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Declaration of Competing Interest

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Keywords

Remote sensing, machine learning, LiDAR, error propagation, Sentinel-2, ALOS PALSAR

Abstract

Information on the spatial distribution of forest aboveground biomass (AGB) and its uncertainty is important to evaluate management and conservation policies in tropical forests. However, the scarcity of field data and robust protocols to propagate uncertainty prevent a robust estimation through remote sensing. We upscaled AGB from field data to LiDAR, and to landscape scale using Sentinel-2 and ALOS-PALSAR through machine learning, propagated uncertainty using a Monte Carlo framework and explored the relative contributions of each sensor. Sentinel-2 outperformed ALOS-PALSAR (R^2 = 0.66, vs 0.50), however, the combination provided the best fit (R^2 = 0.70). The combined model explained 49% of the variation comparing against plots within the calibration area, and 17% outside, however, 94% of observations outside calibration area fell within the 95% confidence intervals. Finally, we partitioned the distribution of AGB in different management and conservation categories for evaluating the potential of different strategies for conserving carbon stock.

Introduction

Tropical forests hold large stocks of carbon and play a key role in the global carbon cycle and its interactions with climate (Bonan et al., 2008; Pan et al. 2011; Mitchard, 2018). Carbon contained in aboveground biomass (AGB) is most susceptible to be emitted through deforestation and degradation, which are important sources of emissions in tropical forests (Houghton et al., 2005; Houghton, 2012; 2013). Accurate estimation of the spatial distribution of AGB and its uncertainty is an important part of the implementation of strategies aimed at reducing emissions through deforestation and degradation throughout the tropics, such as REDD +. However, previous research has underestimated the uncertainty due to inadequate methods for estimating and propagating errors throughout the estimation process (Yunai et al., 2020).

The Yucatan Peninsula, located in the south-eastern part of Mexico, holds one of the largest extents of continuous tropical dry forest in Latin America (Dupuy et al., 2015). Mexico is an active participant in the REDD+ initiative, and particularly, the Yucatan Peninsula is a part of the REDD+ early actions priority areas, due to increasing pressure of permanent conversion to urban areas and the expansion of agriculture (Ellis et al., 2017). Several protected areas targeting conservation of forest resources are located within the Yucatan Peninsula (CONANP, 2017) encompassing old-growth forests. However, the extensive use of traditional agricultural practices, such as slash-and-burn agriculture, as well as other land use such as agricultural areas and pastures for cattle ranching, shapes the landscape outside the protected areas into a mosaic of forest areas in diverse stages of natural regeneration, with biodiversity and forest biomass gradually recovering after abandonment (Dupuy et al., 2012). In line with global policy efforts to restore forests across the tropics, significant areas of the Yucatan Peninsula have been allocated for restoration (CONANP, 2017). Whether this restoration will lead to significant carbon sequestration, and thus help mitigate climate change, will depend on the balance between forest loss through deforestation and degradation (including the exploitation of forest resources) and forest gain from forest regrowth from conservation and natural regeneration of disturbed areas (Houghton, 2013; Chazdon et al., 2016; Lewis et al., 2019).

The balance between forest (re)growth and disturbance determines the distribution of AGB (Williams et al., 2013). Post-disturbance, forest ecosystems can aggrade, accumulating carbon until they reach a quasi-steady state, where gains through growth and recruitment become balanced by mortality losses. At steady state the distribution of AGB within the landscape tends towards a normal distribution (Williams et al., 2013). In disturbed forests, on the other hand, repeated removal of AGB results in a skewed distribution of AGB, resulting in a long tail of low AGB values. Therefore, information on the distribution of AGB can be used to assess the state of AGB stocks in areas under different management strategies.

Reliable estimates of the spatial distribution of forest AGB are essential for effective forest management, to detect areas of loss and assess the success of conservation efforts. To date, AGB across Mexico has been mapped in a number of National (Cartus et al., 2014; Rodriguez-Veiga et al., 2016; Urbazev et al., 2018) and pan-tropical (Saatchi et al., 2011; Baccini et al., 2012., Avitabile et al., 2016) products. However, there are large and systematic uncertainties (Mitchard et al., 2013) with existing maps, which tend to underestimate the AGB in the Yucatan Peninsula (Rodriguez-Veiga et al., 2019; Hernández-Stefanoni et al., 2020), leading to potential underestimation of carbon emissions from deforestation and degradation.

Production of regional AGB maps typically relies on upscaling field estimates of AGB based on a relationship between a network of field inventory plots (Chave et al., 2004; Réjou-Méchain et al., 2019) and remotely sensed data (Goetz et al., 2015). A number of passive sensors (e.g. multispectral optical imagery from Sentinel) 2) and active sensors (e.g. L-band Synthetic Aperture Radar (SAR) from Advanced Land Observation Satellite) (ALOS PALSAR; Shimada, 2010) are available that offer frequent coverage at global scales. Each sensor has its own limitations. Optical data are limited by cloud and smoke, both common in tropical forests (Asner et al., 2001); SAR penetrates clouds, and polarized backscatter has been shown to be sensitive to AGB (Mermoz et al., 2015, Thapa et al., 2015, Mitchard et al., 2009), however, optical and L-band saturate at ~150 Mg ha^{-1} (Lu et al., 2006; Mitchard et al., 2009; Joshi et al., 2017). Compared to tropical wet forests, old-growth tropical dry forest canopies are generally shorter and simpler, and AGB correspondingly lower (Murphy and Lugo 1986). Therefore, the AGB range occupied by tropical dry forests is potentially still within the sensitivity range of L-band systems. Multi-sensor approaches can leverage the strengths of these various data sources to improve AGB estimates (Bispo et al., 2020).

Generating maps of AGB based on satellite data requires calibration against estimations of AGB typically taken from field inventories (e.g. Rodriguez-Veiga et al., 2016; Saatchi et al., 2011; McNicol et al., 2018). High-resolution airborne LiDAR surveys offer the potential to bridge the scale gap between inventory plots and satellite data and enhance the range of training sites over which to calibrate models (Urbazaev et al., 2016; Wulder et al., 2012; Asner et al., 2018; Bispo et al., 2020). LiDAR is particularly powerful as it captures precise information on forest structure without signal saturation in dense tropical forests (Lefsky et al., 1999; Asner et al., 2014). However, the cost of obtaining airborne LiDAR data through on-demand surveys is high. Consequently, publicly available data are typically scarce over many tropical forests. The GEDI mission offers global open, spatially distributed waveform LiDAR (Dubayah et al., 2020), which will undoubtedly facilitate calibration of satellite-based biomass products (e.g. Qi and Dubayah, 2016). However, GEDI has a nominal mission lifetime of two years from its on-orbit checkout in April 2019, thus limiting its scope for future and past monitoring of change in tropical forests. Therefore, it is important to develop methods that utilize spatially limited airborne surveys inside upscaling frameworks and quantify their predictive uncertainty with robust error estimation (Zhao et al., 2020). In developing upscaling frameworks, particularly when working with spatially limited data, it is critical to account for spatial autocorrelation to avoid overfitting and thus greatly overstating the predictive power of upscaled models (Roberts et al., 2017; Ploton et al., 2020).

This research has three core aims: (i) to produce accurate spatially explicit estimations of AGB and its uncertainty in a semi-deciduous tropical dry forest of the Yucatan Peninsula; (ii) to quantify the effectiveness of active and passive sensors and their combination for achieving (i); (iii) to use the spatial distribution of AGB to inform on the state of carbon stock of forest areas under different management and conservation conditions. We develop an upscaling framework that uses airborne LiDAR surveys as an intermediate step to link field inventory AGB estimates to Sentinel 2 and ALOS PALSAR data. First, we generate a LiDAR AGB model, AGB_{LiDAR}, calibrated using field inventory data. Subsequently, we use a machine-learning framework to upscale these AGB_{LiDAR} maps with satellite data from Sentinel 2 and ALOS PALSAR to generate a satellite-based model for AGB, AGB_{SAT}. Previous studies suggest image texture metrics can improve estimates of AGB in dense forests (Castillo et al., 2005; Wood et al., 2012; Thapa et al., 2015; Hernández-Stefanoni et al., 2020). We therefore explore the potential for texture variables to improve the predictive power of our machine-learning models. We assess the effect of spatial resolution in the calibration of the LiDAR-to-satellite model and explore the improvement in performance of multi-sensor models over single-sensor models. We propagate uncertainty through the analysis using a Monte Carlo framework, including a spatially independent cross-validation strategy for robust estimates of errors arising during upscaling (e.g. Roberts et al., 2017). Finally, we use the AGB_{SAT} map to gain insight into the impact of forest management (production vs. protection) on forest biomass, and thus the likely carbon sequestration potential for areas set aside for restoration in this region.

Methods

Study Area

The study area comprises 3600 km^2 of tropical dry forest in the centre of the Yucatan Peninsula, Mexico, located between 20° 09' 39" and 19° 37' 08" N latitude and 89° 16' and 89° 50' 36" W longitude (Figure 1). The vegetation at this site is predominately semi-deciduous tropical dry forest, sitting in the transition zone between deciduous tropical dry forest in the drier northern part of the Peninsula and semi-evergreen tropical forest in the south-west (Rzedowski 2006). Trees in this region are typically 8–15 m tall, and 50–75 % of trees drop their leaves during the dry season, which typically falls between November and April (Carnevali et al., 2003). The limestone terrain underlying this region is characterized by a mixture of low hills (elevation range: 16–216 m) and flat areas. Three protected natural reserves exist within the study area: Kaxil Kiuic Biocultural Reserve (Reserva Biocultural Kaxil Kiuic) (1,800 ha) a private reserve located inside a state protected area: del Puuc Biocultural reserve (Reserva Estatal Biocultural del Puuc) (135,849 ha), and a small fraction (~ 5,000 ha) of the Bala'an K'aax national protected area (128,390 ha) (CONANP 2017) (Figure 1). Several low impact subsistence activities occur in the adjacent forest surrounding the Kaxil Kiuic reserve (swidden agriculture, with some selective logging and cattle grazing) and agricultural fields. Unprotected forest areas are subdivided into areas suitable for production of forest species and areas suitable for forest restoration. These areas were designated according to structural characteristics such various degrees of degradation in the restoration forest and tree cover for production forest. For a detailed description refer to CONAFOR (2013).

[insert Figure 1 around here]

Field inventory data

Field data were taken from two surveys: (i) The Intensive Carbon Monitoring (ICM) site; (ii) a sparser, spatially more extensive dataset across the region, obtained from the Mexican National Forest Inventory (NFI). The majority of plots (20) from the ICM are located within the Kaxil Kiuic Biological Reserve, and 12 are placed outside the reserve boundary in a chronosequence in several ages of abandonment. (Figure 1). In both cases, plots are composed of clusters of four GPS-located circular subplots of 400 m^2. The plots are distributed systematically with one central plot surrounded by three peripheral plots at 90°, 120° and 240° azimuths within a 1 ha sampling area (CONAFOR 2013). Within each plot, height and Diameter at Breast Height (DBH Diameter at 1.30 m) were recorded for all woody plants with DBH > 7.5 cm and each individual was identified to species level. In addition, small stems (2.5 cm ≤ DBH < 7.5 cm) were also measured at the ICM plots, within a central subplot of 80 m^2 (Caamal-Sosa et al., 2016). AGB was calculated for each tree using the allometric equation of Chave et al. (2005) for trees with DBH ≥ 10 cm, and that of Ramirez et al., (2017), for trees with DBH < 10 cm, based on DBH and height from the above-mentioned datasets. Wood densities were taken from Sanaphre-Villanueva et al. (2016) where species were present in the database, otherwise a mean value of wood density at the genus or the plot level were used. Plot AGB was estimated based as the sum of the AGB of all individual trees. In the ICM plots, the contribution of small stems averaged 24.4 ± 13.5 Mg ha^{-1}. This contribution was added to the NFI plots to standardize the two datasets. In total, 33 plots (132 subplots) fell within the LiDAR survey. A further 435 subplots fell outside the survey, providing independent validation of the final upscaled map outside the LiDAR survey.

The workflow of methods applied in this research is displayed in supplementary material 1 and described in more details in the following sections.

LiDAR data

We obtained LiDAR data from NASA's Goddard's LiDAR, Hyperspectral and Thermal (G-LiHT) airborne imager (Cook et al., 2013) available for the study area (Figure 1). The LiDAR point cloud was pre-processed using the USFS FUSION software (McGaughey et al., 2012) resulting in two 1-m resolution raster representing the top of canopy elevation and the underlying topography. The difference in elevation between these surfaces provides a direct estimate of canopy height.

ALOS PALSAR and Sentinel-2 data processing

Two scenes of Advanced Land Observation Satellite Phased Array L-Band Synthetic Aperture Radar (ALOS PALSAR) yearly mosaics at 25 m spatial resolution for the year 2015 were merged to cover the extent of the study area. The images, obtained in digital numbers, were converted to backscatter coefficient by means of the formula provided by Shimada et al. (2010). Afterward, they were pre-processed to obtain gridded, topographically corrected backscatter amplitudes for HH and HV polarizations (Mitchard et al., 2009). The ALOS PALSAR backscatter was processed to remove "speckle" (Woodhouse, 2017) using the standard enhanced Lee filter (Lee 1980), as implemented in the GIS software package ENVI 5.0 (Hernández-Stefanoni et al., 2020).

Two Sentinel 2A scenes corresponding to April 2017 were mosaicked using linear normalization in order to produce a seamless mosaic of the study area. We used the following bands: blue (492.4 nm, hereafter named as Band 1), green (559.8 nm, Band 2), red (664.6 nm, Band 3) and near infrared (832.8 nm, NIR, Band 4) with a spatial resolution (pixel size) of 10 m. Also, we calculated the Normalized difference vegetation index (NDVI).

We also used image texture metrics such as Gray Level Co-occurrence Matrix (GLCM Haralick et al., 1979), since they are able to capture the spatial variability in the spectral response of different elements in the landscape and have been related by previous work to variability in forest structure (Gallardo-Cruz et al., 2012, Wood et al., 2012). These statistics can be categorized into homogeneity and heterogeneity metrics. Higher values in metrics such as contrast and dissimilarity indicate a higher variability in the elements in an area, whereas metrics such as homogeneity, second moment and correlation, indicate similarity within an area. The mean and variance of the surface reflectance of bands in addition to the aforementioned GLCM measures (hereby texture measures) were calculated at the spatial resolution of the LiDAR-satellite upscaling step for all individual bands and for NDVI using scikit-image, a collection of algorithms for image processing in python 3.6 (Van der Walt et al., 2014).

Upscaling field inventory to regional AGB

In order to estimate the spatial distribution of AGB we carried out a two-step process: (1) creation of the LiDAR AGB map, AGB_{LiDAR} at 20 m resolution, corresponding to the resolution of the individual 0.04 ha inventory plots (AGB_{Field}); (2) upscaling AGB_{LIDAR} across the study area using machine learning models based on data from Sentinel 2 and/or ALOS PALSAR to produce AGB_{SAT}.

Spatial mapping of AGB with LiDAR

The first step in upscaling the field inventory AGB estimates (AGB_{Field}) was to extrapolate these across the LiDAR survey extent. To do this we fitted a power law relationship between the AGB of the 0.04 ha inventory plots and the mean top of canopy height (TCH) measured by the LiDAR sensor within the footprint of each 0.04 plot (Figure 2). This follows from the allometric expectation of power law scaling of AGB with tree height, and therefore stand height (e.g. Asner and Mascaro, 2014). To reduce the risk of bias in canopy height estimates from areas of low point density (Roussel et al., 2017), we filtered out areas of the survey with less than 6 pts m^2. We also investigated alternative variants and canopy metrics, including gap fraction (e.g. Jucker et al., 2017), but these did not lead to significant overall improvement in the model under leave-one-out (LOO) cross validation.

To model the power law relationship, we fitted a linear mixed effects model in log-transformed space to account for the hierarchical structure of the inventory data (i.e. four 0.04 ha plots within each plot cluster):

$$[ln(AGB_{LiDAR})]_{i,j} = \alpha + \beta^*[ln(TCH)]_{i,j} + u_i + \varepsilon_{i,j},$$

where i represents the plot cluster, j represents the plot within the cluster, α is the intercept term, β is the fixed effect for $ln(TCH)$, $u_i$represents a random effect associated with the plot cluster i, and $\varepsilon_{i,j}$ represents the residuals for each plot. Finally, after back-transformation of the final estimates, we applied the necessary correction factor (Baskerville, 1972):

$$CF = exp\left(\frac{\sigma^2}{2}\right).$$

where σ^2 is the RMSE of the model fit in log-space. The RMSE under Leave-One-Out (LOO) cross validation (Supplementary 2) was 46.14 Mg ha^{-1} and the R^2 was 0.40, for a spatial resolution of 0.04 ha. Relatively high RMSE values are in line with expectations for small plot sizes (e.g. Mascaro et al., 2011), but relative errors should drop considerably when aggregating across larger regions (Gonzalez et al., 2010).

Upscaling AGB with satellite data

In order to produce spatially explicit estimations of AGB in the Kiuic landscape we upscaled the AGB_{LiDAR} map with the satellite data using random forest regression (Breiman, 2001), with a bootstrap bias correction (Hooker and Mentch, 2018; Xu et al., 2016). Random forest regression is a flexible, non-parametric machine learning algorithm that has previously been employed to fuse LiDAR and satellite data and produce maps of AGB and other structural parameters (e.g. Luther et al., 2019;

Mascaro et al., 2014; Urbazaev et al., 2018; Wulder et al., 2012). Random forest models were fitted using the implementation of scikit-learn in Python (Pedregosa et al., 2011). To optimize the random forest regression models, we employed a Bayesian hyperparameter search seeded with 100 random trials, followed by a further 350 iterations (Bergstra et al., 2011). To determine the best spatial resolution at which to undertake the LiDAR-satellite upscaling, we tested the effect of aggregating to three different spatial resolutions (20 m, 50 m and 100 m). The relative importance of the sensors and textures to explain the variation in AGB in the fitted models was explored based on the drop in R^2 following permutation of each variable (permutation importance e.g. Strobl et al., 2007). Given the strong collinearities between texture metrics for different bands, we permuted all variables associated with (i) each sensor, and (ii) each texture index, to capture their contributions more concisely. Finally, we compared the performance of the combined Sentinel 2/ALOS PALSAR model against single-sensor models to investigate the improvement in predictive power provided by the complementary attributes of these sensors.

Error propagation

Robust characterization of uncertainty is critical to understanding the utility and limitations of remotely sensed maps of AGB (Ploton et al., 2020). Uncertainty arises from a multitude of factors. Uncertainties in the field AGB estimates (Chave et al., 2004), combined with spatial registration errors (Hernández-Stefanoni et al., 2018), crown overlap at plot boundaries (Mascaro et al., 2011); and temporal lags (Babcock et al., 2016; Clark and Kellner, 2012) lead to uncertainties in AGB_{LiDAR}. These uncertainties are compounded by unexplained variance in the subsequent LiDAR-satellite upscaling model. In addition, geospatial data are frequently spatially autocorrelated. In scenarios like this one, the clustered geometry of the available LiDAR data survey precludes the robust inclusion of a spatial effect into the random forest models through additional spatial covariates (e.g. Mascaro et al., 2014). Spatial autocorrelation, if not accounted for, can lead to overfitting resulting in significant underestimation in predictive error during cross-validation and misleading diagnostic analyses regarding feature importance (Roberts et al., 2017; Ploton et al., 2020).

In order to propagate uncertainty in the upscaling process we employed Monte-Carlo simulations to propagate errors across every step of the upscaling framework. Uncertainty in AGB_{field} was estimated based on estimates of uncertainty in the biomass of individual trees, assumed to be 47% of tree AGB (see Chave et al., 2004). Uncertainties between trees were assumed to be independent and thus they were aggregated at the plot-level by adding in quadrature (the square root of the sum of squares), a standard procedure for combining uncorrelated errors (Yanai et al., 2020). Relative errors at the plot level were therefore significantly lower and tended to be dominated by the largest trees. To characterize the uncertainty in AGB_{LiDAR}, we fitted the mixed effects model 100 times. In each iteration we resampled the biomass of AGB_{field} assuming normally distributed uncertainties. We accounted for spatial registration errors by shifting the plot location randomly assuming a standard deviation of 5 m in the plot coordinates. Corresponding uncertainties in TCH were strongly non-normal in some cases, particularly close to forest edges. We did not attempt to account for canopy overlap, or temporal lags. Fitting the model 100 times produced 100 candidate AGB_{LiDAR} maps for upscaling with the satellite data.

To propagate uncertainty across the LiDAR-satellite step, the 100 AGB_{LiDAR} maps were used as the target for an ensemble of 100 random forest models. To account for predictive uncertainty of these models, we also fitted a model to predict the median AGB_{LiDAR} using a 16-fold buffered, blocked cross validation procedure, whereby the training data were split into square blocks (block width 1 km), and randomly allocated to one of the folds. In each iteration, we buffered the validation set by a distance of 500 m to reduce the impact of spatial autocorrelation and therefore minimize overfitting (Note that in the optimization and feature importance calculations, only five folds were used to reduce processing time). This spatial cross-validation was undertaken for the three tested upscaling resolutions (20 m, 50 m and 100 m) to determine the best option for upscaling (Figure 4). Errors in predicted AGB resulting from fitted spatial correlations were modelled by resampling from the residuals from the results of this cross-validation (using median AGB_{LiDAR}). As the residuals were not uniformly distributed along the range of predicted AGB ($AGB_{upscaled}$), residuals were resampled from a 20 Mg ha^{-1} window around the AGB estimate for each pixel. Thus, the 100 x 100 iterations of the upscaling procedure capture both uncertainty in AGB_{LiDAR} propagated through the random forest models, and the predictive uncertainty associated with fitting models with spatially autocorrelated data. We present the median and 95% confidence intervals as our best estimates and uncertainty in the upscaled AGB maps ($AGB_{upscaled}$).

Comparison with other work

The AGB map obtained in this study was compared with previous AGB maps generated by Santoro et al., (2018), Rodriguez-Veiga et al., (2016) and Cartus et al., (2014). We performed a validation between field AGB data used in this study for validation and estimated AGB values from our AGB map and the previously mentioned maps. We also calculated the root mean square error (RMSE) and the relative root mean square error (%RMSE) obtained as the RMSE divided by mean AGB observed values for comparisons.

Relative contributions by sensor

In order to obtain the relative contributions by sensor, we partitioned the information provided by (a) Sentinel 2 reflectance and texture; (b), ALOS PALSAR backscatter and texture; and (c) shared variation, which is the variance in AGB that can be explained by either sensor. Total variation explained by the full model using information from both sensors can be summarized as: $Y = (a + b + c) + \varepsilon$, where ε is variation that cannot be accounted for by the predictor variables. The relative contribution of the two sensors and the shared variation can then be partitioned by comparison against the variance explained by single sensor models using only Sentinel-2 (a + c) and only ALOS PALSAR (b + c).

Results

Calibrating LiDAR biomass estimates at the plot scale

Validation of the AGB TCH model had an R^2= of 0.40, RMSE of 46.14 Mg ha^{-1} between AGB measured by Top of Canopy Height (TCH) and our field calculated AGB (in 400 m^2 plots) (Supplementary 2). Due to spatial uncertainty, heterogeneous canopies can result in large uncertainties in plot TCH, particularly where plots are located at or close to sharp transitions between short, secondary vegetation and old-growth forest. In this case, three field plots showed large residuals in the validation of the AGB TCH model (Figure 2). This derives from the presence of very large trees inside these plots which increase the field calculated biomass considerably, without a corresponding increase in height or TCH. Nevertheless, at 20 m resolution, estimations of AGB using LiDAR TCH show a good fit with the power law relationship (Figure 2).

[insert figure 2 around here]

Upscaling AGB using single sensor and combined models

Models upscaled at 100 m resolution provided greater explanatory power (R^2 = 0.70, RMSE = 27.9%) than either models upscaled at 50 m (R^2 = 0.67, RMSE = 29.8%) or 20 m resolution (R^2 = 0.62, RMSE = 31.8%), after aggregation post-upscaling to the same resolution grid (i.e. 100 m). This highlights that the reduction in noise by averaging spatially prior to upscaling led to a more robust upscaling model. Therefore, we only consider the 100 m resolution models from now onwards.

The upscaled models were clearly able of distinguishing forest from non-forest cover (Figure 3). However, sensitivity to AGB variations within the forest area was limited, especially for models reliant only on ALOS PALSAR, which had very little explanatory power regarding AGB variations above 100 Mg ha^{-1} (Figure 3). The best upscaling model combined both Sentinel 2 and ALOS PALSAR (R^2 = 0.70; RMSE = 27.8%). In comparison, the Sentinel 2-only model had slightly lower predictive power (R^2 = 0.66; RMSE = 29.5%), while the model solely reliant on ALOS PALSAR performed worst (R^2 = 0.50; RMSE = 36.2%). Sentinel 2 explained a greater amount of variation of AGB (20%) solely compared to ALOS PALSAR (4 %). The majority of the explained variation (46% of the total variance) was shared between both sensors. Uncertainties in the combined model and in the Sentinel 2 model were highest in the mid-range of AGB < 100 Mg ha^{-1}. Conversely, ALOS PALSAR showed higher uncertainty above 100 Mg ha^{-1}, as its sensitivity saturated (Figure 3).

[insert figure 3 around here]

Relative contributions by sensor and variable importance

Sentinel 2 explained a greater amount of variation of AGB (20 %) by itself, compared to ALOS PALSAR (4 %), although a considerable amount of variation was shared between both sensors (46%). Sentinel 2 on its own was able to provide reasonable estimations of AGB in the study area, explaining 66 % in the single sensor model, whereas ALOS PALSAR proved to be less effective explaining 50%, while the combination of sensors provided the best fit (70 %).

The results of the permutation importance under spatial cross-validation highlighted the relative importance of Sentinel 2 reflectance and texture measures over ALOS PALSAR in the random forest model (Figure 4). Moreover, of the texture metrics, only the mean of AGB showed a high importance in the model. Variables relating to heterogeneity (variance, contrast, dissimilarity) had marginal importance. Variables relating to homogeneity (correlation, angular second moment 'ASM') were not important indicated by the low values in permutation importance (Figure 4).

[insert figure 4 around here]

Validation of the AGB random forest model inside vs. outside the LiDAR survey area

AGB showed a much higher fit ($R^2 = 0.49$) and a much lower error (relative RMSE = 24.6%) inside the LiDAR survey extent compared to outside the LiDAR survey area ($R^2 = 0.17$ and relative RMSE = 39.3%) (Figure 5). Importantly, the uncertainty estimates appear to be robust as estimates for all plots inside the LiDAR survey area and 94% of plots outside of the LiDAR survey fell under the 95% confidence intervals for AGB_{Field} and $AGB_{satellite}$. Outside the LiDAR survey extent there is one plot with unusually large trees and exceptionally high AGB_{field} (>300 Mg ha^{-1}), considerably higher than any of the other plots in the inventory. Excluding this plot leads to a significant improvement in the fit outside of the LiDAR area ($R^2 = 0.22$, relative RMSE = 36%).

The validation analysis to compare the AGB maps with previous studies revealed that the RMSE and %RMSE obtained in this study were the lowest compared to the other maps (RMSE= 42.5 Mg ha^{-1} and %RMSE = 35.0 in this study, RMSE= 51.2 Mg ha^{-1} and %RMSE = 42.0 for Santoro et al (2018), RMSE= 57.5 Mg ha^{-1} and %RMSE = 47.0 for Cartus et al. (2016) and RMSE= 90.59 Mg ha^{-1} and %RMSE = 90 in that of Rodriguez-Veiga et al (2014)) (Figure 6).

[insert figure 5 around here]

[insert figure 6 around here]

Spatial distribution of AGB and its uncertainty in the study area

The spatial distribution of AGB (Figure 7) indicates that the higher biomass areas are located in the north-east portion of the window, coinciding with the distribution of the state reserve Reserva Estatal Biocultural del Puuc. Lower biomass areas are distributed around non-forest urban or agricultural areas, where forests are likely to be more degraded. The largest uncertainties are associated to areas with intermediate ranges (50 – 75 Mg ha^{-1}) of AGB (Figure 8).

[insert figure 7 around here]

[insert figure 8 around here]

Land management appears to have a significant effect on forest AGB stocks (Tables 1 and 2). The highest AGB densities by management class were located in the protected reserves of Kaxil Kiuic and Del Puuc Biocultural reserve. Conversely, the small portion of the Bala'an Kaax reserve contained within our study area showed similar AGB to unprotected forest.

Moreover, we found greater areas of high biomass and smaller areas of low AGB in protected areas. Forest areas suitable for production and restoration showed large areas of both low and high AGB.

Comparing the distributions of the median AGB estimates from the Monte Carlo upscaling process there are marked differences between the protected and unprotected areas (Figure 9). Kaxil Kiuic and Reserva Estatal Biocultural del Puuc have higher AGB, with very low frequencies with AGB < 100 Mg ha^{-1}. These distributions contrast with the potential production and restoration areas, which both show much lower frequencies in the upper end of the AGB distributions, and a long tail of AGB < 100 Mg ha^{-1}. This is consistent with these areas of forest being subject to high levels of disturbance (Williams et al., 2013). The portion of the Reserva Bala'an Kaax within the study area has a similar distribution of AGB to forest production and restoration areas, suggesting this area of the reserve may have been subjected to similar degradation pressures.

[insert figure 9 around here]

Discussion

This study provides a spatially explicit estimation of AGB and its uncertainty in a semi-deciduous tropical dry forest of Yucatan using LiDAR data and a combination of information from passive and active sensors. As a first step, LiDAR data was used to estimate AGB using field plot information. The effectiveness of using LiDAR-derived AGB for upscaling plot-based estimations to continuous landscape level estimations has been demonstrated in various forests worldwide (Mascaro et al., 2011, Wulder et al., 2012, Asner et al., 2018). Random Forest models using information from a combination of Sentinel 2 and ALOS PALSAR were able to upscale AGB estimates based on a locally calibrated map of AGB based on LiDAR top-of-canopy height. Several studies have shown that tropical forest AGB can be estimated using ALOS PALSAR backscatter (Mitchard et al., 2013; Hernández-Stefanoni et al., 2020) and Sentinel 2 reflectance (Pandit et al., 2018), however, the combination of both sensors has been little explored (but see Vafaei et al., 2017). To assess the improvement on the precision of estimates by combining active and passive sensors we tested each sensor individually then produced a combined model using information from both sensors. Our results suggest that the estimation of AGB in the semi deciduous tropical forest of Yucatan can be improved through a combination of ALOS PALSAR backscatter information and Sentinel 2 reflectance and texture variables, increasing the variance explained by the best single sensor model from 66% to 70% and reducing the RMSE from 29.5% to 27.8%. This improvement in AGB estimation is similar to the results found in Vafaei et al., (2017) in a subtropical forest in Iran also combining ALOS PALSAR backscatter and Sentinel 2. Furthermore, we tested the contribution of each sensor to explain AGB and found that Sentinel 2 on its own explained a greater amount of variation of AGB, compared to ALOS PALSAR, although the majority of the explained variation was shared between both sensors. One of the main caveats in the sensor combination approach is the difference in spatial resolution between the ALOS PALSAR backscatter (25 m) and Sentinel 2 (10 m). It is possible that this difference has an impact on the amount of variability that can be captured by each sensor at the plot level. Given its higher spatial resolution, Sentinel 2 could capture a greater range of variability of AGB within the plots than ALOS PALSAR. Coarser resolutions may not reflect the variability of structure as they contain averaged information from varying heights and may include reflectance from non-forest areas or canopy gaps within the same pixel (Lu, 2006).

We tested the use texture information as a way to quantify the variability of reflectance and backscatter within the plots and related this to LiDAR-estimated AGB. In this case, the upscaled models were principally reliant on the mean with limited additional contributions to the predictive power added by texture information. Other studies that have used texture information from ALOS PALSAR backscatter (Thapa et al., 2015; Hernández-Stefanoni et al., 2020) and Sentinel 2 reflectance (Pandit et al., 2019) have found large improvements in estimations of AGB by capturing the spatial variability and minimizing sensor saturation. To test the effect of spatial resolution in the upscaling process we compared models with different resolutions and found that an upscaling resolution of 100 m increased the fit of the best model by 8% and decreased the errors by 3.9%, compared to upscaling at 20 m resolution (Supplement 3). This suggests that the aggregation of information prior to upscaling might improve models and reduce the overall errors. However, as there is a trade-off between the information lost and the reduction of error when aggregating information (Camel, 2003), we chose not to aggregate further than 100 m, as this would reduce the spatial information gained from Sentinel's 10 m resolution. The comparison with the work of Santoro et al., (2018), Rodriguez-Veiga et al., (2016), and Cartus et al., 2014 suggests that by performing a bias-corrected upscaling procedure we were able to reduce the error, thus, improving upon previous AGB mapping efforts in the dry forests of Yucatan. Such procedures can be used to produce AGB maps to inform regional and national strategies for reducing greenhouse gas emissions such as REDD+.

Furthermore, by propagating errors through each step of the upscaling process and applying a spatially independent validation procedure, we were able to produce a robust estimation of errors (94%

of field AGB estimates for aggregated plot clusters overlap within the estimated 95% confidence interval outside of the LiDAR survey area). While the error propagation estimates appear to be robust, it is evident from the distribution of residuals (Figure 8) that there remains a trend in the residuals highlighting a tendency to underpredict the AGB of higher biomass field plots and overpredict the AGB at low biomass field plots. This suggests that the bootstrap bias correction was not sufficient to fully remove the bias in the random forest models, possibly a consequence of spatial correlations. Given that degradation and deforestation act to lower AGB, this outstanding source bias will likely lead to conservative estimates of the AGB differences between protected and unprotected forests, and therefore conservative estimates of restoration potential. This result suggests an improvement of previous efforts to estimate AGB in semi-deciduous dry forests of the Yucatan Peninsula using active sensors such as ALOS PALSAR (Hernandez-Stefanoni et al., 2020) and national scale efforts (Cartus et al., 2014; Rodriguez-Veiga et al., 2016). Previous attempts to map AGB across Mexico have found a wide range of AGB values in the Yucatan Peninsula reaching 150 Mg ha^{-1} (Hernandez-Stefanoni et al., 2020; Rodriguez-Veiga et a., 2016; Cartus et al., 2014) and greatest uncertainties in the lower end of the AGB distribution (Rodriguez-Veiga et al., 2016). The spatial distribution of uncertainty showed that the largest uncertainties were associated to the middle range of AGB distribution (Figures 7 and 8) and it is derived from the underrepresentation of areas with this range of AGB values ranging between 25 and 75 Mg ha^{-1} in the calibration data (Figure 8). However, in accordance with Hernandez-Stefanoni et al. (2020), estimates were also found to be constrained by the range of AGB variation captured by LiDAR data available across the calibration landscape. In particular, the predictability of the upper bounds of the biomass ranges was severely affected by the lack of LiDAR coverage in the very high biomass forest (> 200 Mg ha^{-1}). Therefore, areas with high biomass, located in the north-east of the window area, in the protected area of "del Puuc Biocultural reserve", are underrepresented in the LiDAR survey with only a portion of the area, corresponding to the location of "Kaxil Kiuic Biocultural reserve", represented by both field and LiDAR data (Figure 1). To estimate AGB in tropical forests where forest protection areas and areas where disturbances such as slash-and-burn agriculture shape the spatial variability of forest AGB, the accuracy of estimates will depend on the distribution of LiDAR and field data available across all the possible ranges of AGB. As it has been previously cautioned, the range of variability in AGB captured by both the LiDAR data and the forest inventory constrained the next stages of the analysis (Hernadez-Stefanoni et al., 2020), limiting the predictability in the lower and upper ranges of our estimated AGB. In order to reduce the uncertainty in AGB mapping, future upscaling efforts could aim for a more thoroughly distributed airborne sampling campaign that better characterizes the full range of AGB values in the landscape. Moreover, uncertainty in the upper and lower ranges of AGB was reduced when combining information from both sensors, suggesting that the combination of these sensors is an effective way to improve AGB mapping.

Within the study region, larger areas with high biomass were found in the protected areas of "del Puuc Biocultural reserve" and "Kaxil Kiuic Biocultural Reserve", which were created for the conservation of forests and their environmental services (Table 2). In particular, the Kaxil Kiuic protected area shows a more symmetric distribution with the highest mean AGB (Figure 9; Table 2) indicating a large proportion of this area may be approaching a steady state condition (Williams et al., 2013). However, several other low impact activities such as extraction of woody species for fuel, and agricultural and pastures for cattle ranching take place inside del Puuc Biocultural reserve. This is reflected in the tail of low AGB values in this area, although significantly less prevalent than outside the forest reserves. The study region has a long history of land use, mainly for slash-and-burn agriculture, also practiced presently in the area (Ellis et al., 2017). The effect of the more recent repeated disturbance is reflected in the AGB distributions of the production forest, which have skewed AGB distributions with a long tail of low AGB (Figure 9). Critically, regions allocated for restoration have large areas with low AGB (Table 2) and similar AGB distributions to existing production forest (Figure 9). Therefore, while there is potential for substantial gains in aboveground carbon stocks through restoration, whether these gains are realized is likely to be dependent on these restored forests being protected and allowed to develop into high biomass old-growth systems (Lewis et al., 2019; Chazdon et al., 2016).

Conclusions

LiDAR data proved a useful upscaling tool for calibrating and validating satellite models of AGB, however, the reliability of these estimates is constrained by the degree to which the sampled areas represent the range of AGB values found in the whole landscape, to avoid potential biases when upscaling outside the training area. The sensitivity to within-forest variation in AGB was more limited particularly in the upper end of the AGB range, thus limiting our ability to predict AGB in high biomass forest areas.

We found that the information from active (ALOS PALSAR backscatter) and passive (Sentinel 2 reflectance) sensors can be combined to improve spatially explicit estimations of AGB in semi-deciduous tropical forest. However, Sentinel 2 explained a higher proportion of the variance in the combined model and performs better than ALOS PALSAR when considered separately. We believe the methods described in this study can be used to improve estimations of AGB and its uncertainty in tropical forests. Using a combination of LiDAR and satellite data, we upscaled LiDAR estimates of AGB across a landscape of semi-deciduous forest in the Yucatan peninsula to gain insights on the distribution of AGB in different categories of forest protection. The frequency distributions of AGB obtained from our maps highlighted the benefits of protected areas for maintaining forest carbon stocks. On the other hand, a significantly greater portion of the areas designated for restoration currently have low AGB, comparable to the distribution of AGB in existing production forest. The similarity in the distributions of these categories suggests areas of restoration should be effectively protected for carbon sequestration, biodiversity conservation and for other important ecosystem services, which can take several decades to reach old-growth forest values.

We believe the information obtained can provide insights on the state of the AGB stock in different management or protection categories in the region and thus aid conservation, restoration, and sustainable management policies in the semi-deciduous forests of the Yucatan Peninsula.

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Availability of data and materials

The ALOS PALSAR data used in this study was downloaded from (https://www.eorc.jaxa.jp/ALOS/en/top/obs_top.htm). The LiDAR data can be accessed at (https://gliht.gsfc.nasa.gov/). Data from national forest inventory in Mexico can be obtained by request to CONAFOR (Comisión Nacional Forestal, https://www.gob.mx/conafor).

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Table 1. Mean AGB and confidence intervals (CI) [Mg ha $^{-1}$] for protected areas and areas without protection in the Kiuic area.

Management condition	Site	AGB	CI
Protected	Kaxil Kiuic	129.14	125 - 134
	Reserva Estatal Biocultural del Puuc	126.13	122 - 132
	Bala'an Kaax	100.64	97 - 104
Without protection	Restoration	106.63	103 - 110
	Production	99.23	96 - 103

Table 2. Summary of the area occupied by different AGB classes for different management conditions, with 95 confidence intervals provided in parentheses. Area in size classes is expressed as percentage relative to total area (last column).

AGB class (Mg ha^{-1})	Area by AGB Class (%)							Total Area (km^2)
	0-25	**25-50**	**50-75**	**75-100**	**100-125**	**125-150**	**>150**	
Kaxil Kiuic (protected)	0.2 (0.0/0.3)	1.0 (0.5/1.6)	4.5 (3.2/5.8)	11.8 (9.5/14.0)	26.5 (23.1/29.7)	30.3 (27.8/32.6)	25.7 (20.8/32.3)	18.5
Reserva Estatal Biocultural Del Puuc (protected)	2.3 (2.0/2.6)	3.1 (2.6/3.5)	5.3 (4.5/6.0)	10.6 (9.2/11.9)	22.1 (19.1/24.7)	27.4 (25.1/28.9)	28.7 (23.8/35.7)	697.0
Bala'an kaax (protected)	7.2 (5.9/8.3)	9.4 (8.3/10.4)	10.5 (9.3/11.7)	15.2 (12.7/16.7)	25.0 (23.3/26.9)	20.0 (18.5/21.8)	12.1 (9.9/14.9)	53.3
Production forest	10.2 (9.6/10.7)	6.6 (6.1/7.1)	8.0 (7.1/8.8)	13.5 (12.1/14.5)	24.2 (22.5/25.5)	21.3 (20.1/22.9)	13.2 (11.0/16.5)	2154.2
Restoration forest	7.6 (6.8/8.2)	6.9 (6.2/7.5)	8.1 (7.2/8.8)	12.8 (11.4/14.0)	23.1 (21.0/24.9)	22.4 (21.3/23.7)	17.6 (14.7/21.7)	216.8

Figure captions

Figure 1. Location of study area in Mexico (upper-right box) and location of protected areas within study area, LiDAR and field data used in this study. National Protected Area (Bala'an K'aax), State Protected Area (del Puuc Biocultural Reserve) (CONANP 2017) and private protected area (Kaxil Kiuic Biocultural Reserve). Areas without protection are subdivided into areas suitable for production and those suitable for restoration (CONAFOR 2015).

Figure 2. Comparison of field inventory AGB and LiDAR TCH for the 0.04 ha inventory plots, shown with a series of example plots (numbers in blue) highlighting variations in TCH across the range of AGB spanned by the plot network. In the first panel, the line is the fitted relationship between field AGB and plot TCH. Error bars (horizontal and vertical lines) represent the uncertainty in plot field AGB (points), and the uncertainty (both 50% CI and 95% CI shown) in plot TCH, modelled by randomly sampling the TCH with positional uncertainty.

Figure 3. Regression lines, R^2, RMSE and relative %RMSE based on a five-fold buffered-blocked cross-validation between LiDAR estimated AGB (AGB_{lidar}) and upscaled AGB ($AGB_{satellite}$) for models using both sensors a), Sentinel 2 reflectance and textures b), and ALOS PALSAR and textures c). The dashed line represents the 1:1 relationship, the solid and dotted lines represent the median estimate and 95% confidence interval for a 20 Mg ha^{-1} moving window across the predicted AGB range ($AGB_{satellite}$).

Figure 4. Permutation importance based on permutation of different aggregated input variables corresponding to specific sensors (green) and texture measures (grey).

Figure 5. Regression lines of the validation of the upscaled AGB against field inventory data inside and outside the LiDAR survey area. Points represent clusters of four 400 m^2 plots (1600 m^2), uncertainty is shown as vertical and horizontal lines.

Figure 6. Comparison of observed AGB (obtained with field data used for validation)) and predicted AGB values (mapped AGB of different studies). The predicted values were obtained from Santoro et al. (2018), Rodriguez-Veiga et al. (2016), and Cartus et al. (2014). Solid lines indicate the regression between observed and predicted AGB, while dashed gray line shows a 1:1 relationship.

Figure 7. Spatial distribution of AGB (left pane) and its uncertainty (right pane) in the sudy area. Grid lines are spaced 10 km. Letters correspond to the location of officially designated protected areas within the study landscape: A) Kaxil Kiuic Biocultural Reserve, B) del Puuc Reserva Biocultural reserve C) National protected area Bala'an K'aax. Dark blue color corresponds to non forest areas such as urban settlements, agriculture, and water bodies.

Figure 8. Residuals from field-calculated AGB (inventory) - upscaled AGB (satellite) in Mg ha –1 distributed by categories of AGB.

Figure 9. Kernel-Density Estimation (KDE) plots showing the frequency distribution of AGB [Mg ha^{-1}] in protected areas (‘Kaxil Kiuic’ Kaxil Kiuic Biocultural reserve, ‘del Puuc’ del Puuc Biocultural reserve, ‘Bala’an Kaax’, Bala’an Kaax protected area) vs unprotected areas (areas designated for restoration and production), based on the median AGB per pixel from the Monte Carlo upscaling process.