basal area (m^2)	14	0.011 [0.005; 0.017]	0.032 [0.022; 0.042]	BA = 0.01 + 0.03 × Elev.Mad.Med	0.81	0.007	33%
Volume (m^3)	14	0.008 [0.003; 0.014]	0.028 [0.020; 0.037]	V = 0.01 + 0.03 × Elev.Mad.Med	0.81	0.007	39%

Note: Height was predicted from the canopy height model (CHM), Stand density was predicted from the treetop detection (N_{UAV}), and Basal area and Volume were predicted from MAD Median (Elev.Mad.Med), the best point cloud metric. Values in square brackets are 95% confidence intervals for intercept (β_0) and slope (β_1). Accuracy of fit (R^2) and validation (absolute and relative root mean square error (RMSE and rRMSE, respectively)) are included for all models.

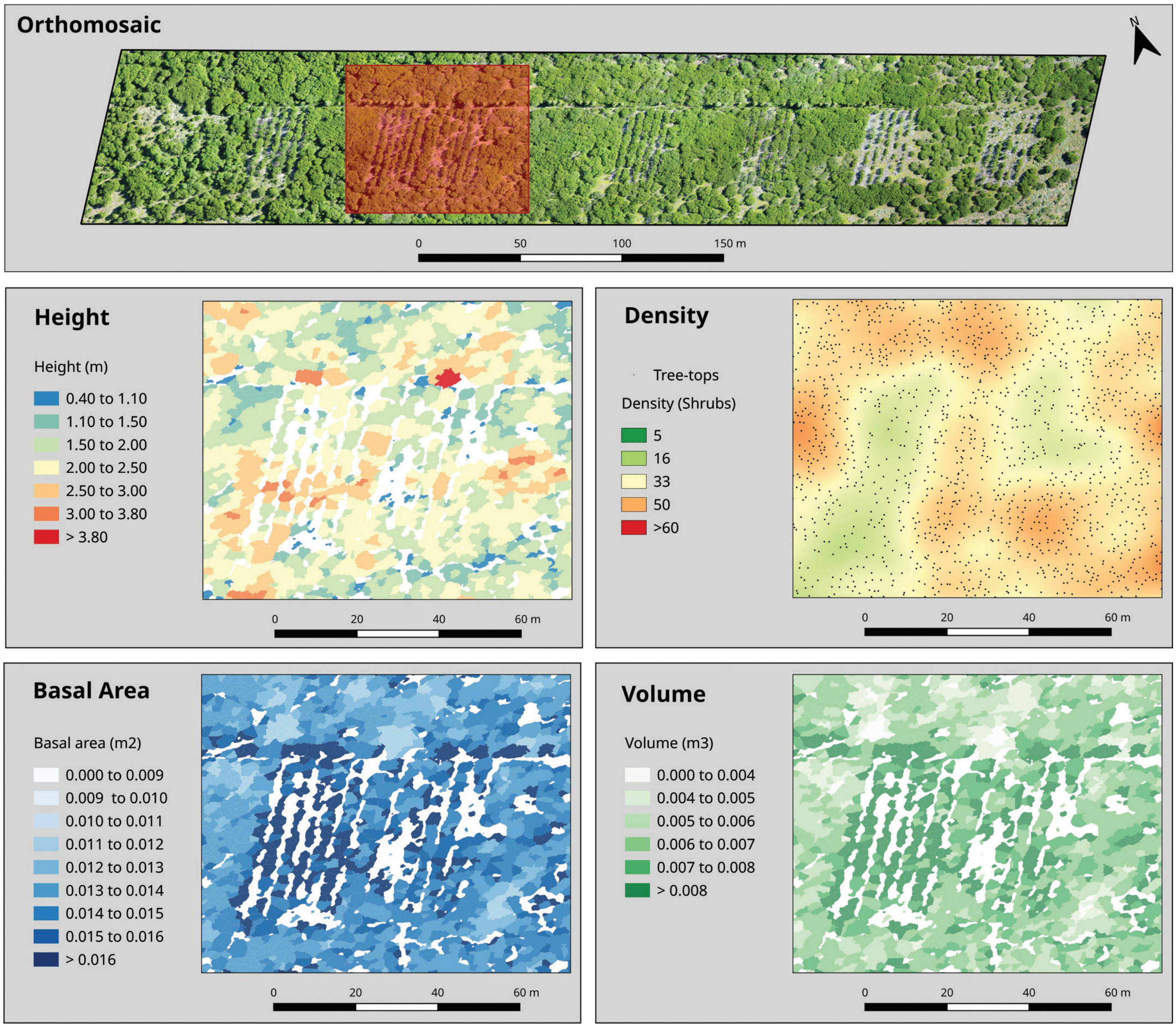
Fig. 5. Structural attributes predicted from UAV imagery. Attributes measured in the field are shown on the *y* axes, and the UAV spatial information used for prediction is shown on the *x* axes. Black lines indicate the fitted model predictions, and grey areas indicate their 95% confidence intervals. Elev.Mad.Med, median of the absolute deviations from the overall median. [Color online.]



data entry. On the contrary, UAV data collection and processing required 2 workdays: 0.5 workdays to program the flight, 0.5 workdays to carry out the flight, and 1 workday for mapping. Fieldwork was only required during the flight operation. In northern Patagonia, the fee for a technician working in the field is approximately US\$120 per workday and the fee for an assistant is US\$40 per workday. Nonetheless, monetary costs are not directly comparable because UAV equipment is more expensive (purchase, depreciation, and high crash risk). UAVs could provide reliable information about shrubland structure with a smaller time commitment.

Even though this study has not developed a novel methodological approach, it represents a starting point for the estimation of structural attributes in shrublands using UAVs. The results of this paper complement those of Prošek and Šímová (2019), who demonstrated, by using a multispectral sensor, that PPCs improve shrubland classification at the species level in the west of Czechia. Although the results from northern Patagonia are encouraging, some issues should still be explored. For instance, to improve shrubland stock quantification from UAV technology, a different allometric approach could be tested. In forests, allometric functions to estimate crown diameter or volume often use DBH as an input; however, allometric equations do not perform as well for shrubs with very small basal diameters and shorter heights (such as those in our study). In our study, individual shrubs were readily detected by crown segmentation (R^2 = 0.93, rRMSE = 13%), so relationships between volume and crown diameter could be tested for *N. antarctica* to estimate stocks directly from UAV products. From a technical point of view, estimations could be improved by increasing the quality of the point cloud, for example, by increasing overlapping or planning cross-flight grids. Overlapping values above 80% (in this study, both front and side overlap was 75%) are used to improve penetration between objects for a more effective and consistent reconstruction (Goodbody et al. 2019). In addition,

Fig. 6. Maps of stand attributes derived from UAV spatial models. [Color online.]



the sampling units (plots, transects, and trees) were marked on the ground and then located on the orthomosaic. This allowed UAV information to be coregistered and compared with the field data. Some studies suggest georeferencing the point cloud using ground control points (GCPs) with submetric precision Global Navigation Satellite System (GNSS) receivers (Tomaštík et al. 2017), but such receivers are not as widely available as less precise GPS units. Despite the challenges and methodological aspects that need to be solved, our study provides useful information for advancing biomass and stock quantification of shrubland ecosystems using UAV technology.

5. Conclusions

This study has shown that UAV technology can reliably map structural attributes in shrubland ecosystems. Prediction models of common structural attributes were fitted with reasonable precision comparable with those obtained in high-value forest stands. Therefore, this technology could overcome some of the difficulties faced when estimating stocks in shrublands and woodlands. Efficiency and cost in data acquisition, which are key problems to solve in shrubland management, could be addressed by applying UAVs. Rapidly mapping attributes such as height, density, basal area, and volume at stand level with high spatial resolution would provide foresters with timely and accurate information for decision-making. The study is a first test for the application of UAVs as a tool to characterize structure and quantify stock in shrublands. Hence, some methodological aspects could be improved to obtain better estimations. However, the results have been satisfactory and suggest that the use of UAVs is potentially useful for shrubland management.

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References

Alonzo, M., Andersen, H.E., Morton, D., and Cook, B. 2018. Quantifying boreal forest structure and composition using UAV structure from motion. Forests, **9**(3): 119. doi:10.3390/f9030119.

Anderson, K., and Gaston, K.J. 2013. Lightweight unmanned aerial vehicles will revolutionize spatial ecology. Front. Ecol. Environ. **11**(3): 138–146. doi:10.1890/120150.

Autoridad Nacional de Aviación Civil (ANAC). 2015. Provisional regulation for unmanned aerial vehicles. Resolution No. 527/15.

Baena, S., Moat, J., Whaley, O., and Boyd, D.S. 2017. Identifying species from the air: UAVs and the very high resolution challenge for plant conservation. PLoS One, **12**(11): e0188714. doi:10.1371/journal.pone.0188714. PMID:29176860.

Banu, T.P., Borlea, G.F., and Banu, C. 2016. The use of drones in forestry. J. Environ. Sci. Eng. **5**: 557–562. doi:10.17265/2162-5263/2016.11.007.

Beucher, S., and Meyer, F. 1993. The morphological approach to segmentation: the watershed transformation. *In* Mathematical morphology in image processing. Marcel Dekker Inc., New York. pp. 433–481.

Coulin, C., Aizen, M., and Garibaldi, L. 2019. Contrasting responses of plants and pollinators to woodland disturbance. Austral Ecol. **44**(6): 1040–1051. doi:10.1111/aec.12771.

Easterday, K., Kislik, C., Dawson, T.E., Hogan, S., and Kelly, M. 2019. Remotely sensed water limitation in vegetation: insights from an experiment with unmanned aerial vehicles (UAVs). Remote Sens. **11**(16): 1853. doi:10.3390/rs11161853.

Francis, J.K. 1988. The relationship of bole diameters and crown widths of seven bottomland hardwood species. USDA For. Serv. Res. Note SO-328. U.S. Department of Agriculture, Forest Service, Southern Forest Experiment Station, New Orleans, La., USA. doi:10.2737/SO-RN-328.

Frey, J., Kovach, K., Stemmler, S., and Koch, B. 2018. UAV photogrammetry of forests as a vulnerable process. A sensitivity analysis for a structure from motion RGB-image pipeline. Remote Sens. **10**(6): 912. doi:10.3390/rs10060912.

Gallopin, G. 1978. Estudio integrado de la cuenca del Río Manso Superior (Río Negro, Argentina). Descripción general de la cuenca. Anales Parques Nacionales, **14**: 161–230.

Getzin, S., Wiegand, K., and Schöning, I. 2012. Assessing biodiversity in forests using very high-resolution images and unmanned aerial vehicles. Methods Ecol. Evol. **3**: 397–404. doi:10.1111/j.2041-210X.2011.00158.x.

Getzin, S., Nuske, R.S., and Wiegand, K. 2014. Using unmanned aerial vehicles (UAV) to quantify spatial gap patterns in forests. Remote Sens. **6**(8): 6988–7004. doi:10.3390/rs6086988.

Goldenberg, M.G., Cardoso, Y.A., Oddi, F.J., and Garibaldi, L.A. 2019. Fuelwood energy characteristics and biomass equations of the dominant species of northern Patagonia shrublands. South. For. [In press.] doi:10.2989/20702620.2019.1686693.

Goodbody, T.R.H., Coops, N.C., and White, J.C. 2019. Digital aerial photogrammetry for updating area-based forest inventories: a review of opportunities, challenges, and future directions. Curr. For. Rep. **5**: 55–75. doi:10.1007/s40725-019-00087-2.

Grosfeld, J., Chauchard, L., and Gowda, J.H. 2019. Debates: ¿Podemos manejar sustentablemente el bosque nativo de Patagonia Norte? Ecol. Austral. **29**: 156–163. doi:10.25260/EA.19.29.1.0.775.

Gznárová, A., Mokroš, M., Surový, P., Slavík, M., Pondelík, M., and Merganič, J. 2019. The crown diameter estimation from fixed wing type of UAV imagery. Int. Arch. Photogramm. Remote Sens. Spatial Inf. Sci. **XLII-2/W13**: 337–341. doi:10.5194/isprs-archives-XLII-2-W13-337-2019.

Gyenge, J., Fernández, M.E., Sarasola, M., de Urquiza, M., and Schlichter, T. 2009. Ecuaciones para la estimación de biomasa aérea y volumen de fuste de algunas especies leñosas nativas en el valle del Río Foyel, NO de la Patagonia argentina. Bosque, **30**(2): 95–101. doi:10.4067/S0717-92002009000200005.

Harrell, F.E., Jr. 2001. Regression modeling strategies — with applications to linear models, logistic regression, and survival analysis. Springer, Cham, Switzerland. doi:10.1007/978-3-319-19425-7.

Isenburg, M. 2018. LAStools: efficient LiDAR processing software. Version 181001, unlicensed. Available from http://rapidlasso.com [accessed 10 December 2019].

Kachamba, J.D., Ørka, O.H., Gobakken, T., Eid, T., and Mwase, W. 2016. Biomass estimation using 3D data from unmanned aerial vehicle imagery in a tropical woodland. Remote Sens. **8**(11): 968. doi:10.3390/rs8110968.

Lencinas, M.V., Martínez Pastur, G., Cellini, J.M., Vukasovic, R., Peri, P., and Fernández, M.C. 2002. Incorporación de la altura dominante y la clase de sitio a ecuaciones estándar de volumen para *Nothofagus antarctica* (Forster f.) Oersted. Bosque, **23**(2): 5–17. doi:10.4067/S0717-92002002000200002.

McGaughey, R. 2018. FUSION/LDV: software for LiDAR data analysis and visualization. U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station.

Naveh, Z. 2007. Culture and landscape conservation: a landscape-ecological perspective. *In* Ecology today: an anthology of contemporary ecological research. *Edited by* B.P. Gopal, P. Pathak, and K.G. Sayena. International Scientific Publications, New Delhi. pp. 19–48. *In* Transdisciplinary challenges in landscape ecology and restoration ecology. Landscape Series, Vol. 6. Springer, Dordrecht, Netherlands. doi:10.1007/1-4020-4422-4_10.

Ota, T., Ogawa, M., Mizoue, N., Fukumoto, K., and Yoshida, S. 2017. Forest structure estimation from a UAV-based photogrammetric point cloud in managed temperate coniferous forests. Forests, **8**(9): 343. doi:10.3390/f8090343.

Panagiotidis, D., Abdollahnejad, A., Surový, P., and Chiteculo, V. 2017. Determining tree height and crown diameter from high-resolution UAV imagery. Int. J. Remote Sens. **38**(8–10): 2392–2410. doi:10.1080/01431161.2016.1264028.

Peri, P.L. 2011. Carbon storage in cold temperate ecosystems in southern Patagonia, Argentina. *In* Biomass and remote sensing of biomass. *Edited by* I. Atazadeh. IntechOpen. doi:10.5772/20294.

Plowright, A. 2018. ForestTools: analyzing remotely sensed forest data. Version 0.2.0. Available from https://CRAN.R-project.org/package=ForestTools.

Popescu, S.C., and Wynne, R.H. 2004. Seeing the trees in the forest: using LiDAR and multispectral data fusion with local filtering and variable window size for estimating tree height. Photogramm. Eng. Remote Sens. **70**(5): 589–604. doi:10.14358/PERS.70.5.589.

Popescu, S.C., Wynne, R.H., and Nelson, R.F. 2003. Measuring individual tree crown diameter with LiDAR and assessing its influence on estimating forest volume and biomass. Can. J. Remote Sens. **29**(5): 564–577. doi:10.5589/m03-027.

Prošek, J., and Šímová, P. 2019. UAV for mapping shrubland vegetation: does fusion of spectral and vertical information derived from a single sensor increase the classification accuracy? Int. J. Appl. Earth Obs. Geoinform. **75**: 151–162. doi:10.1016/j.jag.2018.10.009.

Puliti, S., Ørka, H.O., Gobakken, T., and Næsset, E. 2015. Inventory of small forest areas using an unmanned aerial system. Remote Sens. **7**: 9632–9654. doi:10.3390/rs70809632.

QGIS Development Team. 2019. QGIS Geographic Information System. Open Source Geospatial Foundation Project. Available from http://qgis.osgeo.org.

R Core Team. 2019. R: a language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. Available from https://www.R-project.org.

Reque, J.A., Sarasola, M., Gyenge, J., and Fernández, M. 2007. Silvicultural characterization of the mixed ñire forests of northern Patagonia as a basis for sustainable forestry. Bosque, **28**(1): 33–45. doi:10.4067/S0717-92002007000100006.

Rossi, F.C., Fritz, A., and Becker, G. 2018. Combining satellite and UAV imagery to delineate forest cover and basal area after mixed-severity fires. Sustainability, **10**: 2227. doi:10.3390/su10072227.

Shahbazi, M., Théau, J., and Ménard, P. 2014. Recent applications of unmanned aerial imagery in natural resource management. GISci. Remote Sens. **51**(4): 339–365. doi:10.1080/15481603.2014.926650.

Shin, P., Sankey, T., Moore, M.M., and Thode, A.E. 2018. Evaluating unmanned aerial vehicle images for estimating forest canopy fuels in a ponderosa pine stand. Remote Sens. **10**(8): 1266. doi:10.3390/rs10081266.

Tang, L., and Shao, G. 2015. Drone remote sensing for forestry research and practices. J. For. Res. **26**: 791–797. doi:10.1007/s11676-015-0088-y.

Tomaštík, J., Mokroš, M., Saloň, Š., Chudý, F., and Tunák, D. 2017. Accuracy of photogrammetric UAV-based point clouds under conditions of partially open forest canopy. Forests, **8**(5): 151. doi:10.3390/f8050151.

Torresan, C., Berton, A., Carotenuto, F., Filippo Di Gennaro, S., Gioli, B., Matese, A., et al. 2017. Forestry applications of UAVs in Europe: a review. Int. J. Remote Sens. **38**(8–10): 2427–2447. doi:10.1080/01431161.2016.1252477.

Veblen, T., Donoso, C., Kitzberger, T., and Rebertus, A. 1996. Ecology of southern Chilean and Argentinean *Nothofagus* forests. *In* The ecology and biogeography of *Nothofagus* forests. *Edited by* T. Veblen, R.S. Hill, and J. Read. Yale University Press, New Haven, Conn. pp. 293–353.

Waite, C., Van der Heijden, G., Field, R., and Boyd, D. 2019. A view from above: unmanned aerial vehicles (UAVs) provide a new tool for assessing liana infestation in tropical forest canopies. J. Appl. Ecol. **56**: 902–912. doi:10.1111/1365-2664.13318.

White, J.C., Coops, N.C., Wulder, M.A., Vastaranta, M., Hilker, T., and Tompalski, P. 2016. Remote sensing technologies for enhancing forest inventories: a review. Can. J. Remote Sens. **42**(5): 619–641. doi:10.1080/07038992.2016.1207484.

Zhang, J., Hu, J., Lian, J., Fan, Z., Ouyang, X., and Ye, W. 2016. Seeing the forest from drones: testing the potential of lightweight drones as a tool for long-term forest monitoring. Biol. Conserv. **198**: 60–69. doi:10.1016/j.biocon.2016.03.027.

Zhao, K., and Popescu, S. 2007. Hierarchical watershed segmentation of canopy height model for multi-scale forest inventory. *In* ISPRS Workshop on Laser Scanning 2007 and SilviLaser 2007, 12–14 September 2007, Espoo, Finland. pp. 436–441.