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Volume 2

Planet Care from Space

Edited by Dessena M.A., Melis M.T and Rossi P.

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A SPATIAL APPROACH FOR MULTI-TEMPORAL ESTIMATION OF FOREST GROWING STOCK VOLUME AND ABOVEGROUND CARBON POOL. A CASE STUDY IN TUSCANY (ITALY).

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ABSTRACT: Within the United Nations Framework Convention on Climate Change (UNFCCC) and the Paris Agreement's Enhanced Transparency Framework, national greenhouse gas inventories are the key requirement to report GHG emissions by sources and removals by sinks, being the central element of transparency and understanding of the impact of climate mitigation. In this framework, quantitative information about forests plays a pivotal role in national and international monitoring programs and reporting activities. National forest inventories (NFI), complemented by wall-to-wall maps of forest variables, are usually the primary source of such information. NFIs are not designed as monitoring tools, since they are updated only every 5 or 10 years, but models can be used to produce annual carbon stock changes and fluxes. Following the approach of the FOR-EST model we present here a spatial approach to update growing stock volume (GSV) changes for years between national forest inventories, taking Tuscany (Italy) as a case study. The GSV update is mainly driven by the GSV current increment, predicted with forest types-specific growth models derived from yield tables. The spatial-explicit estimation of GSV is based on an initial GSV map, forest types, and forest disturbances maps. The spatial approach has provided comparable results with the original FOR-EST model, reaching a relative root mean square error (RMSE%) of 8.3% against the data reported by Italy under the UNFCCC. We also validated the results of our approach against an independent dataset of 342 circular plots distributed over the study area, measured between 2006 and 2019, reaching a mean RMSE% of 42 % and an R^2 of 0.55 across the years.

1. INTRODUCTION

Updated information about forests are essential in national and international forest inventories, monitoring programs, and reporting activities (FAO, 2015). Under the United Nations Framework Convention on Climate Change (UNFCCC) and under the incoming Enhanced Transparent Framework (ETF) under the Paris Agreement, each Party must report periodically an inventory of its annual anthropogenic greenhouse gases (GHGs) emissions by sources and removals by sinks .
According to the Intergovernamental Panel on Climate Change (IPCC) Guidelines (IPCC, 2006), forestry-related emissions and removals have to be assessed for five carbon pools (i.e. above-ground and below-ground biomass, deadwood and litter, soil), usally acting as carbon sink or source. National Forest Inventories (NFI) are usually the key data source in the estimation process. While NFIs are usually updated every 5-10 years, UNFCCC guidances force the Parties to provide annual forestry-related carbon stock change or flux estimates. To accomplish this goal, there is the need to estimate carbon stock changes in the years between consecutive NFIs, with a methodology based on annually measured forest parameters, rather than a simple interpolation between years (Federici et al., 2008). For such purposes, Federici et al. (2008) developed a methodology to update carbon stock changes in the five UNFCCC carbon pools in Italy, called the FOR-EST model. The FOR-EST is based on NFI GSV data and species-specific growth curves derived from yield tables, used to estimate the annual current increment. The model can estimate the annual GSV at the regional level by adding to the previous year GSV the current increment and subtracting the losses due to natural mortality, harvesting, and forest fires. Finally, the GSV is converted to AGB and then to carbon stock by species-specific parameters.

Nowadays, the NFI ground surveys can be used with remotely sensed data to produce continuous spatial predictions of forest variables (the so-called wall-to-wall maps) (Kangas et al., 2018, Vangi et al., 2021). Wall-to-wall data can be integrated into decision support systems and used to produce small area estimations by aggregating pixel-level predictions. From a retrospective point of view, remote sensing data can provide valuable baseline information for understanding forest dynamics and carbon fluxes changes (Matasci et al., 2018). In this context the Landsat time-series data has valuable potential for studying vegetation trends with an annual/seasonal frequency, thanks to its 30 m spatial resolution, a revisiting time of 16 days, a spectral range between visible and short wave infra-red, and more than 35 years of earth observation missions.
This study aims to estimate annual GSV and above-ground carbon pool for all the years after the last Italian NFI (2005) until 2019 at 23x23 meter spatial resolution in the Tuscany region in central Italy. The approach proposed adapted the FOR-EST workflow carrying out the annual estimation on a spatial basis

2. MATERIALS

2.1 Study area

The study was carried out in the administrative region of Tuscany, in central Italy, which covers 22,992 km^2 (Fig. 1). According to the 2nd NFI (INFC, 2007), Tuscany is the most wooded region in Italy, with forests and other wooded lands covering 1,086,000 ha, about 47% of the region. Forests are dominated by deciduous oaks (*Quercus pubescens* W., *Q. cerris* L.), with 414,000 ha, followed by chestnut (*Castanea sativa* Mill.) (177,000 ha) and European beech (*Fagus sylvatica* L.) (76,000 ha).

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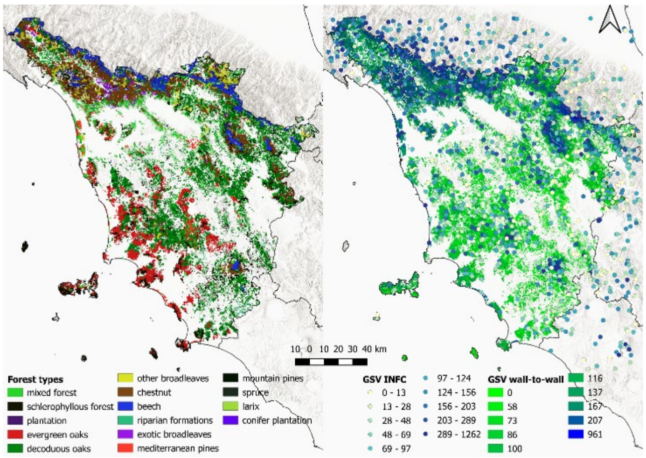

Figure. 1 - Study area. Forest types from CLC 2006 (left); GSV map with NFI field plots used to build it (right).

2.2 2005 GSV map

For the assessment of GSV in the years following the last NFI, we used as initial GSV data the GSV map produced by Chirici et al. (2020) for Tuscany. This map consists of GSV predictions created with the random forests model with Landsat and other predictors at 23m x 23m resolution for all forest pixels. Such pixel size mimics the area of the field plots measured in the field in the NFI program. The pixel-level predictions ranged between 0 and 690 m^3ha^{-1} with a standard deviation of 68.5 m^3ha^{-1}. A more detailed description of the method used to produce the GSV map for 2005 is provided by Chirici et al. (2020).

2.3 CLC IV level

Information and distribution of forest types were derived from the IV level of the Corine Land Cover (CLC) map for the reference years 2006, 2012, and 2018. CLC uses a minimum mapping unit (MMU) of 25 hectares (EEA, 2007). The IV level used in this study were produced by the *Istituto Superiore per la Protezione e la Ricerca Ambientale* (ISPRA). To derive the CLC forest types maps, we first rasterized the vector product to the 23m × 23m spatial resolution of the 2005 GSV map. Then we masked out the non-forest categories by assigning them to the "non-forest" class, retaining the categories 2.2.4 and 3.x, for a total of 18 forest types.

2.4 Yield tables

The collection of national yield tables was used to model the current increment of forests, being the only source that provides both GSV and current volume increment at the regional level (Federici et al., 2008). Yield tables reported the GSV and current increment as a function of forest age for 27 species within 13 genera. The 27 species were linked to CLC forest types with specific harmonization bridges developed for this study, to maintain the characteristics of the data based on different definitions, enabling their comparability at a higher hierarchical level

3. METHODS

3.1 Forest disturbances map

For the multitemporal spatial estimation of GSV, data on the spatial distribution of forest disturbances in the period 2005-2019 were needed. These data were produced with the three indices three dimensions (3I3D) algorithm, developed by Francini et al. (2021). 3I3D is an unsupervised algorithm that requires no input parameters or calibration to predict the probability of forest change by analyzings the trend over three consecutive years of three photosynthetic activity indices (3I) used as the axes of a three-dimensional space (3D). Following this procedure, we used the Best Available Pixel (BAP) procedure (Griffiths et al 2013; White et al., 2014) producing a cloud-free composites for every year to predict all forest disturbances (MMU = 500 m^2) that occurred in the study area over the study period. Using these maps, we calculated for each disturbed pixel the “age” as the number of years since the last disturb using 2019 as the reference year.

3.2 Overwiew of the model

GSV and carbon stock were predicted at the pixel level, using GSV and forest age as unique drivers. The GSV prediction relies on growth models derived from yield tables based on the initial GSV, the forest types distribution and forest disturbances. The spatial prediction of GSV for years not covered by the NFI was accomplished differently for undisturbed forest areas (i.e., those not subject to logging, fire, or other disturbances) and disturbed ones due to the lack of spatial information on the residual GSV after disturbing events. In the former areas, for each year and each CLC forest type, the GSV (referred to GSV_n) was computed from the previous year GSV (GSV_{n-1}) by adding the current increment calculated with the first derivative of the Richards function (Federici et al. 2008). In the latter areas, the GSV_n was calculated as a function of the numbers of years since the last disturbance (forest age), based on the relationships between age and GSV for each CLC forest type, derived from yield tables. The methodologies are described in detail below.

3.3 Models for undisturbed areas: the Richards growth function

Following the original idea of Federici et al. (2008), we used an age-indepentent relation to model the current increment. Types-specific growth models were constructed using data from national yield tables, and the bridges developed *ad hoc*. The first derivative of the Richards function was used to calculate the current increment as a function of GSV. This function is bounded and monotonic with four parameters and is defined by the following equation:

$$y = a \cdot \left[1 - e^{(\beta - kt)}\right]^{-\frac{1}{v}} \qquad (1)$$

With the following constraints for the parameters: a, k > 0; -1 ≤ β ≤ ∞; v ≠ 0. In the models building, the GSV represents the independent variable x, while the dependent variable y is the correspondent current increment.

3.4 Models for disturbed areas: polynomial regression

While the age could not be appropriate for estimating the productivity in natural stands, in most disturbed forest stands the regrown trees are in the same age class, forming an even-aged stand, at least for the first years after a disturbing event. This is the case of clearcuts, the most common forest disturbances in the study area. In such a situation, forest age can be used to predict growth at stand level.

To construct types-specific models between age and GSV, a second-order polynomial regression model was chosen.

3.5 GSV and carbon stock estimation

In undisturbed areas, we followed the approach developed by Federici et al. (2008). Starting from the initial GSV (GSV_{n-1}) map produced by Chirici et al. (2020), the current increment per hectare (m^3 ha^{-1} y^{-1}) was computed with the Richards function (described in § 3.1) for every CLC forest type, thus obtaining the current increment map for the year *n-1*. For each year, the GSV_n (m^3ha^{-1}) was computed from the previous GSV_{n-1} map adding the current increment map for the year *n-1* and subtracting losses due to natural mortality. The average mortality rate used for the calculation was 0.116%, for evergreen types, 0.117% for deciduous types, and 0.1165% for mixed types, under the GPG for LULUCF (Good Practice Guidance for Land Use, Land-Use Change, and Forestry) (IPCC, 2003).
In disturbed areas, identified by the 3I3D algorithm for each year and each CLC type, the GSV was computed by applying the type-specific growth models described in § 3.2, derived from the yield tables. The age of the disturbed forest for year *n* was used as the independent variable to predict the GSV_n in each disturbed pixel, resulting in a GSV map of forest disturbances for each year between 2005 and 2019.
The final GSV map for year *n* was obtained by overlaying the GSV_n map of the disturbed forest with the GSV_n map of the undisturbed one.
GSV maps were converted to AGB maps to obtain the forest carbon stock map for each year between 2005 and 2019 (t ha^{-1}), following the approach presented in Federici et al. (2008).
Carbon stock maps were derived by applying the default carbon fraction factor of 0.50 to AGB maps, following the methodology reported in the IPCC guidelines for GHGs inventory (IPCC, 2006). The pixel-level predictions of volume and stored carbon were aggregated at regional level for each year.

3.6 Validation data

To validate the annual GSV estimation results, we used independent field data from 342 circular plots from an independent dataset created for research activities, distributed over the study area and measured between 2006 and 2019. The plots were representative of all forest types in the study area. The mean GSV in the validation dataset is 263 m^3 ha^{-1}, with a standard deviation of 154 m^3 ha^{-1}. The maps' accuracies were evaluated in terms of R^2, bias and relative root mean square error (RMSE%).

4. RESULTS

The total and average values of volume and carbon stock for each year, aggregated at the regional level, are reported in Table 1.
The aggregated results were compared with the output of the FOR-EST model for the same period (2005-2019). We obtained an RMSE% of 8% and 3% and an R^2 of 0.96 and 0.99, respectively for GSV and carbon stock. Based on the spatial approach, the increase in GSV over 2005-2019 was 49 million m^3 moving from an average of 50.5 m^3 ha^{-1} to 71.8 m^3 ha^{-1}. Carbon stock increased by 574 million t in the same period, moving from 56.9 t ha^{-1} to 79.3 t ha^{-1}. The forest types that mainly contributed were deciduous oaks and chestnut forests, followed by mixed forests and sclerophyll forests.

5. DISCUSSION

The comparison of total carbon stock obtained by the aggregation of pixel level predictions and FOR-EST model is reported in figure 2.

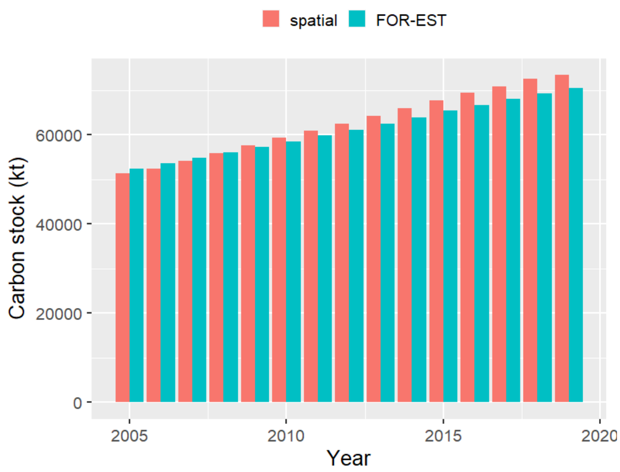

Figure 2 – comparison of the total carbon stock from the spatial approach and FOR-EST model.

Although our approach leads to a progressive overestimation of the total GSV over the years, probably due to the underestimation of current increments combined with the larger forest area of CLC maps than used in the FOR-EST model, these results are very much consistent with the original estimates produced by FOR-EST for the Tuscany region and included by Italy in the official Italian Greenhouse Gas Inventory 1990-2019 (ISPRA, 2021).

Table 1 – Total and mean GSV and carbon stock at regional level over the period 2006-2019

Year	Total GSV (m^3)	Mean GSV (m^3/ha)	Total carbon stock (t)	Mean carbon stock (t/ha)
2006	149105791	133.0	52382916	56.9
2007	155082179	138.3	54078735	58.8
2008	160892582	143.5	55849730	60.8
2009	166806469	148.7	57570615	62.9
2010	172755928	154.1	59315614	64.8
2011	178385510	159.1	60845914	66.7
2012	184028522	164.1	62519046	68.6
2013	189586992	169.1	64187677	70.3
2014	194778958	173.7	65915830	72.1
2015	200192558	178.5	67633748	73.9
2016	205563897	183.3	69381644	75.7
2017	210858665	188.0	70859048	77.6
2018	216270899	192.9	72545155	79.3
2019	221268502	197.3	73380336	79.3

The accuracy assessment against the independent validation set is reported in Figure 3. When we compared our GSV results with the independent dataset we found an R^2 of 0.55, in line with other studies (Immitzer et al., 2016; Chirici et al., 2020) considering that we were not able to use Airborne Laser Scanning (ALS) data, that the Italian forests are very complex and that a high resolution forest map was not available. Furthermore, other limitations of this approach can be listed: the use of outdated yield tables, which probably lead to an underestimation of types-specific current increment, as reported by Federici et al. (2008); the underestimation of forest disturbances, especially in high forests of Apennine areas, where silvicultural treatments are based on continuous canopy cover approaches which are not always visible from satellite images.

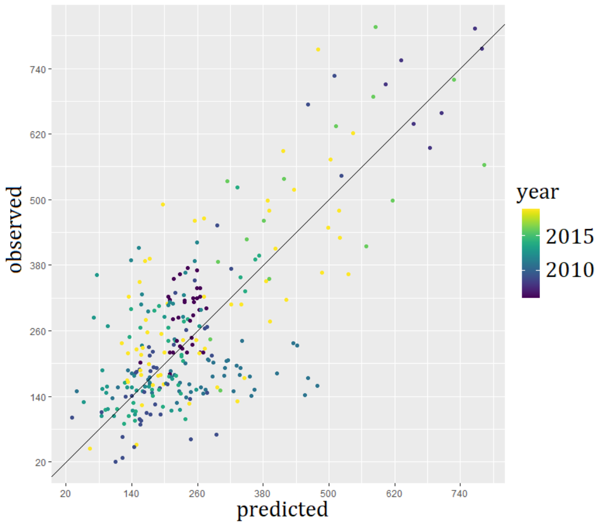

Figure 3 - Predicted against observed GSV for the validation set.

6. CONCLUSION

The proposed approach has provided the first multitemporal spatial estimations of GSV and carbon stock in the study area and it could be applied at a national scale, using the 2005 GSV map produced by Vangi et al. (2021) and integrating the regional databases of forest disturbances (natural or anthropogenic) and yield tables, if available. The approach uses GSV as a unique driver for deriving the above-ground biomass and carbon stock change in areas never disturbed by harvest, fire, or other forest disturbances, representing 93,3% of the total forest land in the investigation period. In disturbed areas it was possible to derive the age of the forest, thanks to the 3I3D algorithm, to apply age-dependent relationships available in yield tables.
The 23m × 23m resolution GSV and carbon stock maps produced in the study can support the requirements of national and regional forest bodies and produce small area estimation, augmenting the spatial resolution of traditional NFI design-based estimates (Chirici et al., 2020).
The availability of the new NFI data (INFC 2015) will provide new important information for the calibration and validation of this approach. The availability of an official high-resolution national forest map and wall-to-wall multitemporal ALS data is also essential to improve the quality of GSV and carbon stock spatial estimations.

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Planet Care from Space

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This volume, organized in 7 thematic chapters, includes 45 contributions.

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