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José Alberto Benítez-Andrades · Paula García-Llamas · Ángela Taboada · Laura Estévez-Mauriz · Roberto Baelo *Editors*

Global Challenges for a Sustainable Society

EURECA-PRO The European University for Responsible Consumption and Production

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Preface

The Second EURECA-PRO Conference on Responsible Consumption and Production provides an interdisciplinary forum for practitioners, academics, and scientific experts on the most recent advances to achieve UN Sustainable Development Goal 12 (SDG12), embracing the challenges posed by the European Green Deal. As such, the conference aims to represent a unique place to share experiences, scientific results, and visions for making the EU's economy sustainable by covering all sectors, especially transport, energy, agriculture, buildings, and industries. The conference also aims to constitute a benchmark for leading researchers in the SDG12 field to discuss current and future challenges, opportunities, and innovative solutions considering the technological, humanistic, economic, social, and environmental dimensions of responsible consumption and production.

Alliance consists of nine higher education institutions: Montanuniversität Leoben (Austria), Technische Universität Bergakademie Freiberg (Germany), Technical University of Crete (Greece), Universidad de León (Spain), Silesian University of Technology (Poland), University of Petrosani (Romania), University of Applied Sciences Mittweida (Germany), Hasselt University (Belgium), and University of Lorraine (France). EURECA-PRO integrates their joined forces to become the global educational core hub and interdisciplinary research and innovation leader in environmental and social framework development under the umbrella of SDG12, effectively contributing to the European Higher Education Transformation Agenda. Through the implementation of five Research Lighthouse Missions (LH) (LH1: 'Responsible Material Flows', LH2: 'Environment and Water', LH3: 'Sustainable Materials and Products', LH4: 'Clean Energy', and LH5: 'Process Automation and Industry 4.0'), EURECA-PRO is creating a research environment focused on actively developing solutions to SDG12 current global challenges.

In this book, readers will find excellence-based communications dealing with the following five topics: (i) Smart and Healthy Societies (LH2 and LH5), (ii) Recycling, Reuse, and Longer Lasting Products (LH1 and LH3), (iii) Clean Air, Freshwater, Healthy Soil, and Biodiversity (LH2), (iv) Cleaner Energy and Cutting-Edge Clean Technological Innovation (LH4) and (v) Industry 4.0. (LH5).

Thanks to the participants and the organising team for giving us this opportunity. The rest of us have no choice but to take advantage of it. On behalf of the organising committee, we hope you enjoy reading the content of the papers included in this book.

León, Spain

José Alberto Benítez-Andrades
Paula García-Llamas
Ángela Taboada
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Roberto Baelo

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Plenary Sessions

Mapping and Estimation of Carbon Dioxide Storage in Forest Plantations. The Contribution of the Sentinel-2 Time Series in Increasing Estimates Precision

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Abstract. Forest restoration activities and tree plantations play an important role in combating global warming. On the other hand, quantifying their carbon storage is a challenging task due to very short rotations and the effort and costs required for field analysis, often in remote and hardly accessible regions. In this context, remote sensing combined with new cloud computing platforms offers unprecedented opportunities for monitoring tree plantations globally. In this study, we implemented and demonstrated over a 20-ha tree plantation in Guatemala an approach that exploits Sentinel-2 imagery time series derived metrics and cloud-free composites for mapping carbon storage. Ground data were collected over 20 plots (10-m radius) to train and validate our model, which performance resulted in high ($R^2 = 0.69$, RMSE = 35%). Plus, we estimated the amount of carbon stored in the study area and the relative confidence intervals. Using exclusively the ground data, we estimated the average net equivalent CO_2 as 4.95 Mg ha^{-1} ± 0.9 Mg ha^{-1}, with a confidence interval of 95%. Nevertheless, exploiting the herein presented model and statistical procedure, the estimate was much more precise and the ratio between the variances of the design-based and the model-assisted estimates was 7.1, meaning that, by using remote sensing data, it is possible to reduce the ground sample size by a factor of 7.1 while obtaining estimates with the same precision of those do not exploiting remote sensing data. This is a crucial point for meaningful reducing the effort and the cost required for collecting data on tree plantations while still obtaining statistically rigorous estimates.

Keywords: Forest · Carbon · Restoration · Remote sensing

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1 Introduction

Avoiding dangerous climate change requires the removal of vast amounts of carbon dioxide from the atmosphere, as well as drastic cuts in emissions [1]. Forests must play a part in the climate change battle as they are a critically important component of the global terrestrial carbon cycle [2]. Accordingly, the G20 (Nov. 2021) proposal to plant 1 billion trees by 2030 to fight the climate crisis has been accepted, as trees restoration and emissions reduction have been considered among the most effective strategies for climate change mitigation. Plantations for timber production, such as poplar (*Populus* spp.) in Europe, cedar (*Cedrela* spp.) in Central and South America, and mahogany (*Swietenia* spp.) in Asia, are well suited for climate change mitigation due to their fast-growing performance [3]. They also provide other ecosystem services, such as erosion prevention, soil protection, water quality, and habitat for many species [4], and they are also used for phytoremediation. On the other hand, quantifying and monitoring over time the amount of carbon stored by those plantations is challenging, mainly due to very short rotations, which increase the effort and costs required for field analysis.

In this context, remote sensing satellite missions provide a huge amount of consistent and open access data [5, 6] that can provide detailed information over very large areas [7–9]. In addition, the Copernicus Earth observation program of the European Union recently developed the Sentinel-2 mission, which provides data with 10–60-m spatial resolution and revisits times of 2–3 days at mid-latitudes.

This study exploits the Sentinel-2 time series to predict the amount of carbon stored in forest plantations. Herein, we focus on a study area in Guatemala for which we have ground data collected over 20 plots that were used for model training and validation, and for providing estimates with 95% confidence interval of the total and average amount of carbon stored over the study area.

2 Materials

2.1 Study Area

The study area consists of a forest plantation of 20.31 ha located in the community of Monte Carmelo in the commune of La Libertad in the Petén department, Guatemala (16° 50′ 59.57″ N; 90° 2′ 39.24″ W). The study area includes 1111 trees per hectare, for a total of about 20.31 * 1111 = 22,564 trees. Each tree is given nine square meters of space. Half of the trees in the study area are cedar (*Cedrela odorosa*) and the remaining half is mahogany (*Swietenia macrophylla*), both species of great cultural and economic importance. The two species are planted alternately with each other across the study area.

2.2 Ground Data

For training and validating our models and estimating the amount of carbon in the study area, we constructed a reference sample by randomly selecting 20 plots (10-m radius) within the study area (Fig. 1). For each plot, the species, the height, and the diameter at the breast height (DBH) of each tree were measured. In total, 730 trees were measured on the ground. The surveys were carried out in June 2022, when each tree was of twenty-one months of age.

Fig. 1 The study area (blue) and sample plots (red)

2.3 Sentinel-2 Data

For predicting the carbon storage, we used data from the Sentinel-2 (S2) mission, which has a wide swath (290 km) with a spatial resolution of 10–60-m, depending on spectral bandpass, and a revisit frequency of 2–3-days at mid-latitudes [10]. The S2 Multispectral Instrument (MSI) provides 14 spectral bands: visible (*blue*, *green*, *red*) and *nir* at the 10-m resolution, Red edge (*redE1, redE2, redE3, redE4*), and SWIR (*swir1, swir2*) at the 20-m resolution, three atmospheric bands (*B1, B9, B10*), and a quality assurance band (*QA60*) at a 60-m spatial resolution that was used in this study for mask out clouds from images [8].

An up-to-date S2 image archive can be found in Google earth engine [11], from which we selected all S2 images acquired over the study area between 2020-09-01 and 2022-08-31. For each image, we increased the number of available bands by calculating seven additional spectral indices: (i) the Normalized Difference Vegetation Index NDVI, (ii) the Normalized Burn Ratio NBR, (iii) the Enhanced Vegetation Index EVI, and the Tasseled Cap (iv) Wetness TCW, (v) Greenness TCG, (vi) Brightness TCB, and (vii) Angle TCA. As a result, we obtained a set of 17 predictors for each image, the ten S2 bands at 10–20 m spatial resolution, and the seven additional indices we calculated. All 17 predictors were resampled at the 10-m resolution.

3 Methods

3.1 Per Plot CO_2 Calculation

We calculated the above-ground biomass for each plot using the function presented in Chave et al. [12] for tropical species:

$$Ba = 0.0673\left(\rho D^2 H\right)^{0.976}$$

where Ba is the above-ground biomass, ρ is the species-specific wood density, D is the tree DBH, and H is the tree height. The wood densities of the two species are 0.4 and 0.5 for cedar and mahogany, respectively [13]. For each tree, we then calculated the below-ground biomass by exploiting the Mokany et al. function [14]:

$$Bs = 0.489Ba^{0.89}$$

where Bs is the below-ground biomass and Ba is the above-ground biomass. The constant 0.489 is the root shot ratio commonly used for tree species. Then, the total biomass was the sum of above and below-ground biomass

$$Bt = Ba + Bs$$

The total carbon content was calculated by applying the default carbon fraction factor of 0.5 provided by the IPCC [15]:

$$Ct = \frac{Bt}{2}$$

where Ct is the total carbon content. Finally, the equivalent CO_2 content was calculated using a conversion factor derived from the CO_2 molecular weight:

$$CO_{2_{eq}} = Ct(3.6667)$$

3.2 Sentinel-2 Predictors

The time-series spectral behavior of each pixel can be indeed described by harmonic functions with four parameters (constant, sine, cosine, time). For each pixel and predictor, four harmonic function coefficients were calculated to identify the pixel harmonic trend (Fig. 2). Each pixel harmonic trend function was further used to calculate the amplitude, the phase, and the root mean square error (RMSE). For more details on harmonic predictors calculation see [16].

As a result of this step, we obtained for each pixel a set of 17 (the S2 bands) per 7 (the harmonic function parameters) for a total of 119 predictors from now on referred to as *harmonic predictors.*

To quantify the advantage of using *harmonic predictors*, and thus for comparison purposes, we calculated more standard cloud-free composite predictors too, using all S2 imagery selected (Sect. 2.3). To do it, we used a state-of-the-art cloud-free composites methodology named *medoid* [17]. The Medoid composite processing aims to populate the final image composite with the pixels with surface reflectance values as similar as possible to the median calculated considering the whole image collection. In brief, medoid compares each band's pixel surface reflectance values to the median bands' spectral values of that pixel in all selected images. Then, the bands' spectral values from the pixel closest to that median value (using Euclidean spectral distance) were chosen.

As a result of this step, we obtained a set of 17 (the S2 bands) per 4 (the Medoid seasonal composites) for a total of 68 predictors referred to as *medoid predictors.*

Fig. 2 Example of NDVI pixel time series (red) and the corresponding fitted harmonic function (blue)

3.3 CO_2 Mapping

To map carbon storage across the study area by exploiting S2 predictors and the ground data, we used random forests (RF), a well-known supervised machine learning approach [18]. Although RF is known to be insensitive to the number of variables, a variables selection procedure was performed to reduce the burden of data collection and improve efficiency. To do it, we used the VSURF package [19] within the R statistical software. The package implements a stepwise selection procedure that performs a backward elimination and then a forward selection in three steps, based on importance measures and error rate internally calculated by the RF algorithm. Finally, the best set of variables is chosen and the redundancy in the predictors is minimized.

Using the set of variables chosen with VSURF, the RF model is trained with net equivalent CO_2 stock as the dependent variable and S2 predictors as independent ones. Other RF tuning parameters were kept with their default values: the number of trees in the forest was 500 and the number of variables chosen at each split was p/3, where p is the number of independent variables.

RF performance was assessed in terms of root mean squared error (RMSE) by using the out-of-bag error (OOB) estimate, which removes the need for a test set and which, unlike cross-validation (CV), performance estimates are unbiased [18]. The internal estimates of OOB were also used to order by importance variables selected using VSURF, using as criteria the percentage increase of mean square error (MSE%) that occurs when that variable is randomly permuted in the model [18]. Finally, to obtain the carbon stock map over the study area, we used the model fitted with the set of predictors previously selected, which obtained the best performance in terms of RMSE. The result was a regular map of predicted carbon stock with a spatial resolution of 10 m.

3.4 CO_2 Estimation

The mean and total values of net equivalent CO_2 stock absorbed in the study area were inferred using the design-based estimators originally proposed by Horwitz and Tompson [20], which permit unbiased estimation of the sampling variance. The Horwitz-Tompson

(HT) estimator for the mean is simply the sample mean:

$$\hat{\mu}_{HT} = \overline{y}$$

where $\overline{y}$ is the sample mean.

The standard error (SE) for the estimator can be expressed as:

$$SE(\hat{\mu}_{HT}) = \sqrt{\frac{\sigma^2}{n}}$$

where σ^2 and n are the sample variance and size, respectively.

The HT estimator for the total is:

$$\hat{\tau}_{HT} = N\overline{y}$$

where N is the population size, which is typically unknown in forest inventories. A good approximation of N can be given by A_a/A_{plot} where A_a is the area of the study and A_{plot} the area of the field plot. The sampling SE of the total is given by:

$$SE(\hat{\tau}_{HT}) = \sqrt{N^2\frac{\sigma^2}{n}}$$

The mean and total values of net equivalent CO_2 stock absorbed in the study area were also estimated by using a model-assisted estimator, which exploits the RF model and remote sensing data used to construct the 10-m resolution net equivalent CO_2 stock map. More specifically, model-assisted, generalized regression estimators were used to infer the mean and total value of carbon absorbed in the whole study area [21–23]. From a statistical standpoint, the model-assisted estimator for the mean can be expressed in the following form:

$$\hat{\mu}_{ma} = \frac{1}{N}\sum_{\mathrm{i}=1}^{N}\hat{\mathrm{y}}_{\mathrm{i}} - \frac{1}{n}\sum_{\mathrm{j}=1}^{n}\left(\hat{\mathrm{y}}_{\mathrm{j}} - \mathrm{y}_{\mathrm{j}}\right)$$

where $\hat{\mu}_{ma}$ is the model-assisted estimation of the mean, N is the number of forest pixels in the study area, $\hat{\mathrm{y}}_{\mathrm{i}}$ is the model prediction for the ith map unit, n is the field sample size (i.e., 20 plots), $\hat{\mathrm{y}}_{\mathrm{j}}$ is the model prediction for the ith field plot and y_{j} is the measured value in the ith plot.

The model-assisted estimator has two components: the mean of the map-predicted values for the whole study area (leftmost term) and a correction term based on the mean residual of the plot sample (rightmost term). The effect of the latter term is to remove bias from the model, which makes the estimator asymptotically unbiased (i.e., bias goes to zero at large sample sizes). The SE for the estimator is:

$$SE(\hat{\mu}_{ma}) = \sqrt{\frac{1}{n(n-1)}\sum_{j=1}^{n}\left(e_j - \overline{e}\right)^2}$$

where n is the sample size, $e_j = \widehat{y_j} - y_j$ and $\overline{e} = \frac{1}{n}\sum_{j=1}^{n} e_j$

Similarly, the model-assisted estimator for the net equivalent CO_2 total can be expressed as

$$\hat{\tau}_{ma} = \sum_{i=1}^{N} y_i - \frac{\mathrm{N}}{\mathrm{n}}\sum_{\mathrm{j=1}}^{\mathrm{n}}\left(\hat{\mathrm{y}}_j - \mathrm{y}_j\right)$$

Särndal et al. [21, p. 402] give the SE of the model-assisted estimator for the total:

$$SE\left(\hat{\tau}_{ma}\right) = \sqrt{N^2\left(\frac{1}{n} - \frac{1}{N}\right)\sum_{j=1}^{n}\frac{\left(e_j - \overline{e}\right)^2}{n-1}}$$

which can also be expressed as [21, p. 276]:

$$SE\left(\hat{\tau}_{ma}\right) = \sqrt{\hat{V}\left(\hat{\tau}_{HT}\right)\left(1 - R^2\right)}$$

where $\hat{V}\left(\hat{\tau}_{HT}\right)$ is the HT estimator of the variance under simple random sampling and R^2 is the determination coefficient of the prediction model. With $R^2 = 1$ the variance is 0 and the estimate coincide with the real value. Indeed, the reduction in variance gained using the model-assisted estimator is directly linked to the model performance.

Finally, to assess the efficiency of the model-assisted estimator for both the mean and total value, we compared the estimates against the design-based estimates produced just from the field plots through the relative efficiency coefficient (RE):

$$RE = \frac{\widehat{Var}\left(\hat{E}_{HT}\right)}{\widehat{Var}\left(\hat{E}_{ma}\right)}$$

where $\widehat{Var}\left(\hat{E}_{HT}\right)$ and $\widehat{Var}\left(\hat{E}_{ma}\right)$ are the estimated variance of the design-based and model-assisted estimates, respectively. Values of RE greater than 1 are evidence of greater precision in the model-assisted estimates [22–25]. RE coefficient can be interpreted as the factor by which the original sample size would have to be increased to achieve the same precision as that achieved using the remotely sensed auxiliary data.

4 Results

After the variable selection, 21 variables were chosen as the best candidates for prediction. These include three *medoid* and 18 *harmonic* predictors (Fig. 3), confirming the relevance of *harmonic predictors*. The most important variables were the sine of the NIR band, followed by the sine of the red edge 3 bands and the sine of the red edge 2 bands.

The final OOB error in terms of RMSE was 1.74 Mg ha^{-1} or 35% of the mean net equivalent CO_2 stock measured in the field. The R^2 was 0.69, indicating that S2 data provide meaningful information for predicting CO_2. The RF model was used to predict

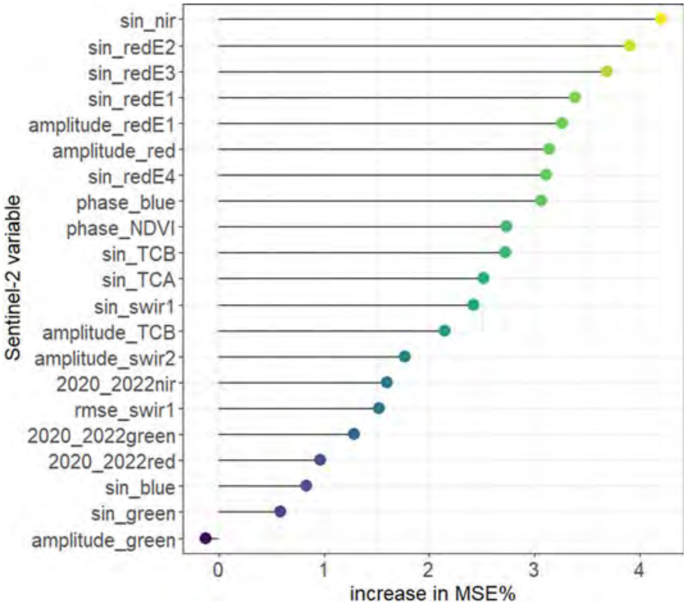

Fig. 3 Sentinel-2 variables importance

Fig. 4 Net equivalent CO_2 stock map generated with RF model. In blue the study area grid, while red dots represent the ground samples

net equivalent CO_2 stock over the study area (Fig. 4). Predictions ranged between 3.13 and 7.84 Mg ha^{-1} with a standard deviation of 0.84 Mg ha^{-1}.

Based on the HT estimator, $\hat{\mu}_{HT} = 4.95$ Mg ha^{-1} with a $SE(\hat{\mu}_{HT}) = 0.45$ Mg ha^{-1}. By contrast, based on RF predictions for the entire study area, $\hat{\mu}_{ma} = 4.93$ Mg ha^{-1} with a $SE(\hat{\mu}_{ma}) = 0.17$ Mg ha^{-1}, which corresponds to an RE coefficient of 7.1, demonstrating more effective results with the model-assisted estimator. Analogous results were obtained for the total carbon stock for which the model-assisted estimator outperformed the HT one ($\hat{\tau}_{HT} = 118.47$ Mg with a $SE(\hat{\tau}_{HT}) = 10.87$ against $\hat{\tau}_{ma} = 125.76$ Mg with $SE(\hat{\tau}_{ma})$ $= 8.73$), with a RE coefficient of 1.54 (Table 1).

Table 1 Mean $(\hat{\mu})$ and total $(\hat{\tau})$ values of net equivalent CO_2 stock (Mg ha^{-1}) with the design-based and model-assisted estimators

	Deign-based	Model-assisted	RE
$\hat{\mu}$	4.95	4.93	/
$SE(\hat{\mu})$	0.45	0.17	7.1
$\hat{\tau}$	118.47	125.76	/
$SE(\hat{\tau})$	10.87	8.73	1.54

5 Discussions and Conclusion

In this study, we demonstrated the advantage of exploiting S2 data for mapping and estimating net equivalent CO_2 stock in a tree plantation of 20 ha, in Guatemala. Using exclusively the ground data, we estimated the net equivalent CO_2 stocked on average in each 10-m cell over the plantation as 4.95 Mg ha^{-1} ± 0.9 Mg ha^{-1}, with a confidence interval of 95%. Exploiting S2 predictors, random forests, and the model-assisted estimator, the estimate was much more precise, i.e., 4.93 Mg ha^{-1} ± 0.29 Mg ha^{-1}. Indeed, the ratio between the variances of the design-based and the model-assisted estimates (RE, see Sect. 3.4) was 7.1. This means that, by using remote sensing data, it is possible to reduce the ground sample size by a factor of 7.1 while obtaining estimates with the same precision of those do not exploiting remote sensing data. This is a crucial advantage to reduce costs associated with ground data acquisition. Among the 21 predictors selected by the random forests model, 18 were *harmonic predictors* and just 3 were *medoid predictors*. This confirms the advantage of using time series analysis instead of single images. Accordingly, using *harmonic predictors* the model reached large accuracy with R^2 equal to 0.69 and RMSE up to 35%.

Last but not least, the procedure herein presented exploits open access S2 data and is scalable and replicable globally across other tree plantations. The procedure we presented allows obtaining reliable estimates and 10-m resolution maps informing on the amount of per pixel biomass. This also informs on the tree status, supports the management of the tree plantation, and helps the remote monitoring over time.

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4. FORWARDS

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