https://doi.org/10.5194/egusphere-2024-4094
Preprint. Discussion started: 16 January 2025

Assessing the effect of forest management on above-ground carbon stock by remote sensing

Sofie Van Winckel[1], Jonas Simons[1], Stef Lhermitte[1], Bart Muys[1]
[1]Department of Earth and Environmental Sciences, KU Leuven, Leuven, 3000, Belgium
Correspondence to: Bart Muys (bart.muys@kuleuven.be)

Abstract. As the global community intensifies efforts to combat climate change, insights on the influence of management on forest carbon stocks and fluxes are becoming invaluable for establishing sustainable forest management practices. However, accurately and efficiently monitoring carbon stocks remains technologically challenging. In this study, we aim to 1) leverage the complementary strengths of optical, Light Detection and Ranging (LiDAR) and Synthetic Aperture Radar (SAR) remote sensing technologies to improve overall accuracy and scalability in carbon stock estimation, and to 2) assess the effect of forest management on carbon stock by comparing unconfounded pairs of managed and unmanaged forests in the National Park Brabantse Wouden (Flanders, Belgium). Remote sensing data from Sentinel-2, Sentinel-1, and a canopy height product derived from the Global Ecosystem Dynamics Investigation mission (GEDI) were used as predictors in a generalized additive model (GAM) to estimate carbon stock. The combination of all three remote sensing sources significantly improved model accuracy (R^2=0.68, RMSE=56.35, MAE=50.07) compared to a model using only Sentinel-2 indices (R^2=0.56, RMSE=99.44, MAE=91.40). While field assessment exhibited higher carbon stocks in unmanaged stands compared to managed ones, this difference was not detectable using a remote sensing model that incorporated Sentinel-2, Sentinel-1, and GEDI variables. Potential explanations for this discrepancy include signal saturation and the need for more training data.

1 Introduction

1.1 Problem statement

Increasing forest carbon stocks to enhance the climate mitigation potential is a key component of many international agreements aimed at combating climate change (e.g., Kyoto Protocol, Paris Agreement, European Green Deal). Accurate quantification of forest carbon over time provides the foundation for various initiatives targeting carbon management, especially within ecosystem service frameworks like carbon credit schemes, and the development of climate-smart forest management guidelines. Among different forest carbon pools, above-ground biomass has proven to be the most susceptible to human activities, including forest management practices (Gurung et al., 2015). Since above-ground carbon stocks are easier to measure and can serve as a proxy for below-ground carbon through modeling, they are increasingly considered a valuable indicator of sustainable forest management (Sabatini et al., 2019). However, while forest management practices affect above-ground biomass carbon stocks in different ways, the precise impact of these practices remains poorly quantified. Evidence suggesting that unmanaged forests continue to function as effective carbon sinks, even into later stages of forest development, highlights the need for better localization and protection of these ecosystems (Kun et al., 2020; Luyssaert et al., 2008; Mikolāš et al., 2023). Nevertheless, accurately capturing carbon stocks over large extents presents both technical and logistical challenges, but remote sensing shows cost-efficient and area-covering upscaling potential.

1.2 State of the art and research gaps

1.2.1 Managed versus unmanaged forests

Despite the growing need to understand how to optimize a forest's climate mitigation capacity, controversy persists regarding the influence of management on above-ground carbon stocks (Kalies et al., 2016). On the one hand, natural ecosystems, such as unmanaged forests, may store more carbon due to a higher basal area, increased litter production, and unrestricted biomass accumulation. These natural ecosystems are generally viewed as more stable and resilient compared to heavily modified forests, leading to a more stable storage of carbon (Morel and Nogué, 2019). On the other hand, optimizing species composition in managed forests may enhance productivity and increase carbon stocks (Vayreda et al., 2012). Management may also reduce the susceptibility of a stand to climate disturbances such as wildfires and windthrows, therefore avoiding big losses of carbon stock and assuring carbon stability (Garcia-Gonzalo et al., 2007; Jandl et al., 2007; Ruiz-Peinado et al., 2017; Vayreda et al., 2012). Due to the presence of confounding factors at study sites, such as climate, soil, slope, aspect, and stand history, drawing clear conclusions about the causes of observed differences in carbon stock and the effects of forest management has been challenging in previous research (Nadrowski et al., 2010). Dugan et al. (2017), Melikov et al. (2023) and Ruiz-Peinado et al. (2017) emphasize the need to clarify the relationship between forest management and carbon stock by accounting for or excluding these confounding variables.

1.2.2 Measuring carbon

Traditionally, above-ground carbon has been calculated for individual trees from tree height and diameter at breast height (DBH), wood density, and species-specific carbon concentration factors. This can then be extrapolated using expansion factors to a per-hectare basis (Zianis et al., 2005). While such in-situ methods achieve high accuracy at small extents, it becomes costly and labor-intensive when scaling to larger regions. Spaceborne remote sensing technologies have been widely adopted to expand the reach and efficiency of biomass estimation (Rodríguez-Veiga et al., 2017). Advances in remote sensing have led to a suite of techniques, with each approach offering distinct advantages and disadvantages (Tian et al., 2023).

Passive optical remote sensing has become the predominant method for large-range biomass estimation, due to its extensive data availability, high spatial and temporal resolution and low cost (Tian et al., 2023; Xiao et al., 2019). Vegetation indices, such as the Normalized Difference Vegetation Index (NDVI), are important indicators of biomass. While passive optical remote sensing operates at a resolution suitable for regional assessments, active optical remote sensing such as Spaceborne Light Detection And Ranging (LiDAR) technology generates a detailed 3D profile of forest canopies, offering highly precise measurements at a higher resolution. Synthetic Aperture Radars (SAR) are also active remote sensors, which use microwave signals to capture the vegetation structure, related to the plant's biomass (Sinha et al., 2015). The used signals are backscatter

https://doi.org/10.5194/egusphere-2024-4094
Preprint. Discussion started: 16 January 2025

intensity, frequency and polarization to reflect the vegetation's moisture content, surface roughness, and dielectric properties (Goetz et al., 2009; Xiao et al., 2019). Microwaves penetrate clouds, making it particularly valuable in regions with persistent cloud cover (Xiao et al., 2019).

While each remote sensing method offers unique advantages, their individual limitations constrain the precision and comprehensiveness of forest carbon assessments. Both passive optical sensors and SAR struggle with signal saturation in dense forests with a complex vegetation structure, where increasing biomass no longer affects the sensor signal (Rodríguez-Veiga et al., 2017). They may also suffer more from mixed pixels than LiDAR, when a single pixel captures multiple surface types and complicates accurate biomass estimation. Passive optical sensors, while effective for measuring photosynthetic activity, additionally fail to capture structural characteristics and are hindered by cloud cover, which impairs the signal-to-noise ratio. LiDAR, on the other hand, only measures the structural characteristics of the forest, missing photosynthetic information on tree health and chlorophyll content. Spaceborne LiDAR measurements moreover require interpolation, for example with passive optical remote sensing, because its measurements are not yet area-covering. This can introduce errors, especially in variable forest structures (Lu et al., 2012). Lastly, SAR faces issues with temporal decorrelation and signal interference from environmental factors, further complicating biomass monitoring (Koch, 2010; Xiao et al., 2019).

In conclusion, each technique offers valuable insights but also comes with limitations, which underscore the importance of integrating remote sensing technologies (Jiang et al., 2022; Jiao et al., 2023; Sun et al., 2024). The integration of several remote sensing sources has already proven successful for biomass estimations, but most studies are limited to two sensor types. For example, David et al. (2022) and Forkuor et al. (2020) reported improved model predictions when using SAR and passive optical remote sensing indicators in dryland forest. Hoscilo et al. (2018) reported a saturation effect at 200 tons/ha biomass in temperate forests of Poland when combining SAR and passive optical remote sensors. The combined use of LiDAR, SAR and passive optical remote sensing has, to our knowledge, not yet been investigated to assess above-ground biomass in temperate forests. In this study, we aim to 1) leverage the complementary strengths of optical, LiDAR and SAR remote sensing technologies to improve overall accuracy and scalability in above-ground forest carbon stock modeling and to 2) assess the effect of forest management on carbon stock by comparing unconfounded pairs of managed and unmanaged temperate Atlantic forests in Flanders, Belgium.

2 Materials and Methods

2.1 Study region: National Park Brabantse Wouden

Our study is located in the Brabantse Wouden National Park (BW NP) in central Belgium and was selected by the INFORMA Forest Management Platform to represent the temperate Atlantic forest ecosystems in Europe (Fig. 1a) (INFORMA, 2022). The BW NP encompasses a vast area including 10,000 hectares of forest, composed of several large fragments, including the

https://doi.org/10.5194/egusphere-2024-4094
Preprint. Discussion started: 16 January 2025

Sonian forest and Meerdael forest (Fig. 1a). Since October 2023 it is one of the six National Parks in Belgium, unique for its monumental beeches and oaks, sunken lanes, and meandering rivers (Brabantse Wouden, 2023).

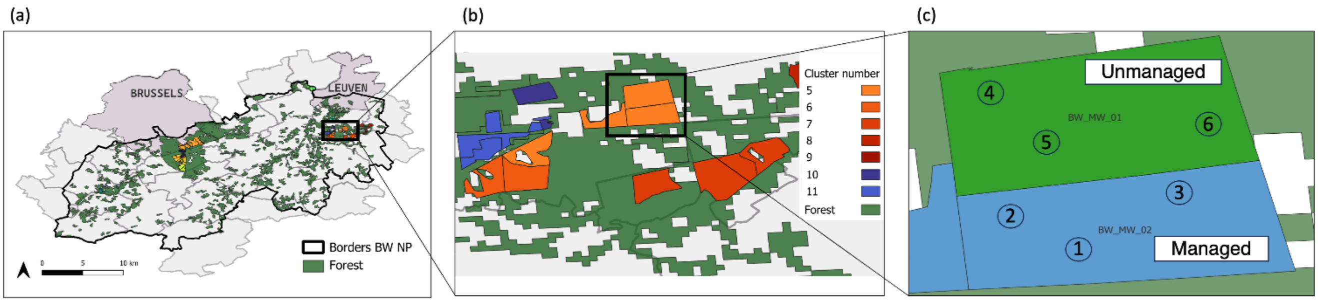


Figure 1: The study site is situated in the Brabantse Wouden National Park (a). Adjacent forest patches were clustered (b), where patches within a cluster only differed in management (c). 3 plots were randomly attributed to each forest patch (c). (The high-resolution forest map from the European Union's Copernicus Land Monitoring Service was used for the creation of this map https://doi.org/10.2909/db1af59f-f01f-4bd4-830c-f0eb652500c1.)

2.2 The effect of forest management on carbon stock

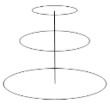
Above-ground carbon stock as calculated from individual tree height and DBH, measured in the field, is considered as the ground truth. The effect of forest management on the carbon stock can thus trustfully be deducted from such field data, which will also serve as calibration data in the remote sensing model.

The database has an orthogonal design, which ensures the minimization of confounding effects (Nadrowski et al., 2010). It consists of a collection of forest patches grouped into clusters, with each cluster containing patches that differ only in management practices (Fig. 1b). Other factors affecting the accumulated carbon stock – such as aspect, soil, dominant species, elevation, slope, climate, and land use and management legacy – are therefore controlled for. Each cluster includes at least one managed and one unmanaged forest patch, with the unmanaged patch having remained undisturbed for at least 20 years (Fig. 1c). For each patch, basic information is available, including forest management details, time since abandonment, and dominant tree species. A random selection of clusters, considering different dominant tree species, was made within the constraints of the IFMP and the time and resources available for field data collection. The resulting selection contained 13 clusters and 26 patches; one managed and one unmanaged forest patch per cluster. Next, three plots were randomly assigned within each patch (Fig. 1c). The size of the patches was not considered, as homogeneity was ensured through the IFMP design. In total, 78 plots were identified across 26 forest patches, representing 13 clusters. Field measurements and remote sensing data were collected from these plots (Fig. 2).

A nested plot design was used, following the thresholds in DBH and tree height as used in the Flemish Forest Inventory (FFI) (Table 1). The system boundaries were defined as standing above-ground biomass (dead or alive), because below-ground biomass or lying deadwood cannot be easily quantified by remote sensing. The DBH and tree height were measured for each tree, according to the nesting levels.

https://doi.org/10.5194/egusphere-2024-4094
Preprint. Discussion started: 16 January 2025

Table 1: Characteristics of the trees per nesting level for BW NP.

	Nesting Level	Plot radius (m)	Tree DBH (cm)	Tree Height (m)
	A	4.5	<7	>2
	B	9	7-39	/
	C	18	>39	/

With site- and species-specific allometric equations, obtained from the FFI, the relationship between carbon stock and tree height and DBH is described, following Eq. (1):

$$Carbon\ stock = \sum_{species} Vstem \times VEF \times WD \times CF \quad (1)$$

where $Vstem$ is the stem volume (m³), VEF is the volume expansion factor (-), WD is the wood density (t/m³) and CF is the carbon factor (-).

The VEF was used to convert merchantable volume to above-ground biomass and was available through the National Inventory Report (2020). The WD is also species-specific and described in the National Forestry Accounting Plan of Belgium (Perin et al., 2018). For the CF, a value of 0.5 was used for all species, as described in the IPCC report (2003) and the National Inventory Report (2020). The stem volume can be calculated using species-specific two-entry tariffs with DBH and height (H) measurements as specified in Eq. (2). The coefficients a, b, c, d and e were derived from Dagnélie et al. (1985), Berben (1983) and Quataert et al. (2011):

$$Vstem = a + b * \pi * DBH + c * (\pi * DBH)^2 + d * (\pi * DBH)^3 + e * H + f * (\pi * DBH) * H + g * (\pi * DBH)^2 * H. \quad (2)$$

The two-entry tariffs are designed for trees with a DBH larger than seven cm. For smaller trees, the volumes were approximated with the volume of a cylinder. Still, for some smaller trees with a DBH between seven and ten cm, the two-entry tariffs resulted in a negative volume. In this case, the volume was recalculated as a truncated cone with a capping diameter of seven cm (Eq. (3), (4), (5)):

$$V_{cone} = \frac{1}{3} * H * \frac{\pi * DBH^2}{4}, \quad (3)$$

$$V_{cone\ top} = \frac{1}{3} * \frac{\pi * DBH}{H * 22} * \frac{0.22^2}{4 * \pi}, \quad (4)$$

$$V_{tree} = V_{cone} - V_{cone\ top}, \quad (5)$$

with DBH and H in meters. These formulas were based on the Flemish Forest Inventory.

After calculation of the carbon stock per tree and then per plot, the mean carbon stock per patch was obtained from the three plots situated in each forest patch (Fig. 2). Finally, the difference in carbon stock between unmanaged and managed patches was calculated per cluster.

We used a Generalized Linear Mixed Model (GLMM) with a gamma-distribution to statistically test the difference between carbon stocks of managed and unmanaged field-measured plots (Wood, 2006). The mean carbon stock per patch was the response variable, management was the fixed effect and the patch was nested in the cluster as a random effect.

2.3 Carbon stock modeling with remote sensing

2.3.1 Data collection and preprocessing

Once the field measurements for calibration were obtained, remote sensing data were extracted and preprocessed for the same forest plots (Fig. 2).

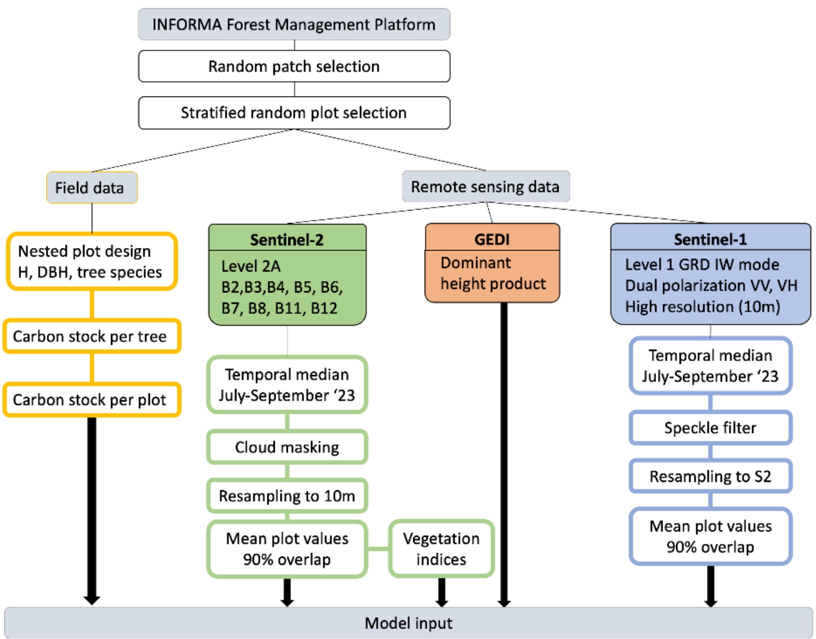


Figure 2: Overview of the data collection process and pre-processing of all data. H=tree height, DBH=diameter at breast height, GRD IW= Ground Range Detected, Interferometric Wide swath mode, S2= Sentinel-2.

First, data from the Sentinel-2 mission (passive optical remote sensing), launched by the ESA Copernicus program, was obtained at level 2A via Google Earth Engine (https://earthengine.google.com/). Data were retrieved for all bands except B1, B9 and B10 because these bands are recorded at 60 m resolution, which is too coarse for analyses at stand level. A three-month period (July 1, 2023 to September 1, 2023) was selected to align with the time frame for field data collection. A cloud masking was performed (filtered with a 60% cloudy pixel percentage, masked with a 40% cloud probability threshold) and all 20-meter resolution bands were resampled to 10 m resolution. Mean band values were then calculated for each selected plot, using a

https://doi.org/10.5194/egusphere-2024-4094
Preprint. Discussion started: 16 January 2025

weighting percentage of 90% overlap between the pixel and the plot area.

Vegetation indices, rather than raw band values, are particularly useful indicators of biomass. An explorative review of relevant scientific literature led to a selection of vegetation indices, derived from Sentinel-2, that have been proven useful indicators for above-ground biomass (AGB) modeling (Table 2) (Chen et al., 2019; Forkuor et al., 2020; Mngadi et al., 2021; Moradi et al., 2022). The mean of each vegetation index per plot was calculated identically to the mean Sentinel band values, to be used later as explanatory variables for above-ground carbon stock.

Table 2: Vegetation indices, derived from Sentinel-2, which were used in this study with respective calculation and reference.

Vegetation index	Explanation	Formula based on Sentinel-2 spectral bands	Source reference
NDVI	Normalized Difference Vegetation Index	$\frac{B8-B4}{B8+B4}$	Chen et al. (2019) Forkuor et al. (2020)
EVI	Enhanced Vegetation Index	$2.5*\left(\frac{B8-B4}{1+B8+6*B4-7.5*B2}\right)$	Mngadi et al. (2021)
LAI	Leaf Area Index	$3.618*EVI-0.118$	Chen et al. (2019)
GNDVI	NDVI with green wavelengths	$\frac{B7-B3}{B7+B3}$	Chen et al. (2019)
NDI45	Normalized Difference Index with B4 and B5	$\frac{B5-B4}{B5+B4}$	Chen et al. (2019)
REDNDVI	NDVI with red wavelengths	$\frac{B8-B7}{B8+B7}$	Forkuor et al. (2020) Mngadi et al. (2021)
STVI1	Stress-related Vegetation Index 1	$\frac{B11*B4}{B8}$	Forkuor et al. (2020)
STVI2	Stress-related Vegetation Index 2	$\frac{B8}{B4*B12}$	Forkuor et al. (2020)
STVI3	Stress-related Vegetation Index 3	$\frac{B8}{B4*B11}$	Forkuor et al. (2020)
SAVI	Soil-Adjusted Vegetation Index	$\frac{B8-B4}{B8+B4+0.5}*1.5$	Moradi et al. (2022)
MCARI	Modified Chlorophyll Absorption Ratio Index	$\left((B5-B4)-0.2*(B5-B3)\right)*\frac{B5}{B4}$	Chen et al. (2019)
PSSRa	Pigment Specific Simple Ratio a	$\frac{B7}{B4}$	Chen et al. (2019)
IPVI	Infrared Percentage vegetation index	$0.5*(NDVI+1)$	Moradi et al. (2022)
ARVI	Atmospherically Resistant Vegetation Index	$\frac{B8-(2*B4-B2)}{B8+(2*B4-B2)}$	Chen et al. (2019)
IRECI	Inverted Red-Edge Chlorophyll Index	$\frac{B7-B4}{\frac{B5}{B6}}$	Chen et al. (2019)
MTCI	MERIS Terrestrial chlorophyll Index	$\frac{B6-B5}{B5-B4}$	Chen et al. (2019)

https://doi.org/10.5194/egusphere-2024-4094
Preprint. Discussion started: 16 January 2025

Second, GEDI, or Global Ecosystem Dynamics Investigation, is a spaceborne LiDAR mission launched in 2018 by NASA to measure the vertical structure of the Earth's forests (Dubayah et al., 2020). GEDI can directly measure the canopy height, a morphological variable that is also measured in the field with conventional methods. However, the measurements are in discrete footprints and thus lack the full coverage of passive optical remote sensing missions such as Sentinel-2. Therefore, a high-resolution canopy height model of the earth (10x10m) was recently developed by ETH using a probabilistic deep learning model to extrapolate height data from the GEDI mission via spectral information from Sentinel-2 (Lang et al., 2022, 2023). Even though the product was developed at a global scale, lacking local calibration and introducing significant uncertainty, it was already successfully used for local carbon stock mapping in the context of the High Carbon Stock Approach (Lang et al., 2021). The product was directly downloaded for the study regions and no preprocessing was needed.

Finally, the Sentinel-1 mission, part of the ESA Copernicus program, is a C-band synthetic aperture radar (SAR) system. Data were acquired at level-1 in Interferometric Wide Swath mode (10m resolution) with dual polarization (VV and VH) for both ascending and descending passes. C-band radars are more sensitive to detecting leaves and needles than trunks and branches, in contrast to P- and L-band SAR (Rüetschi et al., 2018). The shorter wavelength interacts more strongly with smaller vegetation elements with a higher water content. The Sentinel-1 radar emits vertical waves and receives both vertical and horizontal waves (VV and VH respectively), yielding a SAR image. While VV backscatter indicates surface roughness and water content, VH backscatter is rather sensitive to volumetric scattering (Laurin et al., 2018). The amount of backscatter is influenced by the structural attributes of forest canopies and the interactions between surface and volumetric scattering in vegetation, both of which serve as indicators of above-ground biomass (AGB). A Lee speckle filter was applied to the data, which were collected during the same time period as the Sentinel-2 data. Mean plot values for VV and VH were then calculated separately to serve as explanatory variables.

2.3.2 Data analysis

In Fig. 3, the workflow of the modeling process is depicted, as can be followed throughout this section. First, only Sentinel-2 imaging bands and vegetation indices were used as indicators to predict above-ground carbon stock. After optimizing this first model, data from Sentinel-1 and the GEDI height product were added to assess the added value of multi-sensor remote sensing modeling.

https://doi.org/10.5194/egusphere-2024-4094
Preprint. Discussion started: 16 January 2025

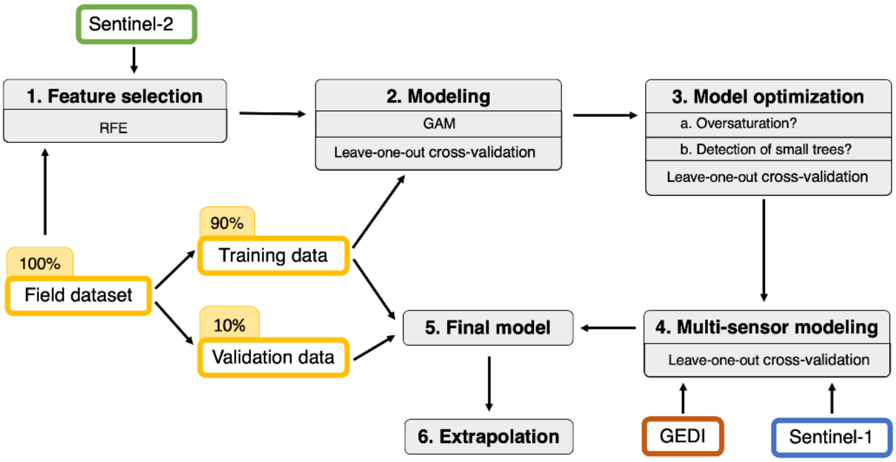


Figure 3: Graphical overview of the data analysis process.

Feature selection. The number of field observations (78), and thus the degrees of freedom, was limited and a selection of the predictive variables (vegetation indices and Sentinel bands) was made by recursive feature elimination (RFE) to avoid overfitting (Kursa and Rudnicki, 2010). Multicollinear variables were identified and excluded from the selection.

Modeling. A Generalized Additive Model (GAM) was chosen as a non-parametric extension of GLMs (generalized linear models) (Hastie and Tibshirani, 1986). The smooth functions make GAMs flexible while maintaining interpretability: a significant advantage compared to the more often used Random Forest algorithms (Wood, 2006). The response variable followed a gamma distribution and all variables were scaled. Neighborhood Cross-Validation (NCV) was identified as the optimal method for estimating smoothing parameters. A fixed value of 1.4 was assigned to the *gamma* parameter and adjustments to the *k values* were deemed unnecessary, following Wood (2006). Leave-one-out cross-validation (LOOCV) was performed to tune the model. A training dataset of 90% of all data points (70) was used in this process, reserving 10% (8) for the validation of the final model (Fig. 3). The root mean square error (RMSE), the mean absolute error (MAE) and the coefficient of determination (R^2) were chosen as model test metrics and used as output from LOOCV to compare the results of different models.

Model optimization. Due to the limited number of observations, we employed Leave-One-Out Cross-Validation (LOOCV) again on the same 90% training dataset during model optimization, aiming for the best model performance by evaluating different scenarios. First, a known limitation of passive optical remote sensing is signal saturation for forests with high complexity and biomass (Rodríguez-Veiga et al., 2017). This may lead to deviating spectral values that are detected, which may negatively affect the model performance. To evaluate oversaturation, the model was run excluding plots where field data showed a biomass greater than 450 tons/ha, which corresponds to a carbon stock exceeding 225 tons/ha. The impact of these underestimated high-biomass plots was evaluated by comparing model validation parameters. Second, small trees are more difficult to detect by passive optical remote sensing. The influence of the small trees in nesting level A was assessed by

https://doi.org/10.5194/egusphere-2024-4094
Preprint. Discussion started: 16 January 2025

comparing the model including all diameter classes with a model containing only trees from nesting levels B and C (Table 1). Then, the diameter threshold of detection by remote sensing was sought, based on improvement or impairment of the validation metrics when iteratively disregarding trees in different diameter percentiles.

Multi-sensor modeling. Finally, the inclusion of height estimates from the ETH product derived from GEDI, along with VV and VH polarization data from the Sentinel-1 mission, was evaluated by incorporating these new explanatory variables into the GAM.

Final model. The final model was constructed using the full 90% training data and validated on the remaining 10% that was isolated in the validation dataset (Fig. 3) and remained unseen during model tuning and optimization.

Model extrapolation. To compare the results of the field measurements with the carbon stocks as predicted by the remote sensing model, the carbon stock was predicted for every pixel of the patches from the IFMP, including both the field-measured patches, and the patches that were not selected by the random sampling (Bolar, 2019). The mean predicted carbon stock was then calculated for each forest patch with the standard error of the mean. The standard error of prediction indicates the uncertainty in each estimate, while the standard error of the mean indicates the deviation of the estimated sample mean from the real sample mean (Goos, 2017). Again, a GLMM was used to statistically compare the carbon stock estimates between managed and unmanaged forest patches.

https://doi.org/10.5194/egusphere-2024-4094
Preprint. Discussion started: 16 January 2025

3. Results

3.1 The effect of forest management on above-ground carbon stock

Results of the statistical analysis on the field measurements show a clear difference between managed and unmanaged forest plots. Unmanaged forest plots store a significantly (alpha=0.05) higher amount of carbon (196.50 ± 61.28 tons/ha) in their above-ground biomass than managed forest plots (143.68 ± 48.90 tons/ha) (Fig. 4a). The unmanaged plots are characterized by a higher variation in carbon stock than the managed plots, where the density curve is negatively skewed (Fig. 4a). Within each cluster, the difference fluctuates between 10 and 180 tons/ha (Figure 4c). From the analysis at patch level, managed patches have a lower carbon stock than unmanaged patches (p-value=0.01, effect size -0.33).

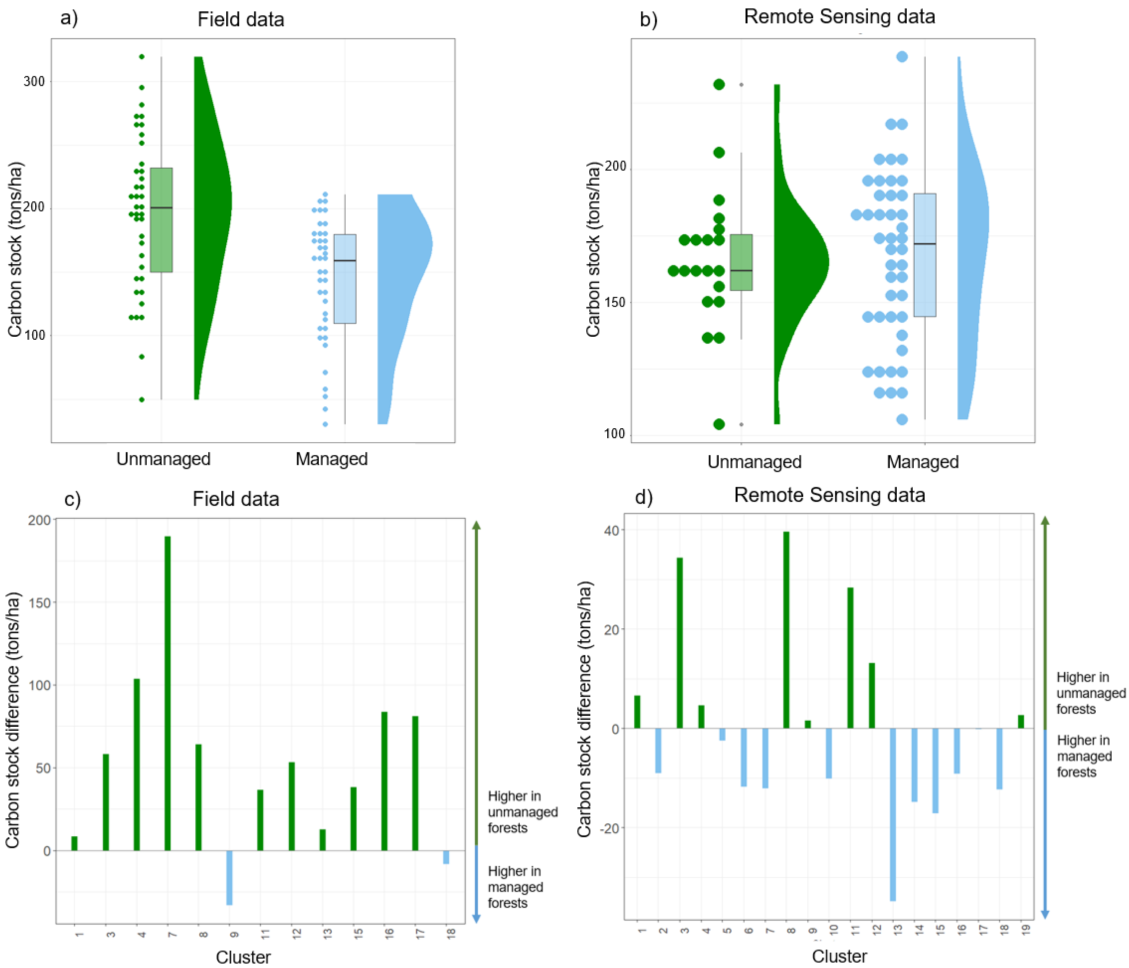


Figure 4: Results of the carbon stock analysis comparing managed and unmanaged forests: a) in the field plots, b) as predicted (mean pixel value per patch) by the remote sensing model, c) by calculating the difference in mean carbon stock per forest patch (unmanaged minus managed) for each cluster as measured in the field, and d) by calculating the difference in mean carbon stock per forest patch (unmanaged minus managed) for each cluster as estimated by the remote sensing model.

https://doi.org/10.5194/egusphere-2024-4094
Preprint. Discussion started: 16 January 2025

The difference in tree count between managed and unmanaged plots is noteworthy, a difference that is mostly reflected in the trees from nesting level A (Table 1), corresponding to the smallest trees (Table 3). Secondly, there is a higher tree density of the largest diameter class (C) in the unmanaged plots. In general, higher and larger trees are measured in unmanaged plots in BW NP.

Table 3: Overview of the plot characteristics in managed and unmanaged forests, measured in the field. The different levels (A,B,C) refer to the nesting levels as defined in Table 1.

	Managed	Unmanaged
Nr of plots	39	39
Nr of trees	1348	884
Species richness	18	19
Mean DBH (cm)		
level A	2	3
level B	16	21
level C	58	59
Mean height (m)		
level A	4	4
level B	14	18
level C	30	31
Mean density (stems/ha)		
level A	2717	580
level B	323	322
level C	89	104

3.2 Carbon stock modeling with remote sensing

Feature selection. The Sentinel-2 variables selected through recursive feature elimination for the Generalized Additive Model (GAM) capture various photosynthetic and structural characteristics of vegetation. These included: B5, B12, GNDVI, STVI3, and MCARI. The red-edge wavelengths are represented, which help detect vegetation density and type. The short-wave infrared wavelengths, along with GNDVI and MCARI, provide insights into photosynthetic capacity and chlorophyll absorption depth. Lastly, near- and mid-infrared bands are included in the stress-related vegetation index.

Modeling. Before model optimization, the validation parameters of the model, at this moment only containing Sentinel-2 variables, were R^2=0.56, RMSE=99.44 tons/ha, and MAE=91.40 tons/ha (Table 4). These validation parameters were not improved by disregarding plots with a high biomass (>450 tons/ha) or by disregarding small trees. A more detailed result of the model optimization can be found in Appendix 1.

https://doi.org/10.5194/egusphere-2024-4094
Preprint. Discussion started: 16 January 2025

Multi-sensor modeling. Incorporating the canopy height estimates from GEDI enhanced both the model fit and predictive capabilities slightly (Table 4). Especially in the high DBH classes, the error decreased (Fig. 5). The introduction of both VV and VH also improved the model fit and predictive power. Again, oversaturation-induced underestimation was significantly reduced, and predictions also improved notably in the lower DBH classes.
The model optimization resulted in a final model, used for extrapolation (Eq. 6).

$$\text{Carbon} \sim \text{MCARI} + \text{B5} + \text{STVI3} + \text{B12} + \text{GNDVI} + 1|\text{Species} + \text{Canopy height} + \text{VH} + \text{VV} \quad (6)$$

Table 4: Evolution of the model validation parameters with the addition of multiple remote sensors.

	Sentinel-2	Sentinel-2 + GEDI	Sentinel-2 + GEDI + Sentinel-1
R²	0.56	0.58	0.68
RMSE (tons/ha)	99.44	98.06	56.35
MAE (tons/ha)	91.40	90.21	50.07

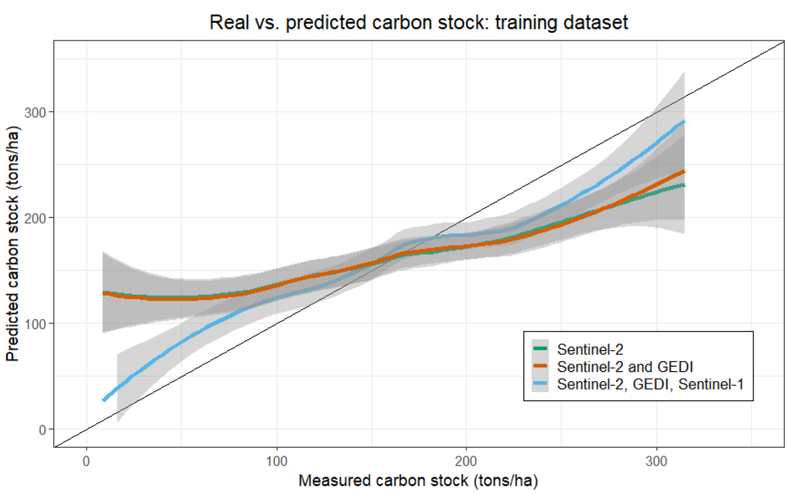


Figure 5: Model prediction accuracy after the model training with different remote sensing components, compared to the bisector of perfect prediction (measured = predicted carbon stock).

245 The final model did not successfully detect the carbon stock difference between managed and unmanaged patches, as measured in the field. The predicted mean carbon stock for the unmanaged patches was 165.89 ± 26.46 tons/ha, for managed patches this was 166.80 ± 32.28 tons/ha (Fig. 4b). It is remarkable that unmanaged patches are overall underestimated, while the opposite is true for managed patches. On average, the standard error of the mean was 1.27 tons/ha and the maximal standard

https://doi.org/10.5194/egusphere-2024-4094
Preprint. Discussion started: 16 January 2025

error of the mean was 5.94 for the smallest patch that only contained 130 pixels. The managed patches have a higher variability in predicted carbon stock compared to the unmanaged patches (Fig. 4b), while again the opposite was true for the data as measured in the field. According to the remote sensing-based model, there is no significant difference between managed and unmanaged patches (α=0.05, p=0.61). For some clusters, almost no difference in carbon stock between the unmanaged and the managed patches is observed (Fig. 4d). For other clusters, a difference up to 40 tons/ha is estimated, however not in a consistent pattern. Compared to the field data, the estimated differences between managed and unmanaged forests are much smaller. No abnormalities were detected in the images of the clusters where a carbon stock difference of over 20 tons/ha was estimated.

4. Discussion

4.1 The effect of forest management on above-ground carbon stock

The field data allowed us to assess the effect of forest management on above-ground carbon stock in a pairwise comparison analysis and was then used as calibration data for a remote sensing model to predict the carbon stock at locations that were not measured in the field. The selection of forest patches, grouped into clusters, made it possible to extract the effect of forest management without confounding factors and includes detailed information about the environmental conditions in the field. From the measured carbon stocks in the field, a significant difference between managed and unmanaged forest patches was detected in BW NP. Tree density was higher in managed plots, primarily due to the predominance of smaller trees belonging to the lowest diameter class (A). A few managed plots were situated in dense regeneration, and unmanaged plots on average thus had fewer but larger trees (in height and diameter). In unmanaged plots, older trees continue growing without harvest, leading to higher biomass and carbon stock. The results align with Vanhellemont et al. (2024), who performed a similar study to compare above-ground carbon pools in set-aside forests and the average forest in Flanders. Even though our measured carbon stocks are higher, due to the fertile soil conditions in the NP BW, a similar trend was reported.

4.2 Carbon stock modeling with remote sensing

The prediction of forest above-ground carbon stock using remote sensing remains technologically challenging. However, this study demonstrates significant potential by combining multiple types of remote sensors, leading to improved model predictions. The study also highlights the limitations of remote sensing, as it was unable to effectively distinguish carbon stock differences between managed and unmanaged forests.

The model fit and predictive accuracy of the GAM in this study was only slightly improved when adding the dominant tree height as estimated from GEDI to the model only containing Sentinel-2 variables. However, LiDAR proved especially useful for biomass prediction at high forest AGB values. Namely, the product was developed with a focus on detecting tall canopies, which typically have large carbon stocks. Our findings align with previous research combining LiDAR and Sentinel-2 for

https://doi.org/10.5194/egusphere-2024-4094
Preprint. Discussion started: 16 January 2025

above-ground biomass estimation, which reported reduced saturation effects and enhanced predictivity of the model (Francini et al., 2022; Puliti et al., 2020).

Alongside the multispectral and LiDAR remote sensing data, we incorporated VV and VH variables sourced from the Sentinel-1 mission. The incorporation of both VV and VH backscatter images into the model effectively mitigated signal saturation and yielded the highest R^2 values, as well as the lowest RMSE and MAE. Especially in dense forest structures, C-band (and X-band) microwave remote sensing proved successful for AGB estimation by Santoro et al. (2011) and Thurner et al. (2014), which is also confirmed by our study.

It is clear that the combination of optical remote sensing (for measuring photosynthetic activity and vegetation health), LiDAR (for measuring vertical forest structure), and C-band SAR (for measuring vegetation structure) improved model performance compared to the use of Sentinel-2 alone (R^2 increased by 12.20%, RMSE decreased by 43.09 tons/ha, MAE decreased by 41.33 tons/ha). This confirms the findings of earlier studies (Chen et al., 2019; David et al., 2022; Forkuor et al., 2020; Hoscilo et al., 2018; Nuthammachot et al., 2022). Possibilities to improve predictions even more may lie in further integration of C-band with L-band SAR, which can enhance the detection of texture features, vegetation diversity, and density (Laurin et al., 2018).

Even though a significant improvement in model performance was noted, the combination of all three sensors did not successfully detect the difference in carbon stock between managed and unmanaged forests. Moreover, the obtained estimated differences in mean carbon per patch did not fully align with the differences measured on the field. The unmanaged patches, which are mostly in the higher biomass ranges, appear to be underestimated by the GAM when considering the conventional field method as the ground truth (Appendix 2). In contrast, the model overestimates the biomass for managed patches. The underestimation of high biomass in unmanaged patches is likely due to signal saturation, a common issue when passive optical remote sensing and SAR struggle to detect complex forest structures. Although excluding plots with biomass greater than 450 tons/ha did not improve the model, a systematic underestimation for plots above 400 tons/ha biomass (200 tons/ha carbon stock) was observed for BW NP. This is most likely due to signal saturation, as noted in several previous studies (Hoscilo et al., 2018; Laurin et al., 2018). Second, low biomasses (mostly managed patches) were overestimated; this corresponds with the research of Hoscilo et al. (2018) and Zhang et al. (2023). A serious underestimation is reported for biomasses lower than 125 tons/ha (Appendix 2). Fewer plots were measured in these outer ranges, which may lead to deviations, as well for low as for high biomasses. A solution could be to separately model managed and unmanaged patches, but more observations are then needed.

Next to the technical limitations as described above, it is possible that the forest has not been left unmanaged for long enough to detect a difference through remote sensing, while it is already detectable by field measurements. The understory, often insufficiently detected by remote sensing, did not appear problematic in our case study as the presence or absence of the smallest trees (<15 cm DBH) did not affect the model fit. Past management intensity was defined as one of the major drivers

https://doi.org/10.5194/egusphere-2024-4094
Preprint. Discussion started: 16 January 2025

for above-ground carbon stock in Atlantic forests by Pires Coelho et al. (2022). Hence, management history may overrule the effect of current management practices in remote sensing analyses.

Future research should focus on multi-sensor remote sensing, with the inclusion of multi-frequency SAR to further reduce signal saturation and improve model predictions. Investigating the effects of different management practices, rotation lengths, and thinning regimes on carbon stock – along with the substitution effect of resulting wood products – as beyond the scope of this study. However, such research could lead to more specific management guidelines and decision rules. Additionally, while maximizing carbon stock is important, it should be noted that managed forests provide various benefits, including wood and non-wood forest products, and regulating and cultural services. Future studies should consider these ecosystem services, alongside carbon stock, in local contexts and explore the trade-offs between them.

5. Conclusion

In this study, a deeper methodological understanding on the potential and limitations of different remote sensing technologies was obtained in a case study where the effect of forest management on above-ground biomass carbon stock was assessed. Research in this domain holds significance in the context of international policy agreements to fight climate change, for example with carbon credit schemes, where accurate assessment of carbon stocks is essential for incentivizing forest conservation and restoration efforts. The combination of passive optical remote sensing, synthetic aperture radar and spaceborne LiDAR significantly improves the estimation of above-ground carbon stock compared to the use of passive optical remote sensing alone. Unmanaged forests were found to store more carbon in their above-ground biomass than managed forests in the temperate Atlantic region.

https://doi.org/10.5194/egusphere-2024-4094
Preprint. Discussion started: 16 January 2025

330 **Appendices**

Appendix 1: Results Model optimization

First, disregarding all plots with a carbon stock >450 tons/ha did not result in a better fit (Table 5): only the MAE decreased remarkably. Even though oversaturation was detected at a level of 200 tons/ha carbon stock when plotting the GNDVI and B5 (the variables that are most prone to oversaturation) for all plots, this did not have a significant influence on the overall model fit. Second, only modeling carbon stock in nesting levels levels B and C (Table 1) did not result in a better fit either for all three validation parameters (Table 5). In a more detailed analysis, we found that leaving trees smaller than 15 cm DBH (50th percentile) out of the calibration dataset did not affect the model fit. While accounting for 50% of the number of trees, they overall only store 4% of the total carbon stock. Trees with a DBH >15 cm contain a substantial amount of carbon and were sufficiently detected by the model. Leaving these trees out of the field dataset resulted in a lower model fit.

Table A1: Evolution of the model validation parameters during model optimization and the addition of multiple remote sensors.

	Before optimization	Without plots >450 tons/ha	Without nesting level A	With GEDI	With GEDI and Sentinel-1
R^2	0.56	0.36	0.54	0.58	0.68
RMSE (tons/ha)	99.44	100.15	116.12	98.06	56.35
MAE (tons/ha)	91.40	68.03	99.14	90.21	50.07

https://doi.org/10.5194/egusphere-2024-4094
Preprint. Discussion started: 16 January 2025

Appendix 2: The distribution of managed and unmanaged plot over the carbon stock range

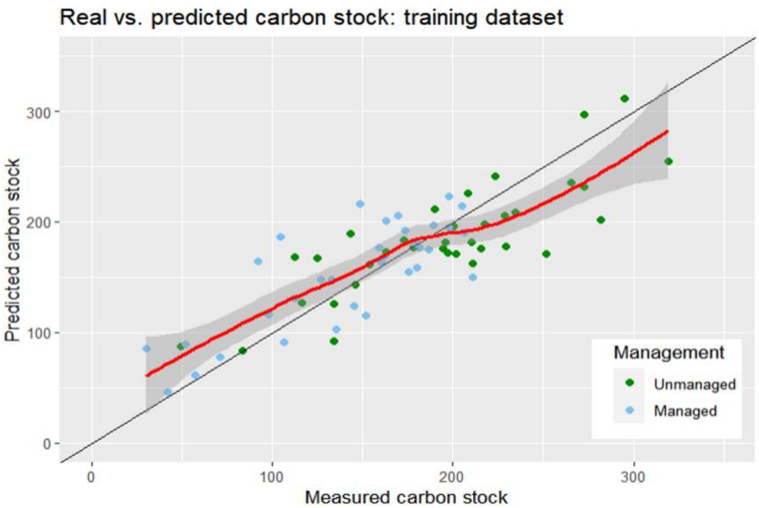


Figure A1: The carbon stock values for all plots in the training data set: predicted by the GAM versus measured in the field. The colour indicates the management.

Code availability. The R code used for this paper will be publicly available upon publication on GitHub: https://github.com/sofievanwinckel/RemoteSensing_CarbonManagement .

Data availability. The data used for this paper is publicly available on GitHub: https://github.com/sofievanwinckel/RemoteSensing_CarbonManagement .

Author contributions. SVW and JS designed the field campaign and carried out the field measurements, under the supervision of BM. The formal analysis, validation and visualization were performed by SVW, under the supervision of JS and BM. SVW prepared the original draft of the manuscript with review and editing contributions of BM, SL and BM.

Competing interests. The authors declare that they have no conflict of interest.

Acknowledgments. We thank the Flemish Agency for Nature and Forest for granting access to the field plots. Many thanks also go to Ilié, Jonas, Marijke, Indy, Stien, Matthias and Hans for their great help with data collection in the field. We acknowledge the support of the Horizon Europe INFORMA project for data access and logistical support. JS was funded through the INFORMA project. The INFORMA project is funded by the European Union's Horizon Europe Programme (GA: 101060309). ChatGPT was used in this paper as a language assistant for improving the writing of this paper and for limited code editing.

The INFORMA project received funding from the EU Horizon Europe Research and Innovation Programme under Grant Agreement No. 101060309.

References

Berben, J.: Dendrometrische studie van de Corsikaanse den, LISEC, Genk, 1983.

Bolar, K.: STAT: Interactive Document for Working with Basic Statistical Analysis, 2019.

Chen, L., Wang, Y., Ren, C., Zhang, B., and Wang, Z.: Optimal Combination of Predictors and Algorithms for Forest Above-Ground Biomass Mapping from Sentinel and SRTM Data, Remote Sens., 11, 414, https://doi.org/10.3390/rs11040414, 2019.

Dagnelie, P., Palm, R., Rondeux, J., and Thill, A.: Tables de cubage des arbres et des peuplements forestiers. Gembloux: Les presses agronomiques de Gembloux., 1985.

David, R. M., Rosser, N. J., and Donoghue, D. N. M.: Improving above ground biomass estimates of Southern Africa dryland forests by combining Sentinel-1 SAR and Sentinel-2 multispectral imagery, Remote Sens. Environ., 282, 113232, https://doi.org/10.1016/j.rse.2022.113232, 2022.

Dugan, A. J., Birdsey, R., Healey, S. P., Pan, Y., Zhang, F., Mo, G., Chen, J., Woodall, C. W., Hernandez, A. J., McCullough, K., McCarter, J. B., Raymond, C. L., and Dante-Wood, K.: Forest sector carbon analyses support land management planning and projects: assessing the influence of anthropogenic and natural factors, Clim. Change, 144, 207–220, https://doi.org/10.1007/s10584-017-2038-5, 2017.

Forkuor, G., Benewinde Zoungrana, J.-B., Dimobe, K., Ouattara, B., Vadrevu, K. P., and Tondoh, J. E.: Above-ground biomass mapping in West African dryland forest using Sentinel-1 and 2 datasets - A case study, Remote Sens. Environ., 236, 111496, https://doi.org/10.1016/j.rse.2019.111496, 2020.

Francini, S., D'Amico, G., Vangi, E., Borghi, C., and Chirici, G.: Integrating GEDI and Landsat: Spaceborne Lidar and Four Decades of Optical Imagery for the Analysis of Forest Disturbances and Biomass Changes in Italy, Sensors, 22, 2015, https://doi.org/10.3390/s22052015, 2022.

Garcia-Gonzalo, J., Peltola, H., Briceño-elizondo, E., and Kellomäki, S.: Changed thinning regimes may increase carbon stock under climate change: A case study from a Finnish boreal forest, Clim. Change, 81, 431–454, https://doi.org/10.1007/s10584-006-9149-8, 2007.

Goetz, S. J., Baccini, A., Laporte, N. T., Johns, T., Walker, W., Kellndorfer, J., Houghton, R. A., and Sun, M.: Mapping and monitoring carbon stocks with satellite observations: a comparison of methods, Carbon Balance Manag., 4, 2, https://doi.org/10.1186/1750-0680-4-2, 2009.

Goos, P.: Inleiding tot statistiek en kansrekenen, Acco, Leuven, 2017.

Gurung, M. B., Bigsby, H., Cullen, R., and Manandhar, U.: Estimation of carbon stock under different management regimes of tropical forest in the Terai Arc Landscape, Nepal, For. Ecol. Manag., 356, 144–152, https://doi.org/10.1016/j.foreco.2015.07.024, 2015.

Hastie, T. and Tibshirani, R.: Generalized Additive Models, Stat. Sci., 1, 297–310, https://doi.org/10.1214/ss/1177013604, 1986.

Hoscilo, A., Aneta, L., Ziolkowski, D., Stereńczak, K., Lisańczuk, M., Schmullius, C., and Carsten, P.: Forest Aboveground Biomass Estimation Using a Combination of Sentinel-1 and Sentinel-2 Data, 9026–9029, https://doi.org/10.1109/IGARSS.2018.8517965, 2018.

https://doi.org/10.5194/egusphere-2024-4094
Preprint. Discussion started: 16 January 2025

INFORMA: Science-based INtegrated FORest Mitigation mAnagement made operational for Europe: INFORMA Forest Management Platform, CORDIS - Eur. Comm., 46, https://doi.org/10.3030/101060309, 2022.

Jandl, R., Lindner, M., Vesterdal, L., Bauwens, B., Baritz, R., Hagedorn, F., Johnson, D. W., Minkkinen, K., and Byrne, K. A.: How strongly can forest management influence soil carbon sequestration?, Geoderma, 137, 253–268, https://doi.org/10.1016/j.geoderma.2006.09.003, 2007.

Jiang, F., Deng, M., Tang, J., Fu, L., and Sun, H.: Integrating spaceborne LiDAR and Sentinel-2 images to estimate forest aboveground biomass in Northern China, Carbon Balance Manag., 17, 12, https://doi.org/10.1186/s13021-022-00212-y, 2022.

Jiao, Y., Wang, D., Yao, X., Wang, S., Chi, T., and Meng, Y.: Forest Emissions Reduction Assessment Using Optical Satellite Imagery and Space LiDAR Fusion for Carbon Stock Estimation, Remote Sens., 15, 1410, https://doi.org/10.3390/rs15051410, 2023.

Kalies, E. L., Haubensak, K. A., and Finkral, A. J.: A meta-analysis of management effects on forest carbon storage, J. Sustain. For., 35, 311–323, https://doi.org/10.1080/10549811.2016.1154471, 2016.

Koch, B.: Status and future of laser scanning, synthetic aperture radar and hyperspectral remote sensing data for forest biomass assessment, ISPRS J. Photogramm. Remote Sens., 65, 581–590, https://doi.org/10.1016/j.isprsjprs.2010.09.001, 2010.

Kun, Z., DellaSala, D., Keith, H., Kormos, C., Mercer, B., Moomaw, W. R., and Wiezik, M.: Recognizing the importance of unmanaged forests to mitigate climate change, GCB Bioenergy, 12, 1034–1035, https://doi.org/10.1111/gcbb.12714, 2020.

Kursa, M. and Rudnicki, W.: Feature Selection with Boruta Package, J. Stat. Softw., 36, 1–13, https://doi.org/10.18637/jss.v036.i11, 2010.

Lang, N., Schindler, K., and Wegner, J. D.: High carbon stock mapping at large scale with optical satellite imagery and spaceborne LIDAR, https://doi.org/10.48550/arXiv.2107.07431, 15 July 2021.

Laurin, G. V., Balling, J., Corona, P., Mattioli, W., Papale, D., Puletti, N., Rizzo, M., Truckenbrodt, J., and Urban, M.: Above-ground biomass prediction by Sentinel-1 multitemporal data in central Italy with integration of ALOS2 and Sentinel-2 data, J. Appl. Remote Sens., 12, 016008, https://doi.org/10.1117/1.JRS.12.016008, 2018.

Lu, D., Chen, Q., Wang, G., Moran, E., Batistella, M., Zhang, M., Vaglio Laurin, G., and Saah, D.: Aboveground Forest Biomass Estimation with Landsat and LiDAR Data and Uncertainty Analysis of the Estimates, Int. J. For. Res., 2012, 436537, https://doi.org/10.1155/2012/436537, 2012.

Luyssaert, S., Schulze, E.-D., Börner, A., Knohl, A., Hessenmöller, D., Law, B. E., Ciais, P., and Grace, J.: Old-growth forests as global carbon sinks, Nature, 455, 213–215, https://doi.org/10.1038/nature07276, 2008.

Melikov, C. H., Bukoski, J. J., Cook-Patton, S. C., Ban, H., Chen, J. L., and Potts, M. D.: Quantifying the Effect Size of Management Actions on Aboveground Carbon Stocks in Forest Plantations, Curr. For. Rep., 9, 131–148, https://doi.org/10.1007/s40725-023-00182-5, 2023.

Mikolāš, M., Piovesan, G., Ahlström, A., Donato, D. C., Gloor, R., Hofmeister, J., Keeton, W. S., Muys, B., Sabatini, F. M., Svoboda, M., and Kuemmerle, T.: Protect old-growth forests in Europe now, Science, 380, 466–466, https://doi.org/10.1126/science.adh2303, 2023.

Mngadi, M., Odindi, J., and Mutanga, O.: The Utility of Sentinel-2 Spectral Data in Quantifying Above-Ground Carbon Stock in an Urban Reforested Landscape, Remote Sens., 13, 4281, https://doi.org/10.3390/rs13214281, 2021.

https://doi.org/10.5194/egusphere-2024-4094
Preprint. Discussion started: 16 January 2025

Moradi, F., Sadeghi, S. M. M., Heidarlou, H. B., Deljouei, A., Boshkar, E., and Borz, S. A.: Above-ground biomass estimation in a Mediterranean sparse coppice oak forest using Sentinel-2 data, Ann. For. Res., 65, 165–182, https://doi.org/10.15287/afr.2022.2390, 2022.

Morel, A. C. and Nogué, S.: Combining Contemporary and Paleoecological Perspectives for Estimating Forest Resilience, Front. For. Glob. Change, 2, https://doi.org/10.3389/ffgc.2019.00057, 2019.

Nadrowski, K., Wirth, C., and Scherer-Lorenzen, M.: Is forest diversity driving ecosystem function and service?, Curr. Opin. Environ. Sustain., 2, 75–79, https://doi.org/10.1016/j.cosust.2010.02.003, 2010.

Nuthammachot, N., Askar, A., Stratoulias, D., and Wicaksono, P.: Combined use of Sentinel-1 and Sentinel-2 data for improving above-ground biomass estimation, Geocarto Int., 37, 366–376, https://doi.org/10.1080/10106049.2020.1726507, 2022.

Perin, J., Bauwens, S., Pitchugin, M., Lejeune, P., Hébert, J., and ANB: National Forest Accounting Plan of Belgium, 2018.

Pires Coelho, A. J., Ribeiro Matos, F. A., Villa, P. M., Heringer, G., Pontara, V., de Paula Almado, R., and Alves Meira-Neto, J. A.: Multiple drivers influence tree species diversity and above-ground carbon stock in second-growth Atlantic forests: Implications for passive restoration, J. Environ. Manage., 318, 115588, https://doi.org/10.1016/j.jenvman.2022.115588, 2022.

Brabantse Wouden: https://www.vlaamsbrabant.be/nl/natuur-en-milieu/brabantse-wouden, last access: 23 October 2023.

Puliti, S., Hauglin, M., Breidenbach, J., Montesano, P., Neigh, C. S. R., Rahlf, J., Solberg, S., Klingenberg, T. F., and Astrup, R.: Modelling above-ground biomass stock over Norway using national forest inventory data with ArcticDEM and Sentinel-2 data, Remote Sens. Environ., 236, 111501, https://doi.org/10.1016/j.rse.2019.111501, 2020.

Quataert, P., Van der Aa, B., and Verschelde, P.: Opstellen van tarieven voro Inlandse eik en beuk in Vlaanderen ten behoe van het berekenen van houtvolumes. Statistische evaluatie van de regressiemodellen en overzicht van de resultaten (technisch rapport deel III), , Rapporten van het Instituut voor Natuur- en Bosonderzoek 2011 (18), 2011.

Rodríguez-Veiga, P., Wheeler, J., Louis, V., Tansey, K., and Balzter, H.: Quantifying Forest Biomass Carbon Stocks From Space, Curr. For. Rep., 3, 1–18, https://doi.org/10.1007/s40725-017-0052-5, 2017.

Rüetschi, M., Schaepman, M. E., and Small, D.: Using Multitemporal Sentinel-1 C-band Backscatter to Monitor Phenology and Classify Deciduous and Coniferous Forests in Northern Switzerland, Remote Sens., 10, 55, https://doi.org/10.3390/rs10010055, 2018.

Ruiz-Peinado, R., Bravo-Oviedo, A., López-Senespleda, E., Bravo, F., and Río, M. D.: Forest management and carbon sequestration in the Mediterranean region: A review, For. Syst., 26, eR04S-eR04S, https://doi.org/10.5424/fs/2017262-11205, 2017.

Santoro, M., Beer, C., Cartus, O., Schmullius, C., Shvidenko, A., McCallum, I., Wegmüller, U., and Wiesmann, A.: Retrieval of growing stock volume in boreal forest using hyper-temporal series of Envisat ASAR ScanSAR backscatter measurements, Remote Sens. Environ., 115, 490–507, https://doi.org/10.1016/j.rse.2010.09.018, 2011.

Sinha, S., Jeganathan, C., Sharma, L. K., and Nathawat, M. S.: A review of radar remote sensing for biomass estimation, Int. J. Environ. Sci. Technol., 12, 1779–1792, https://doi.org/10.1007/s13762-015-0750-0, 2015.

Sun, X., Li, G., Wu, Q., Ruan, J., Li, D., and Lu, D.: Mapping Forest Carbon Stock Distribution in a Subtropical Region with the Integration of Airborne Lidar and Sentinel-2 Data, Remote Sens., 16, 3847, https://doi.org/10.3390/rs16203847, 2024.

https://doi.org/10.5194/egusphere-2024-4094
Preprint. Discussion started: 16 January 2025

Thurner, M., Beer, C., Santoro, M., Carvalhais, N., Wutzler, T., Schepaschenko, D., Shvidenko, A., Kompter, E., Ahrens, B., Levick, S. R., and Schmullius, C.: Carbon stock and density of northern boreal and temperate forests, Glob. Ecol. Biogeogr., 23, 297–310, https://doi.org/10.1111/geb.12125, 2014.

Tian, L., Wu, X., Tao, Y., Li, M., Qian, C., Liao, L., and Fu, W.: Review of Remote Sensing-Based Methods for Forest Aboveground Biomass Estimation: Progress, Challenges, and Prospects, Forests, 14, 1086, https://doi.org/10.3390/f14061086, 2023.

Vanhellemont, M., Leyman, A., Govaere, L., De Keersmaeker, L., and Vandekerkhove, K.: Site-specific additionality in aboveground carbon sequestration in set-aside forests in Flanders (northern Belgium), Front. For. Glob. Change, 7, https://doi.org/10.3389/ffgc.2024.1236203, 2024.

Vayreda, J., Martinez-Vilalta, J., Gracia, M., and Retana, J.: Recent climate changes interact with stand structure and management to determine changes in tree carbon stocks in Spanish forests, Glob. Change Biol., 18, 1028–1041, https://doi.org/10.1111/j.1365-2486.2011.02606.x, 2012.

Wood, S. N.: Generalized Additive Models: An Introduction with R, Chapman & Hall/CRC, Boca Raton, 392 pp., 2006.

Xiao, J., Chevallier, F., Gomez, C., Guanter, L., Hicke, J. A., Huete, A. R., Ichii, K., Ni, W., Pang, Y., Rahman, A. F., Sun, G., Yuan, W., Zhang, L., and Zhang, X.: Remote sensing of the terrestrial carbon cycle: A review of advances over 50 years, Remote Sens. Environ., 233, 111383, https://doi.org/10.1016/j.rse.2019.111383, 2019.

Zhang, H., Zhang, Z., Liu, K., Huang, C., and Dong, G.: Integrating land use management with trade-offs between ecosystem services: A framework and application, Ecol. Indic., 149, 110193, https://doi.org/10.1016/j.ecolind.2023.110193, 2023.

Zianis, D., Muukkonen, P., Mäkipää, R., and Mencuccini, M.: Biomass and stem volume equations for tree species in Europe, FI, 2005.