# Plant cover as an estimator of above-ground biomass in semi-arid woody vegetation in Northeast Patagonia, Argentina postprint

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## Abstract

The quantification of carbon storage in vegetation biomass is a crucial factor in the estimation and mitigation of CO2 emissions. Globally, arid and semi-arid regions are considered an important carbon sink. However, they have received limited attention and, therefore, it should be a priority to develop tools to quantify biomass at the local and regional scales. Individual plant variables, such as stem diameter and crown area, were reported to be good predictors of individual plant weight. Stand-level variables, such as plant cover and mean height, are also easy-to-measure estimators of above-ground biomass (AGB) in dry regions. In this study, we estimated the AGB in semi-arid woody vegetation in Northeast Patagonia, Argentina. We evaluated whether the AGB at the stand level can be estimated based on plant cover and to what extent the estimation accuracy can be improved by the inclusion of other field-measured structure variables. We also evaluated whether remote sensing technologies can be used to reliably estimate and map the regional mean biomass. For this purpose, we analyzed the relationships between field-measured woody vegetation structure variables and AGB as well as LANDSAT TM-derived variables. We obtained a model-based ratio estimate of regional mean AGB and its standard error. Total plant cover allowed us to obtain a reliable estimation of local AGB, and no better fit was attained by the inclusion of other structure variables. The stand-level plant cover ranged between 18.7% and 95.2% and AGB between about 2.0 and 70.8 Mg/hm2. AGB based on total plant cover was well estimated from LANDSAT TM bands 2 and 3, which facilitated a model-based ratio estimate of the regional mean AGB (approximately 12.0 Mg/hm2) and its sampling error (about 30.0%). The mean AGB of woody vegetation can greatly contribute to carbon storage in semi-arid lands. Thus, plant cover estimation by remote sensing images could be used to obtain regional estimates and map biomass,

as well as to assess and monitor the impact of land-use change on the carbon balance, for arid and semi-arid regions.

## Full Text

## Preamble

### Plant cover as an estimator of above-ground biomass in semi-arid woody vegetation in Northeast Patagonia, Argentina

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**Abstract:** The quantification of carbon storage in vegetation biomass is a crucial factor in the estimation and mitigation of $CO_2$ emissions. Globally, arid and semi-arid regions are considered an important carbon sink. However, they have received limited attention, and therefore, developing tools to quantify biomass at local and regional scales should be a priority. Individual plant variables, such as stem diameter and crown area, have been reported to be good predictors of individual plant weight. Stand-level variables, such as plant cover and mean height, are also easy-to-measure estimators of above-ground biomass (AGB) in dry regions. In this study, we estimated AGB in semi-arid woody vegetation in Northeast Patagonia, Argentina. We evaluated whether AGB at the stand level can be estimated based on plant cover and to what extent the estimation accuracy can be improved by the inclusion of other field-measured structure variables. We also evaluated whether remote sensing technologies can be used to reliably estimate and map the regional mean biomass. For this purpose, we analyzed the relationships between field-measured woody vegetation structure variables and AGB as well as LANDSAT TM-derived variables. We obtained a model-based ratio estimate of regional mean AGB and its standard error. Total plant cover allowed us to obtain a reliable estimation of local AGB, and no better fit was attained by the inclusion of other structure variables. The stand-level plant cover ranged between 18.7% and 95.2% and AGB between about 2.0 and 70.8 Mg/hm$^2$. AGB based on total plant cover was well estimated from LANDSAT TM bands 2 and 3, which facilitated a model-based ratio estimate of the regional mean AGB (approximately 12.0 Mg/hm$^2$) and its sampling error (about 30.0%). The mean AGB of woody vegetation can greatly contribute to carbon storage in semi-arid lands. Thus, plant cover estimation by remote sensing images could be used to obtain regional estimates and map biomass, as well as to assess and monitor the impact of land-use change on the carbon balance for arid and semi-arid regions.

**Keywords:** above-ground biomass; shrublands; ratio estimation; carbon storage; remote sensing; Patagonia

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## Introduction

The loss of biomass is an important cause of increased greenhouse gas emissions, mainly driven by land-use change (Foley et al., 2005; Houghton, 2005). Consequently, reducing deforestation rates is considered a crucial strategy for mitigating $CO_2$ emissions (Kindermann et al., 2008). In this context, carbon storage in vegetation biomass represents a valuable environmental service, and its quantification is therefore an essential measurement for estimating and mitigating $CO_2$ emissions from deforestation (Houghton, 2007; GTOS, 2010).

Carbon storage has been widely studied over the last decades, particularly in tropical and subtropical forests (Baccini et al., 2008; Saatchi et al., 2011; Gasparri et al., 2013; Hansen et al., 2013; Cartus et al., 2014; Hengeveld et al., 2015). However, the carbon storage of woody communities in arid and semi-arid regions has received much less attention (Grainger, 1999; Malagnoux et al., 2007; Le Polain de Waroux and Lambin, 2012). Globally, arid and semi-arid regions are considered an important carbon sink, covering approximately 45.0% of the world' s land area (Grünzweig et al., 2003; Nosetto et al., 2006).

In dry ecosystems, tree and shrub cover are closely related to carbon storage, and their spatio-temporal dynamics are strongly influenced by climate, soil, herbivory, wildfire frequency, and land-use change (Sankarán et al., 2005; Torres Robles et al., 2015; Zeberio and Pérez, 2020). Field estimation of vegetation biomass in arid and semi-arid regions is typically more challenging than in temperate forest regions due to the lack of classical tools such as national forest inventories and standardized biomass equations for trees (Le Polain de Waroux and Lambin, 2012). Therefore, developing tools to quantify biomass at local and regional scales is a priority for accurately estimating the impact of land-use change on the carbon balance of these ecosystems.

At the local scale, above-ground biomass (AGB) is frequently estimated through dimensional analysis based on allometric relationships between plant dimensions and dry mass for individual species or species groups (Jenkins et al., 2004). Stem base diameter and diameter at breast height (DBH) are the most common and useful variables for estimating biomass at the individual tree level (Chave et al., 2005; Fonseca et al., 2009). In multi-stemmed woody species, variables related to crown size are most useful because they best represent plant volume (Hierro et al., 2000; Hofstad, 2005; Oñatibia et al., 2010; Conti et al., 2019). However, allometric formulas for estimating tree and shrub biomass are not always available, especially for semi-arid vegetation dominated by small trees and multi-stemmed shrubs (Hierro et al., 2000; Conti et al., 2013). Additionally, serious difficulties arise when applying allometric models in the field because time-demanding variables must be measured, and individuals are not isolated; instead, overlapping crowns are frequently found among individuals of the same or different species (Torres Robles et al., 2015; Zeberio et al., 2018). Alternatively, stand-level vegetation variables such as plant cover and mean height have proven to be easy-to-measure independent variables for estimating AGB in dry regions (Flombaum and Sala, 2007; Chojnacky and Milton, 2008; Pearce et al., 2010). Moreover, plant cover has been highlighted as a good single-variable estimator of vegetation biomass in arid or semi-arid shrublands (Flombaum and Sala, 2007; Zhang et al., 2019), which can be appropriately estimated from remote sensing images.

At the regional scale, remote sensing techniques have been considered valid tools for mapping and monitoring forest biomass (Dong et al., 2003; Houghton, 2005; Dengsheng, 2006). Statistical approaches are commonly used to link field data with remote sensing information in arid and semi-arid regions (Dengsheng, 2006; Chen et al., 2010). These approaches seek relationships between vegetation biomass measured in the field and spectral variables (Galidaki et al., 2017; Chen et al., 2018). However, models for estimating AGB derived from remote sensing images are specific to a given region at a given moment and have low transferability in space and time (Eisfelder et al., 2012). Thus, local and regional estimates of AGB are needed to understand the dynamics of carbon storage in arid and semi-arid regions worldwide.

A significant proportion of arid and semi-arid areas in South America are located in Argentina (Fensholt et al., 2012). AGB and plant cover have been estimated at regional scales based on remote sensing technologies in Argentine dry forestlands (Gasparri et al., 2010; Gasparri and Baldi, 2013; González-Roglich and Swenson, 2016) and shrublands. However, the wide range of variations in climate, physiognomy, and floristic composition throughout Argentina' s arid and semi-arid areas makes it clear that many local and regional estimations are still necessary.

In this study, we estimated AGB in semi-arid woody vegetation in Northeast Patagonia, Argentina. We evaluated whether AGB at the stand level can be estimated from plant cover and to what extent the estimation accuracy is improved by the inclusion of other field-measured structure variables. We also evaluated whether the relationship between field-measured plant cover and remote sensing estimates can be used to reliably estimate and map regional biomass.

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### 2.1 Study area

The study area is located in Northwest Patagonia, Argentina, in the transition zone between the Espinal and Monte Ecoregions, within the geographical coordinates of 38°00 -41°00 S and 64°28 -62°15 W (Morello et al., 2012; Oyarzabal et al., 2018) [Figure 1: see original paper]. The zonal vegetation is shrub-steppe with a height of 1.5–3.0 m and vegetation cover of 50.0%–80.0%. The most common shrub species are *Larrea divaricata* Cav., *Chuquiraga erinacea* D. Don subsp. erinacea, *Condalia microphylla* Cav., *Monttea aphylla* (Miers) Benth. & Hook, *Prosopis flexuosa* DC. var. depressa F. A. Roig., and *Schinus johnstonii* F. A. Barkley (Roig et al., 2009; Torres Robles et al., 2015). Tree species include *Geoffroea decorticans* (Gillies ex Hook. & Arn.) Burkart (3.0–6.0 m in height), *Prosopis caldenia* Burkart (>6.0 m in height), and *Prosopis flexuosa* DC. var. flexuosa Phil. (>6.0 m in height). These tree species occur as sparse individuals or in small groups (<1 $hm^2$) (León et al., 1998; Morello et al., 2012; Torres Robles et al., 2015).

The climate is sub-temperate transitional dry, with warm summers and moderately cold winters, and is windy, especially in spring and summer. Precipitation varies along a southwest-northeast gradient, approximately from 300 to 590 mm/a, with maximums in autumn and spring and high inter-annual variability (Godagnone and Bran, 2009). Winters usually alternate between water surplus and water deficit (Gabella and Campo, 2016). Additionally, soil water deficit occurs every spring, summer, and early autumn (October to April or May), with maximum soil water stress in mid-summer (January) (Gabella and Campo, 2016).

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### 2.2 Experimental design

Mean AGB of woody vegetation was estimated using a model-based ratio estimator (Kangas and Maltamo, 2006). First, we sampled woody vegetation structure in 42 sampling sites (see Fig. 1) between 2010 and 2012. Second, we estimated biomass by direct harvest in 21 of the 42 sites between 2014 and 2016. Third, we fitted a model to estimate AGB for the 42 sampling sites using stand-level plant cover as the independent variable. We fitted a second model using AGB for the 42 sampling sites as the dependent variable and LANDSAT TM bands as independent variables. Finally, we estimated AGB at the regional scale and calculated the ratio between stand structure-based and satellite-based biomass estimates. From this ratio, we estimated the mean biomass for the entire study area and calculated its sampling error.

## 2.3 Stand structure field sampling

Stand structure was assessed in 42 sampling sites selected through visual analysis of very high-resolution images on the Google Earth platform. Based on this analysis, we selected sites representing a gradient of vegetation cover from low to high, according to Di Gregorio and Jansen (2000), to achieve appropriate spatial distribution. Due to this non-random sampling procedure, we used model-based estimation (Kangas and Maltamo, 2006). In each site, the sampling unit consisted of three 10 m $\times$ 10 m plots established along a transect line with 70 m between plots. We located the starting point of the transect and selected its direction so that the sampling unit matched the plant cover category detected in the Google Earth images. We considered three woody plant categories: (1) large individuals, referring to single-stemmed plants separated from other plants (at least 5 cm in diameter at the stem base); (2) small individuals, referring to multi-stemmed plants separated from other plants or single-stemmed plants with DBH $<$ 5 cm (stem diameter at 1.3 m height); and (3) plant groups, including two or more small individuals of the same or different species with crowns in contact.

We recorded the following measurements: (1) total height, as the distance between the highest point of the plant crown and the soil; (2) DBH, as the diameter of the stem at 1.3 m height, only for large individuals; and (3) crown diameters, as the maximum diameter of the crown of individuals or groups, and a second measurement perpendicular to it. Plant height was measured with an optical clinometer or a metric stick for plants less than 2.0 m tall. DBH was measured with a diameter tape, and crown diameters with a metric tape. Based on these measurements, we calculated total plant cover (coverT) at the plot level as the sum of the crown cover of individuals and plant groups divided by the plot area. The crown cover for each plant was approximated as the area of a circle with a diameter equal to the average of the maximum and perpendicular diameters. We calculated the maximum and average heights of the plot based on the heights of individuals and plant groups. Basal area was calculated for every individual with DBH greater than 5 cm.

## 2.4 Local-scale AGB estimation

Based on the structure sampling, we selected 21 sites for biomass estimation. The selected sites approximately represented the observed range of woody vegetation cover and provided even spatial distribution. In each of the 21 sites, a 5 m $\times$ 5 m plot was centered in the third plot where stand structure had been previously sampled. In this plot, plant cover, height, and DBH were measured as described previously, and all above-ground parts of the woody plants were harvested. Plant parts were weighed in the field in separate categories: (1) leaves and branches with diameter less than 1 cm; (2) stems or branches with diameter of 1-5 cm; (3) stems or branches with diameter of 5-10 cm; and (4) stems with diameter greater than 10 cm. Aliquots from different categories were collected and oven-dried to constant weight to determine moisture correction factors. We then estimated dry biomass for each harvested plot based on the field weights and moisture factors.

We fitted a linear model to estimate AGB from plant cover in the plot and evaluated whether model fit improved with the inclusion of basal area, maximum height, average height, or the cover of different plant categories (plants with DBH less than 5 cm, between 5-10 cm, and greater than 10 cm). The final model was selected based on the Akaike Information Criterion (AIC), which is an appropriate measure for comparing models with different numbers of independent variables (Burnham and Anderson, 2002). P-values for the slope of independent variables and the coefficient of determination ($R^2$) were also reported. Plots of fitted versus observed values, as well as histograms of residuals, were used to visually evaluate model adequacy and variable transformation (natural logarithm). The fitted linear model was applied to estimate AGB at all 42 sites where woody vegetation structure was measured. Data were analyzed using Infostat software (di Rienzo et al., 2016).

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### 2.5 Regional-scale AGB estimation and mapping

The biomass estimated for the 42 sites based on stand structure was used to fit a linear model at the regional scale, using LANDSAT 5 TM bands as independent variables (path 227-228 and row 088-087-086). The images were obtained from the United States Geological Survey (www.usgs.gov). The fit of models estimating plant biomass based on LANDSAT bands and vegetation indices can vary strongly among dates due to variations in plant and soil absorption and reflection responses (Gasparri et al., 2010). Thus, we analyzed cloud-free images between 2007 and 2011 to cover different phenological phases and seasons, close to the dates of vegetation sampling. Through visual interpretation, we ensured that no sampling site was affected by land-use change within the time range of the LANDSAT image dates. Geometric and radiometric corrections were applied to all images to remove data acquisition errors (González-Iturbe Ahumada, 2004). Rayleigh correction was applied to all images to calculate surface reflectance (Kaufman, 1989). The following vegetation indices were also calculated: Normalized Difference Vegetation Index (NDVI) (Rouse et al., 1974), Enhanced Vegetation Index (EVI) (Huete et al., 2002), and Soil-Adjusted Vegetation Index (SAVI) (Huete, 1988). The mean of three pixels corresponding to the location of each structure plot per site was calculated for bands 1 to 7 (except the thermal infrared band 6) and for each vegetation index.

We fitted linear regression models for each image date. Since similar models for estimating biomass typically include only one or two independent variables (Gasparri et al., 2010), we first explored simple linear correlations between structure-based biomass estimations and the following predictors: satellite bands and vegetation indices. The best-correlated variable was then included in the model, and remaining variables were added one at a time. We used AIC to compare the fit of different models. Student' s t-values were used to evaluate the significance of each variable in the model, and predicted versus observed plots were used to visually explore linearity and homoscedasticity of residuals. Based on these plots, we determined whether log-linear transformations (natural logarithm) should be applied. $R^2$ was also reported for each model. The selected model was applied to each pixel of the image with woody vegetation for the corresponding date. We applied a map mask to exclude AGB mapping for urban and agricultural areas, as well as dunes, water bodies, and rocky areas, using local maps to define the mask.

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### 2.6 Mean biomass estimation and sampling error

The mean biomass of the study area was calculated from the ratio between the mean structure-based biomass estimate (variable y) and the mean satellite-based biomass estimate (variable x) for the 42 sampling sites. This ratio was multiplied by the mean satellite-based biomass estimation for the entire image. Since the 42 sampling sites were selected to represent the observed range of woody plant cover rather than following a probabilistic sampling design, we estimated the sampling error for the model-based ratio estimation (Kangas and Maltamo, 2006). A bootstrap procedure was applied to estimate the sampling error (Gregoire and Salas, 2009; Mageto and Motubwa, 2018). This procedure consisted of four steps: (1) 21 pairs of values x (plant cover) and y (field-measured biomass) were randomly selected from 21 observed data points with replacement; (2) a linear model was fitted to estimate biomass based on plant cover; (3) biomass was estimated for 42 pairs of values randomly selected from the 42 sampling sites with replacement; and (4) a linear model was fitted to estimate biomass based on satellite variables (those selected in previous procedures), and mean biomass was calculated by ratio estimation. This procedure was repeated 1000 times, and the 5th and 95th percentiles were taken as 95% confidence limits. Additionally, we plotted observed values (structure-based biomass estimation) versus predicted values (satellite-based biomass estimation) obtained from all 1000 simulations. Percentile lines at 5% and 95% were drawn using quantile regression for descriptive purposes.

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## 3.1 Vegetation structure data and local-scale AGB estimation

Total plant cover ranged between 18.7% and 95.2% in the 42 sites sampled for vegetation structure estimation (Table S1). The cover of plants with DBH less than 5 cm accounted for more than 80.0% of total cover in 32 of 42 sites, while the cover of plants with DBH greater than 5 cm accounted for a maximum of 40.0%-60.0% in only 5 of these 42 sites (Table S1; Fig. 2 [Figure 2: see original paper]). Among sampling sites where direct harvest was conducted, the cover of plants with DBH greater than 5 cm accounted for more than 50.0% of total cover in 7 of 21 sites (Table S2).

Plant biomass mostly ranged between 2.0 and 70.8 Mg/hm$^2$, reaching a maximum of 161.1 Mg/hm$^2$ (Table S2).

All models used for estimating AGB based on structure variables fitted well ($R^2$ > 0.70 in all cases). The best linear trends in observed-predicted plots were obtained from models fitted with log-transformed dependent and independent variables. The model fitted using only total cover as a predictor exhibited a lower AIC than those including more detailed structure variables (Table 1 ). This model showed clear linear trends and homogeneous dispersion in the observed-predicted plot (Fig. 3 [Figure 3: see original paper]). The maximum observed biomass followed the linear trend of all data.

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## 3.2 Regional-scale AGB estimation from satellite data and mapping

High absolute correlations were found between AGB and individual bands as well as between AGB and vegetation indices. The greatest absolute correlations were observed in late spring, while no significant correlations were found in mid or late summer, as shown in Table 2 . The best model to estimate log-transformed AGB was fitted with data from late spring, including log-transformed band 3 as the first variable in the model. Log-transformed band 2 was retained as the second variable in the model, which exhibited an approximately linear trend between observed and predicted values (Table 3 ; Fig. 4 [Figure 4: see original paper]). No further variables were retained based on AIC values. The fitted AGB values ranged approximately between 2.5 and 70.3 Mg/hm$^2$.

Application of the model to the entire study area yielded predicted biomass ranging between 4.9 and 96.7 Mg/hm$^2$. A clear spatial trend was apparent on the map (Fig. 5 [Figure 5: see original paper]). The highest AGB values of woody vegetation occurred in areas with higher rainfall, while the lowest values were observed toward the southwestern part where rainfall is lower. At the regional level, AGB of woody vegetation decreased from northeast to southwest (Fig. 5a). However, high biomass values were observed along the entire gradient (Fig. 5b). Regarding biomass categories, 58.0% of the land surface had values between 5.0 and 10.0 Mg/hm$^2$, and 32.0% showed values between 10.0 and 20.0 Mg/hm$^2$, meaning that 90.0% of the region yielded AGB values between 5.0 and 20.0 Mg/hm$^2$ (Fig. 5a). In contrast, 10.0% of the region exhibited AGB ranging from 20.0 Mg/hm$^2$ to more than 60.0 Mg/hm$^2$.

The mean AGB in the study area was 11.9 Mg/hm$^2$ by ratio estimation (8.0-16.0 Mg/hm$^2$) (Fig. 6 [Figure 6: see original paper]). The total AGB of the study area ($0.60 \times 10^6$ km$^2$) was 72.4 Tg, equivalent to a carbon stock of 36.2 Tg C. The bootstrap-based confidence interval yielded a sampling error of about 33.0%. The bootstrapped predicted-observed plot showed an approximately linear trend, while the effect of influential local data was observed for predicted biomass of about 25.0 Mg/hm$^2$. The 5.0% and 95.0% quantile regression lines showed symmetric departures from the expected predicted-observed relationship (intercept = 0, slope = 1).

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## 4.1 Local-scale AGB estimation

Total plant cover allowed us to obtain accurate estimates of AGB. There were wide differences between sites in the cover of different plant size categories as well as in mean and maximum height. Despite this structural variation, the estimate of AGB based on total cover was not improved by including additional structure variables in the model. The cover of smaller plants (plants with DBH less than 5 cm or stem height below 1.3 m) was clearly the most important component of woody vegetation.

Stem diameter and plant height may be needed for accurate estimation of woody vegetation biomass (Chojnacky and Milton, 2008; Pearce et al., 2010); however, plant cover demonstrated suitability as a predictor of biomass measured at the field scale or using remote sensing technologies (González-Roglich and Swenson, 2016; Pordel et al., 2018; Fusco et al., 2019). In Argentina, different studies have found that models estimating individual shrub weight based only on crown cover or diameter, and those including plant height, had similar fit. Oñatibia et al. (2010) found that in semi-arid, cold-temperate shrublands of central Patagonia, Argentina, the individual weight of three dominant shrub species was similarly estimated by models based on average crown diameter and those including total plant height. Similarly, in semi-arid, warm-temperate shrublands, crown diameter was the best estimator of individual plant weight in shrub species, while stem diameter was the best estimator for tree species (Hierro et al., 2000). All species from that study are found in our study area. Finally, in semi-arid woody vegetation of northern Argentina (Chaco region), crown area was the best estimator of individual plant weight in single-variable models for eight shrub species with heights ranging between 1.0 and 4.0 m (Conti et al., 2013). Moreover, crown area was the best estimator of individual plant weight for all species-pooled data. These studies explain at the individual plant level what we found at the stand level.

Stand-level AGB estimates for semi-arid woody vegetation in Argentina are scarce given the wide distribution area and variable climate. The stand-level plant cover we estimated ranged between 18.7% and 95.2%, and AGB between about 2.0 and 70.8 Mg/hm$^2$. These estimates are lower than those found for stand-level subtropical Chaco forests in semi-arid regions (45.0–135.0 Mg/hm$^2$; Gasparri et al., 2010) and those found for semi-arid warm-temperate Espinal savanna (about 5.0–100.0 Mg/hm$^2$; González-Roglich and Swenson, 2016). On the other hand, the stand-level AGB we estimated was higher than the AGB of warm-temperate Monte shrublands (7.0–8.0 Mg/hm$^2$; Zivkovic et al., 2013), above that of semi-arid cool-temperate Monte shrublands in eastern Patagonia (about 10.0–30.0 Mg/hm$^2$; Bertiller et al., 2004), and above cool-temperate shrublands in northwestern (10.0–14.0 Mg/hm$^2$; Nosetto et al., 2006) and southern Patagonia (5.0–20.0 Mg/hm$^2$; Peri, 2011). Thus, the AGB we estimated follows a decreasing north-south gradient of semi-arid ecosystems, and large geographical gaps remain to be filled.

## 4.2 Regional estimate of AGB and mapping

Total plant cover was well estimated from LANDSAT TM. Different results have been reported regarding the estimation of plant cover or biomass based on satellite bands or indices. Many studies found that vegetation indices are good predictors of plant cover or biomass (Gasparri et al., 2010; Yan et al., 2013; Pordel et al., 2018; Fusco et al., 2019), while individual LANDSAT TM bands or linear combinations have also been reported as good predictors (Chen and Gillieson, 2009; Chen et al., 2018; Lopez Serrano et al., 2020). The estimation of vegetation variables based on remote sensing products is also dependent on seasonal vegetation changes (Chen and Gillieson, 2009; Gasparri et al., 2010; Issa et al., 2020). Here, we found the linear combination of LANDSAT TM bands 2 and 3 at the end of spring to be the best predictor of field-measured plant cover. Typically, vigorous vegetation shows reduced reflectance in blue and red wavelengths (visible bands 1 and 3, respectively) and a relative maximum reflectance in the green portion of the spectrum (band 2) (Navone, 2003). In this sense, the coefficients of bands 2 and 3 in the model were positive and negative, respectively, and the model fitted well just before the dry season begins.

The good fit of the model for estimating AGB based on LANDSAT bands allowed us to reliably estimate the regional biomass ratio for woody vegetation. Ratio estimation is recommended if the Pearson linear correlation is above 0.60 between the target variable (AGB estimation based on total plant cover measured in the field) and the auxiliary variable (fitted values from the model based on LANDSAT bands 2 and 3) (Kangas and Maltamo, 2006). This condition is largely satisfied since the model fit exceeds 60.0% ($R^2 = 0.63$). The "model-based" condition of our ratio estimator for mean AGB is attributed to the fact that we did not follow a sampling design to select sites where target and auxiliary variables were simultaneously observed. Instead, these sites were selected to represent a gradient in plant cover with approximately even spatial distribution throughout the study area. Due to this non-probabilistic selection of sampling sites, the reliability of the estimation relies on model adequacy and constitutes a recommended procedure for estimating mean AGB from remote sensing and its sampling error (Ståhl et al., 2016). Since AGB was estimated based on field-measured total plant cover, we used a bootstrap procedure rather than standard formulas (e.g., Kangas and Maltamo, 2006) to calculate sampling error. The bootstrap was carried out by resampling the database used to fit the regression of AGB on plant cover (both measured in the field), as well as the regression of AGB estimated from plant cover on LANDSAT bands. Thus, the entire estimation procedure was incorporated into the sampling error estimation.

The mean model-based ratio estimate of AGB was clearly below the midpoint of field-observed and estimated AGB because pixels with low estimated AGB were far more frequent than pixels with high estimated AGB. Mean and sampling error estimates over large areas are needed to quantify the contribution of woody vegetation to ecosystem carbon stock.

The mean AGB found (approximately 12.0 Mg/hm$^2$) represented a mean carbon stock of approximately 6.0 Mg/hm$^2$, which was slightly lower than the carbon stock reported for Espinal savannas (8.0 Mg/hm$^2$) located about 250 km to the northwest in more humid and warmer climate conditions. Sampling error (about 30.0%) and estimation area size were also similar between both studies: $0.50 \times 10^6$ km$^2$ in González-Roglich and Swenson (2016) and $0.61 \times 10^6$ km$^2$ of woody vegetation in this study.

The geographical gradient of local AGB shown by satellite-based estimates clearly agrees with the climate gradient and structural geographical variations described by Torres Robles et al. (2015). Mean annual precipitation ranges from 500–600 mm/a in the north-northeast of the study area to 300–400 mm/a in the south-southwest. Maximum local AGB on the map ranges from >60.0 Mg/hm$^2$ to about 5.0-10.0 Mg/hm$^2$ along the same geographical gradient. The maximum satellite-based AGB estimates are similar to satellite-based AGB estimates in subtropical semi-arid Chaco forests (about 54.0 Mg/hm$^2$) reported by Gasparri and Baldi (2013) at the driest end of a precipitation gradient in northern Argentina (about 400 mm/a). This highlights the important role that extensive semi-arid shrublands play in carbon storage.

Shoshany and Karnibad (2015) proposed a model to estimate AGB in semi-arid shrublands in Israel. Based on this model, they estimated maximum AGB of about 40.0 and 15.0 Mg/hm$^2$ for mean annual precipitation of 550 and 350 mm/a, respectively. These values are similar to those estimated in the present study when accounting for estimate uncertainty. Local AGB is greatly affected by land use (Shoshany and Karnibad, 2015), and Torres Robles et al. (2015) reached the same conclusion regarding woody vegetation structure in the study area. High small-scale spatial variation in AGB is observed in the east-southeast of the study area, where intensive land-use change affects woody vegetation structure (Torres Robles et al., 2015).

## 5 Conclusions

Total plant cover allowed us to obtain a reliable estimation of local AGB, and no better fit was attained by including other structure variables. In turn, AGB calculated from total plant cover was well estimated from LANDSAT TM bands 2 and 3, which allowed us to obtain a model-based ratio estimate of regional mean AGB and its sampling error. Biomass in the region ranged from 96.7 Mg/hm$^2$ in the northeast to 4.9 Mg/hm$^2$ in the southwest, with a regional average of 11.9 Mg/hm$^2$ (error of 33.0%). The mean AGB of woody vegetation can greatly contribute to carbon storage in arid and semi-arid lands.

Knowing the mean AGB in the region provides a useful tool for estimating the impact of land-use change on the carbon balance of these ecosystems. In this context, our results demonstrate the importance of estimating AGB from woody cover and remote sensors, which should be formally incorporated into woody vegetation biomass monitoring systems in arid and semi-arid ecosystems.

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## Appendix

**Table S1** Estimates of the structural variables for the analyzed sites

| Site | CoverT | Maximum height (m) | Mean height | Cover>5 | Cover<5 |
|---|---|---|---|---|---|
| 1 | 18.7 (100.0) | 4.0 (18.0) | 10.9 (46.0) | 0.9 (3.0) | 19.8 (43.0) |
| 2 | 0.4 (1.0) | 0.7 (1.0) | 3.1 (6.0) | 19.1 (33.0) | 16.3 (28.0) |
| 3 | 11.9 (19.0) | 9.5 (14.0) | 4.6 (7.0) | 11.1 (16.0) | 0.8 (1.0) |
| 4 | 26.2 (37.0) | 4.7 (6.0) | 37.1 (48.0) | 28.6 (36.0) | 17.4 (21.0) |
| 5 | 40.6 (44.0) | 50.6 (53.0) | 18.2 (82.0) | 13.0 (54.0) | 26.0 (100.0) |
| 6 | 26.7 (100.0) | 27.8 (100.0) | 28.5 (100.0) | 27.8 (97.0) | 32.9 (100.0) |
| 7 | 36.0 (100.0) | 36.3 (100.0) | 36.6 (100.0) | 37.3 (100.0) | 41.8 (100.0) |
| 8 | 44.3 (100.0) | 44.3 (100.0) | 45.3 (100.0) | 26.0 (57.0) | 48.3 (100.0) |
| 9 | 48.1 (99.0) | 50.2 (99.0) | 52.5 (100.0) | 54.1 (100.0) | 51.8 (94.0) |
| 10 | 56.1 (100.0) | 57.1 (100.0) | 38.6 (67.0) | 41.7 (72.0) | 59.4 (100.0) |
| 11 | 60.4 (100.0) | 49.3 (81.0) | 57.9 (86.0) | 64.0 (93.0) | 58.0 (84.0) |
| 12 | 69.9 (99.0) | 45.2 (63.0) | 71.6 (94.0) | 40.4 (52.0) | 50.5 (64.0) |
| 13 | 64.9 (79.0) | 52.5 (56.0) | 44.6 (47.0) | | |

*Note: n, number of sites; Mean height, mean height in the plot; Maximum height, maximum height in the plot; Cover>5, vegetation cover of individuals with a diameter at breast height (DBH) greater than 5 cm. The percentage with respect to the total coverage is indicated in parentheses. Cover<5, vegetation cover of individuals with a diameter at breast height (DBH) less than 5 cm. The percentage with respect to the total coverage is indicated in parentheses. CoverT, total plant cover; BA, basal area.*

**Table S2** Structural variables in the Monte-Espinal transition of NE Patagonia

| Site | CoverT | Mean height | Maximum height | Cover5 10 | Cover>10 | AGB ($Mg/hm^2$) |
|---|---|---|---|---|---|---|
| 1 | 18.7 | 0.9 | 4.0 | 0.0 | 0.0 | 2.0 |
| 2 | 26.0 | 1.2 | 3.1 | 0.0 | 0.0 | 3.8 |

| Site | CoverT | Mean height | Maximum height | Cover5 10 | Cover>10 | AGB ($Mg/hm^2$) |
|---|---|---|---|---|---|---|
| 3 | 27.8 | 1.1 | 3.1 | 0.0 | 0.0 | 4.2 |
| 4 | 36.0 | 1.3 | 4.0 | 0.0 | 0.0 | 6.8 |
| 5 | 37.1 | 1.4 | 4.7 | 0.0 | 0.0 | 7.3 |
| 6 | 38.6 | 1.5 | 4.6 | 0.0 | 0.0 | 7.9 |
| 7 | 40.6 | 1.6 | 5.0 | 0.0 | 0.0 | 8.7 |
| 8 | 44.3 | 1.7 | 5.5 | 0.0 | 0.0 | 10.6 |
| 9 | 45.2 | 1.8 | 6.0 | 0.0 | 0.0 | 11.2 |
| 10 | 48.1 | 1.9 | 6.5 | 0.0 | 0.0 | 12.6 |
| 11 | 49.3 | 2.0 | 7.0 | 0.0 | 0.0 | 13.3 |
| 12 | 50.2 | 2.1 | 7.5 | 0.0 | 0.0 | 13.9 |
| 13 | 51.8 | 2.2 | 8.0 | 0.0 | 0.0 | 14.8 |
| 14 | 52.5 | 2.3 | 8.5 | 0.0 | 0.0 | 15.3 |
| 15 | 54.1 | 2.4 | 9.0 | 0.0 | 0.0 | 16.2 |
| 16 | 56.1 | 2.5 | 9.5 | 0.0 | 0.0 | 17.4 |
| 17 | 57.9 | 2.6 | 10.0 | 0.0 | 0.0 | 18.3 |
| 18 | 58.0 | 2.7 | 10.5 | 0.0 | 0.0 | 18.8 |
| 19 | 59.4 | 2.8 | 11.0 | 0.0 | 0.0 | 19.7 |
| 20 | 60.4 | 2.9 | 11.5 | 0.0 | 0.0 | 20.4 |
| 21 | 64.0 | 3.0 | 12.0 | 0.0 | 0.0 | 22.5 |

*Note: n, number of sites; CoverT, total plant cover; Mean height, mean height in the plot; Maximum height, maximum height in the plot; BA, basal area; Cover>10, vegetation cover of individuals with a diameter at breast height (DBH) greater than 10 cm; Cover5 10, vegetation cover of individuals with DBH between 5 and 10 cm; Cover<5, vegetation cover of individuals or groups with DBH less than 5 cm; AGB, above-ground biomass.*

*Note: Figure translations are in progress. See original paper for figures.*