KU LEUVEN

FACULTEIT BIO-INGENIEURSWETENSCHAPPEN

Assessing the effect of forest management on carbon stock and sequestration by remote sensing

Beoordeling van het effect van bosbeheer op de koolstofvoorraad en -vastlegging door middel van teledetectie

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Dit proefschrift is een examendocument dat na de verdediging niet meer werd gecorrigeerd voor eventueel vastgestelde fouten. In publicaties mag naar dit proefwerk verwezen worden mits schriftelijke toelating van de promotor, vermeld op de titelpagina.

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Scientific summary

Forest ecosystems absorb about 27% of the annual fossil fuel emissions worldwide and store 45% of the terrestrial carbon. As the global community intensifies efforts to combat climate change, insights on the influence of management on these forest carbon stocks are becoming invaluable for establishing sustainable forest management practices. Because controverse on the subject within the scientific community remains, this study aims to clarify the relation between forest management and carbon. State-of-the-art remote sensing techniques were used to quantify aboveground biomass carbon stocks in forests for an Atlantic (National Park Brabantse Wouden, Flanders, Belgium) and a Mediterranean (Catalunya, Spain) study region. Comparable pairs or triplets of managed and unmanagedhghgh(§hghgh(§ forests were used to assess four research questions: 1) Is multisource remote sensing superior for estimating above-ground biomass carbon stock, compared to passive optical remote sensing alone? 2) What is the effect of forest management on this carbon stock? 3) What is the effect of forest management on carbon sequestration? 4) What is the effect of forest above-ground biomass carbon stock and management on crown fire vulnerability? Reference carbon stocks were obtained from field measurements in both study regions, serving as ground truth for calibration and validation of regression models with remote sensing based carbon stock predictions. Remote sensing data were then retrieved from Sentinel-2, Sentinel-1, and a canopy height product (GEDI), from which a selection of variables served 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=57.16, RMSE=13.17, MAE=11.34) compared to the model using only Sentinel-2 indices (R^2=22.00, RMSE=29.19, MAE=18.33). While unmanaged forest field plots showed a higher measured carbon stock in Belgium, this difference was not detected through remote sensing. In Spain, no significant influence of forest management on carbon stock was measured and no successful model was obtained, likely due to high topographic heterogeneity and unsuccessful detection of lower woody vegetation. Additionally, no significant effect of forest management on carbon sequestration was found in Belgium. This is opposed to the research hypothesis but could be explained by the limited period of non-management (at least 20 years but never more than 50 years) and inherent deficiencies of remote sensing based information. Lastly, the highest crown fire vulnerability class comprised only unmanaged plots, with most of the lowest class being managed plots. However, more observations are necessary for a statistically solid result.

Wetenschappelijke samenvatting

Bossen absorberen ongeveer 27% van de jaarlijkse wereldwijde uitstoot van fossiele brandstoffen en stockeren 45% van de terrestrische koolstof. Met toenemende wereldwijde inspanningen om klimaatverandering te bestrijden, is inzicht in de invloed van bosbeheer op koolstofvoorraden essentieel voor de ontwikkeling van duurzame bosbeheerpraktijken. Toch blijft er controverse bestaan over dit onderwerp; deze studie heeft als doel om de relatie tussen bosbeheer en koolstof te verduidelijken. Geavanceerde teledetectietechnieken werden gebruikt om de koolstofvoorraden te kwantificeren in een Atlantische (Nationaal Park Brabantse Wouden, Vlaanderen, België) en een Mediterrane (Catalonië, Spanje) studieregio. Vergelijkbare paren of tripletten van beheerde en onbeheerde bossen werden gebruikt om vier onderzoeksvragen te beantwoorden: 1) Is de combinatie van meerdere teledetectie-bronnen superieur voor het schatten van de bovengrondse koolstofvoorraad, vergeleken met enkel passieve optische teledetectie? 2) Wat is het effect van bosbeheer op deze koolstofvoorraad? 3) Wat is het effect van bosbeheer op koolstofvastlegging? 4) Wat is het effect van de bovengrondse koolstofvoorraad en het bosbeheer op de kwetsbaarheid voor kruinbranden? De koolstofvoorraad werd berekend uit veldmetingen in beide onderzoeksgebieden. Teledetectiegegevens werden vervolgens opgevraagd van Sentinel-2, Sentinel-1 en een kruinhoogteproduct (GEDI), waaruit een selectie variabelen diende als voorspellers in een gegeneraliseerd additief model (GAM) om de koolstofvoorraad te schatten. De combinatie van de drie teledetectiebronnen verbeterde de nauwkeurigheid van het model aanzienlijk (R^2=57,16, RMSE=13,17, MAE=11,34) vergeleken met het model dat alleen Sentinel-2 indices gebruikte (R^2=22,00, RMSE=29,19, MAE=18,33). Terwijl onbeheerde bospercelen in België een hogere gemeten koolstofvoorraad vertoonden, werd dit verschil niet gedetecteerd via teledetectie. In Spanje werd geen significante invloed van bosbeheer op de koolstofvoorraad gemeten en werd geen succesvol model verkregen, waarschijnlijk vanwege de hoge topografische heterogeniteit en de gebrekkige detectie van lagere houtachtige vegetatie. Bovendien werd er in België geen significant effect van bosbeheer op koolstofopslag gevonden. Dit is in tegenspraak met de onderzoekshypothese, maar kan verklaard worden door de beperkte periode van niet-beheer (minstens 20 jaar maar nooit meer dan 50 jaar) en inherente tekortkomingen van op teledetectie gebaseerde informatie. Tot slot bestond de hoogste kwetsbaarheidsklasse voor kruinbranden enkel uit onbeheerde percelen, terwijl het grootste deel van de laagste klasse uit beheerde percelen bestond. Er zijn echter meer waarnemingen nodig voor een statistisch solide resultaat hieromtrent.

List of symbols and abbreviations

In alphabetical order:

AGB	Above-ground Biomass
C	carbon
CCI	Climate Change Initiative
CO2	Carbon dioxide
CPF	Centre de la Proprietat Forestal
DBH	Diameter at Breast Height
DTM	Digital Terrain Model
ESA	European Space Agency
ETH	the Eidgenössische Technische Hochschule Zürich
EU	European Union
GAM	Generalized Additive Model
GEDI	Global Ecosystem Dynamics Investigation
GEE	Google Earth Engine
GHG	greenhouse gas
GLM	Generalized Linear Model
GLMM	Generalized Linear Mixed Model
IFMP	Informa Management Platform
IW	Interferometric Wide swath
LASSO	Least Absolute Shrinkage and Selection Operator
LiDAR	Light Detection and Ranging
LOOCV	Leave One Out Cross-Validation
MAE	Mean Absolute Error
NASA	National Aeronautics and Space Administration
NDVI	Normalized Difference Vegetation Index
NFI	National Forest Inventory
NP BW	National Park Brabantse Wouden
REDD	Reducing Emissions from Deforestation and Degradation
RF	Random Forest
RFE	Recursive Feature Elimination
RMSE	Root Mean Squared Error
RS	Remote Sensing
SAR	Synthetic Aperture Radar
SEM	Standard Error of the Mean
UNFCCC	United Nations Framework Convention on Climate Change

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I. Introduction

In this chapter, we start with a short introduction to the natural carbon cycle and the role of carbon in climate warming. The carbon cycle is a complex interplay between different reservoirs and in our research, we exclusively focused on forests and their importance in the carbon cycle. Next, the importance of carbon stability will be illustrated by the effect of wildfires, and an elaboration on fire vulnerability will clarify the relevance of forest management in this context with a focus on the Mediterranean region. Additionally, the state of the art for measuring and modeling carbon and wildfire vulnerability will be explored. Next, the current controversy in the literature on the interaction between forest management and carbon will be discussed, exposing research gaps. Finally, the research objectives and hypotheses for this master thesis research will be formulated.

1. Problem statement

1.1. The natural carbon cycle

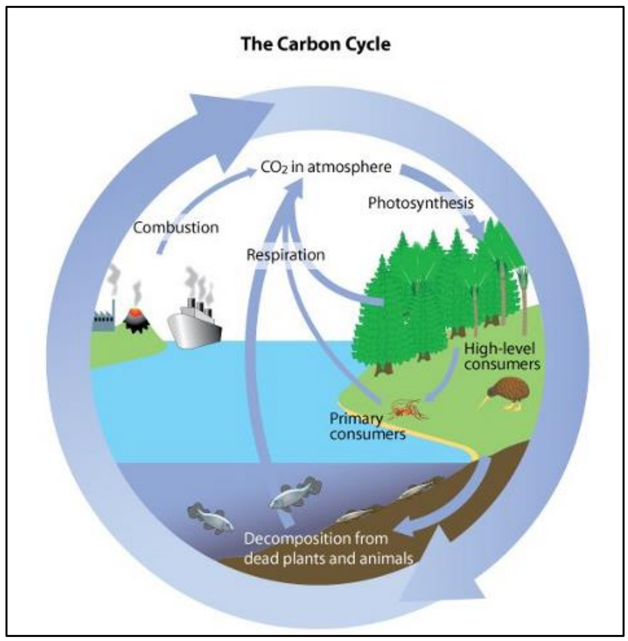


Figure I.1: Visual representation of the carbon cycle (Pearson education, 2008)

Different carbon reservoirs can be identified in the global carbon cycle: the hydrosphere, the geosphere, the atmosphere, and the biosphere (Ajani et al., 2013). The natural carbon cycle consists of a continuous exchange of carbon between these reservoirs (Figure I.1). In the context of this thesis, the focus is on the atmosphere and the biosphere. Carbon is released into the atmosphere through natural processes like volcanic eruptions and respiration on the one hand and unnatural (=induced by human behavior) processes like the combustion of fossil fuels, industrial emissions and agriculture on the other hand. Plants take up atmospheric carbon in the form of carbon dioxide (CO_2) through photosynthesis; this is a process called carbon sequestration. After carbon sequestration, the carbon is stored in the biomass of the plants. When the plant dies (if not burned), the carbon is transferred to the soil pool and eventually stored in fossil fuels (Vashum & Jayakumar, 2012). Within the biosphere, carbon is stored in five pools: above-ground and below-ground biomass, deadwood, litter, and the soil itself (Brockerhoff et al., 2017; IPCC, 2007). From these, above- and below-ground biomass are, together with the soil, the biggest carbon sinks within the forest pool (World resource institute, z.d.). The amount of carbon stocked in each sink is the result of a complex relationship between forest productivity, species composition and the disturbance history of the site (Sabatini et al., 2019). The retention time of carbon in each reservoir determines its role in regulating the amount of carbon in the atmosphere (Ajani et al., 2013).

1.2. The role of carbon in climate warming

The atmosphere consists of approximately 0.04% CO_2 (Mohd Zaki et al., 2018; Vashum & Jayakumar, 2012). Despite this small percentage, CO_2 functions as a crucial greenhouse gas (GHG), warming the earth with its heat-trapping properties (Ajani et al., 2013; IPCC, 2007). An unnatural increase in atmospheric carbon is causing global warming of the earth, mainly due to the combustion of fossil fuels during industrialization, deforestation and farming (European Commission, z.d.). Vashum and Jayakumar (2012) state that about 60% of the observed climate change can be related to the increased concentration of CO_2. The other 40% is related to other greenhouse gas increases such as methane, nitrous oxide and fluorinated gases. The dominance of CO_2 can be attributed to its long lifetime and tremendous quantities of emissions (European Commission, z.d.). The global scale at which CO_2 is emitted asks for worldwide initiatives to reduce atmospheric carbon, and several international treaties were established over the last decades.

1.3. International treaties to reduce GHG emissions

In 1992, the United Nations Framework Convention on Climate Change (UNFCCC) was formed to find solutions for the rapid climate change by reducing worldwide emissions of CO_2 and other GHG (Mohd Zaki et al., 2018). Since then, many international conferences have been held by the UNFCCC, setting binding obligations for GHG reduction like the Kyoto Protocol since 1997 and the Paris Agreement since 2015. The EU wants to achieve carbon neutrality by 2050, obtaining a balance between carbon sources and sinks, among others through carbon credit schemes (Forsius et al., 2023). Therefore, it is crucial to obtain quantitative and accurate data on carbon stocks and carbon sequestration rates.

Deforestation is the second-largest source of atmospheric carbon (after the emission of fossil fuels) and accounts for 18% of the GHG emissions worldwide, releasing yearly about 5.8 billion tons of CO_2 into the atmosphere (Holloway & Giandomenico, 2009; UNFCCC, z.d.). It is therefore also a major sector of focus to combat climate change (UNESCAP, z.d.). With that in mind, the REDD (Reducing Emissions from Deforestation and Degradation) Policy, later extended to REDD+, was designed by the UNFCCC. The REDD+ goals aim to achieve the conservation and expansion of existing forests while halting and reversing forest loss and degradation (FAO, z.d.; Holloway & Giandomenico, 2009).

1.4. The importance of forests

In these international initiatives against climate change, forests are crucial. They provide many direct and indirect contributions to human well-being and benefit, the so-called ecosystem services (Brockerhoff et al., 2017; Nocentini et al., 2022). Examples are water purification, wood provision, recreation and climate regulation. Carbon sequestration is such a forest ecosystem service, where forests regulate the climate, mitigate climate change and support the carbon cycle (Brockerhoff et al., 2017). Moreover, they provide a long-term stock of the carbon they sequester. Forest ecosystems absorb about 27% of the annual fossil fuel emissions worldwide and store 45% of the terrestrial carbon (Jandl et al., 2015; Rodríguez-Veiga et al., 2017a; Thammanu et al., 2021). Even when harvested, the carbon remains stored in the wood products and is only released when the wood is rotten or when used as fuel (Storms et al., 2022). However, forests do not only function as a carbon sink, they are also one of the main sources of CO_2 through deforestation, forest fires, forest degradation and decomposition (Bellassen & Luyssaert,

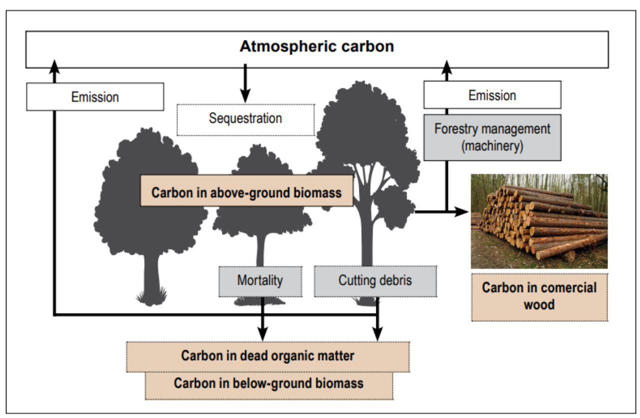


Figure I.2: Forest carbon sources and sinks (Cervera et al., 2022).

2014; Lasco & Pulhin, 2003) (Figure I.2). The plethora of interactions and processes consequently brings a certain complexity when studying carbon in forest ecosystems.

Forests are degrading worldwide due to climate change and as a result, the provision of ecosystem services is severely affected (Brockerhoff et al., 2017). Furthermore, forest ecosystems most at risk for degradation are often also the ecosystems that store the most irrecoverable carbon like mangroves and old-growth forests (FAO, 2022). In this context, climate-smart forestry offers solutions to build resilient forests, mitigate climate change and increase sustainable provision of ecosystem services (Nabuurs et al., 2018). However, climate-smart forest management comes with many challenges, and several social, ecological and economic aspects must be considered, including their interactions (Nabuurs et al., 2018). Moreover, the stability of carbon pools should be protected, more than just the quantity of the carbon that is stocked.

1.5. Carbon and wildfires

There is a certain duality in the relationship between carbon in forests and climate change. On the one hand, a warmer climate and higher CO_2 concentrations can lead to faster growth, longer growing seasons and therefore more carbon sequestration (Boisvenue & Running, 2006; Jandl et al., 2015). On the other hand, more frequent and extreme disturbance events like extreme droughts, forest fires, pests and storms counter this phenomenon. Wildfires are such a disturbance posing a threat to the forest carbon stock. Nevertheless, fire can be an essential process for the regeneration of some tree species like Aleppo pine (*Pinus halepensis),* growing in the fire-prone Mediterranean forests. The high temperature is needed to open the cones and release the seeds (Elvira et al., 2021). This pyrophyte species then thrives on burnt soils making use of the reduced competition and the fertility of the ashes (Elvira et al., 2021). However, fire can also destroy entire ecosystems and greatly reduce ecosystem services by burning biomass on a large scale (Brockerhoff et al., 2017). The natural periodicity and intensity of wildfires is altered by climate change and direct human interference, both preventing ecosystems to recover and re-establish successfully. Wildfires typically lead to carbon losses in the above-ground stock directly, via the burning of finer fuels like foliage and leaf litter, and indirectly, through the death and decomposition of living vegetation such as shrubs and trees

(Wilson & Bradstock, 2022). This impact very much depends on the forest type and the fire regime.

Common management practices to increase resilience to wildfires consist of fuel isolation, modification, and species conversion (Piqué et al., 2011). Examples of adaptations to the vertical structure are the increase of the crown base height, the decrease in tree density and the reduction of the surface fuel load. Next, low pruning, thinning from below, prescribed fires and targeted grazing are techniques that are commonly used on stand scale to lower the fire risk (Alcasena et al., 2021). On a larger scale, fuel break networks and strategic points of intensive management are used to avoid mega-fires (Alcasena et al., 2021). However, fire prevention management poses its own set of challenges. Namely, stand-level management is not always sufficient to reduce fire risk at a larger scale. Moreover, possible negative effects on biodiversity and ecosystem functioning need to be considered as well (Tilman et al., 2000).

Confusion in the literature arises from differing formulations concerning fire risk and prevention. On the one hand, there is the risk for ignition: the probability of a fire to occur (wildfire likelihood). On the other hand, there is the risk of the fire spreading to an uncontrollable and destructive size (wildfire intensity) (Alcasena et al., 2021; Oliveira et al., 2012). In what follows, fire vulnerability will be used as the term to assess wildfire intensity, indicated by the risk of a crown fire.

As mentioned before, the stability of carbon stock in the forest is crucial to take into account, next to the quantity of carbon and the rate of carbon sequestration. The fire vulnerability can serve as a proxy to assess the stability of the carbon stock in wildfire-sensitive regions. A higher carbon stock means a higher fuel load and thus a higher chance for a mega-fire. However, the correlation between carbon stock and the risk of crown fires is non-linear due to its complex nature: several meteorological, topographic, vegetation-specific and anthropogenic factors influence the fire vulnerability. Additionally, the forest structure and spatial distribution of biomass are crucial in this assessment (Piralilou et al., 2022; Szpakowski & Jensen, 2019). In an ideal scenario, a forest would have a high carbon stock, mainly stored in the crown layer without ladder vegetation. This way, the fire cannot reach the crowns and does not evolve into a mega-fire. Nonetheless, a forest with a complex structure and a dense understory also has a stronger microclimate and a higher moisture content, which may lead to a reduced risk for wildfires. Of the several influencing factors, forest structure is the only one that can be altered by management to decrease the susceptibility for a mega-fire (Selkimäki & González-Olabarria, 2017, Piqué et al., 2011).

1.6. Wildfires in Mediterranean forests

According to Nocentini et al. (2022), Mediterranean forests have been identified as a major hotspot to climate change, and the long summer droughts, steep slopes and elevated temperatures make Mediterranean forests extra susceptible to destructive wildfires (Chuvieco & Congalton, 1989). Moreover, land use changes over the past century, such as the abandonment of rural areas and the homogenization of landscapes, have heightened the risk of mega-fires by eliminating natural fire breaks and increasing land degradation. Even though 96% of the current wildfires by number do not exceed 10 ha, the 4% that remains contributes to over 90% of the annual total area burned (Piqué et al., 2011). These large wildfires are difficult to control and propagate at a high speed. The fire spreads through the tree crowns and is outside the capacity of extinguishing systems (Piqué et al., 2011). Moreover, post-fire regeneration is severely affected in structure and diversity by crown fires and the presence of seeds for regeneration is less evident as large areas are destroyed (Marzano et al., 2012).

To conclude, highly complex interactions exist between forest management, carbon stock and sequestration. In drought-prone (e.g. Mediterranean) regions, the forest vulnerability for a crown fire complicates this relation even more. With international treaties and goals in mind, thorough knowledge of the subject is crucial for climate-smart forestry (Piao & Wang, 2023). This knowledge allows us to optimize the carbon stock and sequestration within forests to their climate mitigation potential. Above-ground carbon stock can be quantified relatively easily and can, through modeling, be related to below-ground carbon. It is thus considered a sustainable forest management indicator (Sabatini et al., 2019).

2. State of the art

2.1. Measuring above-ground carbon in the field

Depending on site and species, an allometric equation can be developed to describe the relationship between biomass and diameter at breast height (DBH) and/or tree height (Vashum & Jayakumar, 2012). The biomass is then directly related to the carbon stock, summed over the whole plot and extrapolated to the forest stand. This method is most commonly used to calibrate and validate other models predicting carbon stock. National Inventories monitor tree DBH and height with a regular periodicity. The rate of carbon uptake (sequestration) can then be analyzed by comparing the carbon stocks over a certain period of time. However, it is a very time-consuming method and hence difficult to use on a large scale. Moreover, allometric relationships need to be available for the region and species of interest. There is also a lack of harmonized protocols used on an international scale, and collected data by National Inventories can therefore often not be integrated (Gschwantner et al., 2019).

2.2. Measuring above-ground carbon with remote sensing

Remote sensing (RS) techniques are widely used in the estimation of carbon stock in forests as it is known to be a cost- and time-efficient way (Rodríguez-Veiga et al., 2017). However, the combination with ground measurements is necessary to obtain accurate and reliable results (Rodríguez-Veiga et al., 2017b; Vayreda et al., 2012a). RS opportunities reach far, ranging from Synthetic Aperture Radar (SAR) to passive optical RS to the newest techniques of Light Detection and Ranging (LiDAR) (Xiao et al., 2019).

First, Synthetic Aperture Radar (SAR) RS can measure biomass with active microwave signals that penetrate clouds (Xiao et al., 2019) (Figure I.3 a). A major advantage of SAR is the capability to measure in all weather, and in day and night. Backscatter intensity, frequency and polarization are the main variables used to estimate biomass based on the sensitivity to moisture, surface roughness and dielectric properties (Goetz et al., 2009; Xiao et al., 2019). A volumetric analysis of the vegetation exposes structural characteristics, depending on the wavelength (Sinha et al., 2015). P- and L-band are more sensitive to branches and trunks while the shorter wavelengths in C- and X-band rather detect volumetric scattering on leaves and needles (Laurin et al., 2018). The primary limitations are temporal decorrelation, signal saturation, interference, and sensitivity to roughness (Koch, 2010; Xiao et al., 2019). Especially shorter wavelengths such as with C-band and X-band SAR have difficulties penetrating the forest canopy, and reach a saturation level when an increase in canopy closure and biomass is not detected anymore (Sinha et al., 2015). The level of saturation depends on the polarization, the wavelength and the vegetation characteristics. The combination of shorter and longer wavelengths offers opportunities to reduce this saturation, but an increased time and labor input is necessary. Even though SAR mostly measures at low spatial resolution, difficult for estimations at stand level, several successful above-ground biomass estimations have been carried out with SAR (Santoro et al., 2011; Sarker et al., 2013).

Second, passive optical RS techniques record electromagnetic (EM) radiation coming from a natural source like the sun and emitted by or reflected on plants (Figure I.3 b). Vegetation indices like the Normalized Difference Vegetation Index (NDVI) (Table II.8 for formula) measure the amount of radiation absorbed by the plant; in the case of NDVI for the red and ultra-red wavelengths). It can be associated with biomass as an indicator of gross primary production, indicating how photosynthetically active the tree is (Tian et al., 2023; Xiao et al., 2019). Such vegetation indices often seasonally change and the correlation with above-ground biomass thus depends on the time of the year (Zhu & Liu, 2015). Zhu & Liu (2015) showed that the fall season shows the highest correlation between NDVI and above-ground biomass. The study of Forkuor et al. (2020) compared the use of passive optical RS and SAR to estimate above-ground biomass, which resulted in an R^2 value of 83% using Sentinel-2 vegetation indices, compared to 66% with SAR. Moradi et al. (2022) obtained a maximum accuracy of 86% using Sentinel-2 bands and vegetation indices for Mediterranean forests. However, in plots with a high biomass, saturation leads to underestimation of the biomass (Tian et al., 2023). This signal saturation depends on the forest type, species composition and vegetation structure, but also on the type of sensor (polarization, wavelength position) (Mutanga et al., 2023). The saturation problem arises predominantly from the red band, where chlorophyll absorption becomes unresponsive with a high canopy closure. Additional foliage or vegetation will not be detected as the upper layers, responsible for most red reflectance, have already absorbed maximal light. According to Mutanga et al. (2023), no uniform method has been found yet to overcome signal saturation issues. However, NDVI was found to be highly sensitive to signal saturation, and the use of other vegetation indices might mitigate saturation problems. Moreover, the exclusive use of passive optical remote sensing techniques comes with a certain error because a major part of carbon is stored in non-photosynthetic parts, and calibration with field data is necessary. The main limitations of optical remote sensing are mixed pixels, cloud cover and signal saturation for forests with a higher complexity in structure (Rodríguez-Veiga et al., 2017b). Moreover, measurements can only be done during daytime. There is, nonetheless, the advantage of a long history of data collection and processing, global coverage, high spatial and temporal resolution and a low cost (Xiao et al., 2019).

Third, with spaceborne Light Detection And Ranging (LiDAR), a laser signal is sent to the earth and reflects on the vegetation and on the ground. By measuring the signal return time, the distance to the object can be derived (Figure I.3 c). Like so, a 3D forest structure can be created from the point cloud that is created and accurate height and canopy area can be measured. It does not suffer from the limitations of passive optical RS but has some disadvantages of its own. It measures separate geographical points and interpolation is thus necessary to create a wall-to-wall map. Moreover, LiDAR only measures structural parameters while biomass is also related to other parameters like tree density and species composition (Denghsheng Lu et al., 2012). Compared to passive and SAR remote sensing techniques, LiDAR is also a rather recent technique, and LiDAR satellites therefore often have a shorter operation period.

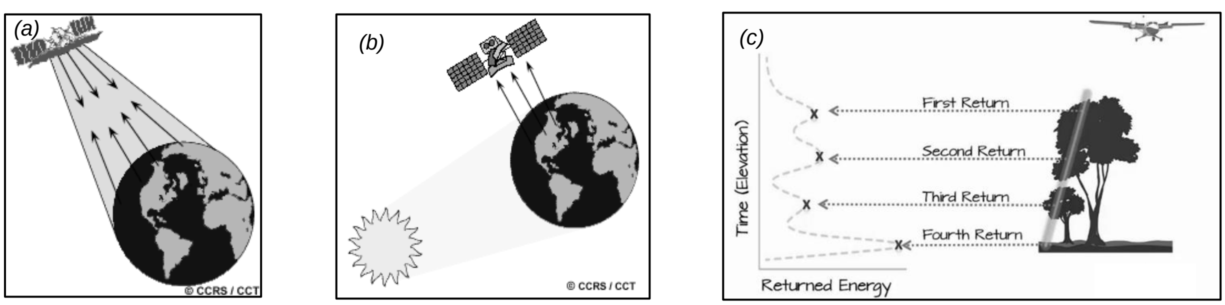


Figure I.3: Remote sensing techniques used for above-ground biomass monitoring: (a) Synthetic aperture radar (SAR), (b) passive optical remote sensing and (c) LiDAR

Combining different data sources (SAR, optical RS, LiDAR) is recommended to combine the advantages of both techniques and obtain a higher accuracy for carbon stock measurements on stand scale (Rodríguez-Veiga et al., 2017b). Moreover, signal saturation of optical remote sensing and SAR can be reduced (Mutanga et al., 2023).

2.3. Modeling above-ground carbon stock

Empirical modeling techniques are mostly used to relate remote sensing data with field measurements in a data-driven approach (Xiao et al., 2019). Non-parametric machine learning algorithms such as Random Forest and neural networks have gained popularity over the traditional parametric multiple regression analyses because of the ability to capture complex and high-dimensional relationships (Tian et al., 2023). Chen et al. (2019), David et al. (2022) and Moradi et al. (2022) report promising results for above-ground biomass prediction from passive optical RS and SAR, outperforming parametric methods. Machine learning and deep learning methods are also successfully used to fuse different remote sensing sources, for example LiDAR and optical remote sensing (Lang et al., 2021). Next to empirical models, mechanistic models simulate the net primary production based on various ecosystem processes, but these methods are complex and require a high data input for parameterization.

2.4. Wildfire vulnerability

Wildfires are complex natural phenomena in terms of spread and severity of destruction (Piralilou et al., 2022). Topographical, meteorological, anthropological and vegetation variables are most commonly used to assess the fire vulnerability. Topographical variables such as elevation, slope and aspect indicate the possibility of a rapid fire propagation, but also give relevant information on the micro-climate. Meteorological parameters such as the spatial distribution of precipitation, temperature and wind speed are mostly useful at larger scales (region-wide). As most fires are human-induced (95% of the wildfires in Spain (Gobierno de España, 2020)), the distance to roads, campsites and villages are often considered when estimating the fire probability. For research at stand scale however, vegetation structural parameters are predominantly used. The canopy bulk density, canopy cover, shrub height, foliage biomass, vegetation indices, maximum height, mean height and standard deviation of height indicate structural heterogeneity. Most studies compute an index based on fire-influencing factors as mentioned above, measured by remote sensing, field inventories and historical records (Chéret & Denux, 2011; Piralilou et al., 2022; Pradhan et al., 2007). LiDAR is often used to measure structural parameters, and passive optical remote sensing indicates fuel type and vegetation characteristics. More advanced methods use complex modeling and machine learning to tackle the highly dimensional and non-linear input data (Mohajane et al., 2021). Support vector machines, Bayesian Belief Networks and Random Forest are common algorithms used, and wildfires can then be linked to estimated carbon emissions, economic losses from mortality and carbon credits for fuel management plans (Alcasena et al., 2016, 2021). For direct applications in the field however, mostly simple decision rules are used to assess fire vulnerability, as high expertise and big data are required for complex modeling.

3. Research gaps

3.1. Managed versus unmanaged forests

Trees sequester carbon through photosynthesis, a process that is highly influenced by temperature, tree age, forest structure and local climate (Kern et al., 2021a). These are all parameters that forest management can alter. Forest management can thus be a valuable tool in optimizing the carbon sequestration capacity and consequently the carbon stock. From the different carbon pools in the biosphere reservoir, above-ground biomass has proven to be the most susceptible to human modifications like management (Gurung et al., 2015a). However, much controversy still exists in literature about the net influence of management on above-ground carbon stock and sequestration in forests (here discussed separately).

First, regarding forest carbon stock, the long-accepted vision in forestry states that natural ecosystems like unmanaged forests store a larger amount of carbon than managed systems (Bellassen & Luyssaert, 2014). This would be because of the higher stand density, higher litter production and unrestricted growth (no harvest). Pires Coelho et al. (2022) also reported a reduced carbon stock in managed Atlantic forests specifically, most probably due to favoring of certain tolerant tree species that have a lower carbon stock capacity. Moreover, Ajani et al. (2017) found that the carbon stock in natural ecosystems is more stable over long time periods, while highly modified ecosystems often are less resilient.

However, despite the many studies supporting this first point of view, forest management has also been found to increase carbon stock through an increase in productivity (Noormets et al., 2015; Pukkala, 2017a; Ruiz-Peinado et al., 2017a; Thammanu et al., 2021). This is achievable through the planting of specific species mixtures with a focus on certain productive species (Brockerhoff et al., 2017; Garcia-Gonzalo et al., 2007a). Management can lead to a high stand productivity in the longer term by reducing competition, even while being a CO_2 source in the short term (Vayreda et al., 2012a). The higher sequestration leads to a higher carbon stock. Moreover, sustainable wood products can keep the carbon stored and meanwhile reduce emissions as a substitute for cement and steel industries (Pukkala, 2017a). Additionally, forest management could decrease the susceptibility 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).

In conclusion, management can have different effects on carbon stocks and the net result remains unclear in many ecosystems. Liao et al (2010), Luyssaert et al. (2008) and Bellassen & Luyssaert (2014) therefore mention a gap in research around the subject. In figure I.4, a visual overview of the discussed arguments is given.

Second, the long accepted vision on carbon sequestration states that sequestration is lower in unmanaged systems like old-growth forests because they cease to sequester carbon once an upper threshold is reached (Gurung et al., 2015a; Schwaiger et al., 2019). The current European treaties therefore only propose that these forests should be protected to maintain the carbon stock rather than optimized in carbon sequestration to decrease atmospheric carbon (Luyssaert et al., 2008). However, Luyssaert et al. (2008) refute this idea with their study of old-growth forests, providing compelling evidence that carbon sequestration continues in old natural forests, even when the climax succession stadium has been reached. Other studies also state that unmanaged forests continue growing and thus keep sequestering carbon (Gurung et al., 2015a; Jandl et al., 2007; Kun et al., 2020; Liao et al., 2010). When the forest has a high above-ground biomass, more individual trees die, and a new recruitment canopy layer maintains the productivity at a faster rate than the decomposition of the dead trees.

Garcia-Gonzalo (2007) and Bellassen & Luyssaert (2014) propose to increase the timber yield and carbon sequestration at the same time, pursuing a win-win strategy in production and carbon-smart forestry. However, this is only effective if the harvested timber is stored in sustainable wood products, preserving the stored carbon. Next to climate change, other global problems, including a growing population, have severe effects on forests worldwide (Noormets et al., 2015). Intensification in forest management is necessary to meet the growing needs for forest products and functions. However, much conflicting evidence exists about how this intensification (and forest management in general) affects the carbon stock and sequestration in a forest ecosystem (Noormets et al., 2015).

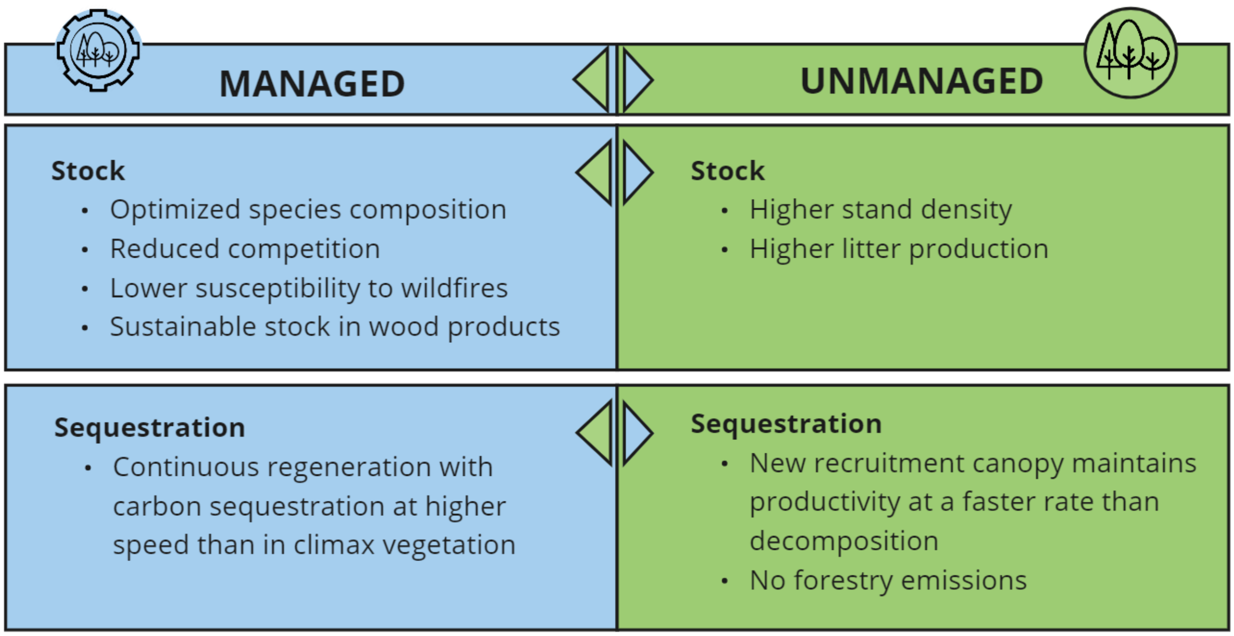


Figure I.4: Visual representation of current controversies in literature regarding the influence of forest management on carbon stock and sequestration

3.2. Forest fire vulnerability, carbon stock and management

The multifunctionality of the forest provides a wide range of ecosystem services, but also intertwines with many trade-offs, which are often underrepresented in management and research endeavors (Brockerhoff et al., 2017; Luyssaert et al., 2018). The carbon stocked in the above-ground biomass is for example closely related to the fire vulnerability of the forest stand in dry-sensitive regions. In this context, wildfire resilience can serve as an illustration of carbon stability, and poses a trade-off with carbon stock: it can be more advantageous in dry regions to manage a forest only to moderate carbon stock and thus protect it from wildfires. Only a limited number of studies have been performed regarding the impact of management on fire behavior and the effect of wildfires on carbon stock (Brockerhoff et al., 2017; Ruiz-Peinado et al., 2017a).

4. Research objectives and hypotheses

This study aims to clarify the relation between forest management and carbon for an Atlantic (National Park Brabantse Wouden, Flanders, Belgium) and a Mediterranean (Catalunya, Spain) study region through remote sensing analysis techniques. Pairs or triplets of managed and unmanaged forest patches from the INFORMA Forest Management Platform will be used for this research. The following research questions were chosen:

1. Is multisource remote sensing superior for estimating above-ground biomass carbon stock, compared to passive optical remote sensing alone?
2. What is the effect of forest management on above-ground biomass carbon stock?
3. What is the effect of forest management on carbon sequestration?
4. What is the effect of forest above-ground biomass carbon stock and management on crown fire vulnerability?

The research hypotheses are outlined based on above-mentioned theoretical background and literature.

1. The combination of LiDAR, SAR and passive optical remote sensing is expected to be more accurate in the estimation of carbon stock than only passive optical remote sensing. Advantages of different remote sensors can be combined, and deficiencies can be accommodated.
2. We hypothesize that unmanaged forests have a higher above-ground biomass carbon stock as most management practices consist of the removal of biomass.
3. Unmanaged forests are however expected to have a lower carbon sequestration capacity, based on the traditionally dominating scientific vision.
4. It is expected that a higher above-ground biomass carbon stock correlates with a higher fire vulnerability because a higher fuel load is then present. Management is expected to have a positive influence on carbon stock stability and is thus expected to reduce the crown fire vulnerability. Creating fire-resistant forests is

already an important management goal in Catalunya, where the steep slopes and drought susceptibility lead to a high chance for disturbances.

Overall, Belgian forests are expected to show a higher carbon stock and sequestration than Catalunyan forests as trees grow much bigger in height and diameter due to the cooler climate.

II. Materials & Method

1. Study regions

Two study regions have been selected from the INFORMA Forest Management Platform. The research will take place in the National Park Brabantse Wouden (Flanders, Belgium) and in the autonomous region of Catalunya (Spain). These regions represent the Atlantic and Mediterranean forest ecosystems in Europe, respectively.

1.1. National Park Brabantse Wouden

The National Park Brabantse Wouden (NP BW), located in the heart of Belgium, encompasses a vast area exceeding 10,000 hectares. Within this expanse lie several fragmented forests, including Hallerbos, Zoniënwoud, and Meerdaalwoud (Figure II.1 a). Since October 2023 it is one of the six National Parks in Belgium, unique because of its monumental beeches and oaks, sunken lanes, and meandering rivers (Provincie Vlaams-Brabant, 2023).

The NP BW is located at an elevation of around 45m above sea level and have an average yearly temperature of 12°C (WorldData, 2023). The maritime climate assures mild winters, moderately warm summers, and a significant amount of rainfall throughout the year (around 850mm) (KMI, 2024). Due to climate change however, more droughts and extreme temperatures occur during summer. A varying topography with hillslopes, plateaus and valleys correspond with varying soil types across the territory from sandy soils in the east to loamy sand and loam in the central and west part (VPO, 2017). Soils in the region are known for their fertility.

The main tree species are *Fagus sylvatica, Quercus robur, Acer pseudoplatanus* and *Pinus sylvestris*. Windstorms, droughts, pests, diseases, and fragmentation are key challenges in the region (INFORMA, 2022).

1.2. Catalunya

The selected forests in Catalunya represent the Mediterranean forests in Europe (INFORMA, 2022). Catalunya is an autonomous region situated in the northeast of Spain (Figure 1). It encompasses an area of 3,210,700 ha, and with most of the population concentrated in the coastal areas, around 58% of the area is covered with natural forests

(Figure II.1 b) (Ascaso-Sastrón et al., z.d.; Toda, 2006). A lot of variation exists in topography, with the northern part of Catalunya (already in the Pyrenees) reaching almost 3000 m of altitude while the coastal areas are situated at sea level. The high heterogeneity in topography (from the Pyrenees to the sea) reflects in the variety of climates, soil types, tree species and structures. Most of the forests are privately owned (CTFC, 2021).
The main tree species are *Pinus nigra, Quercus ilex* and *Quercus faginea*. Key challenges for management are drought and forest fires (INFORMA, 2022).

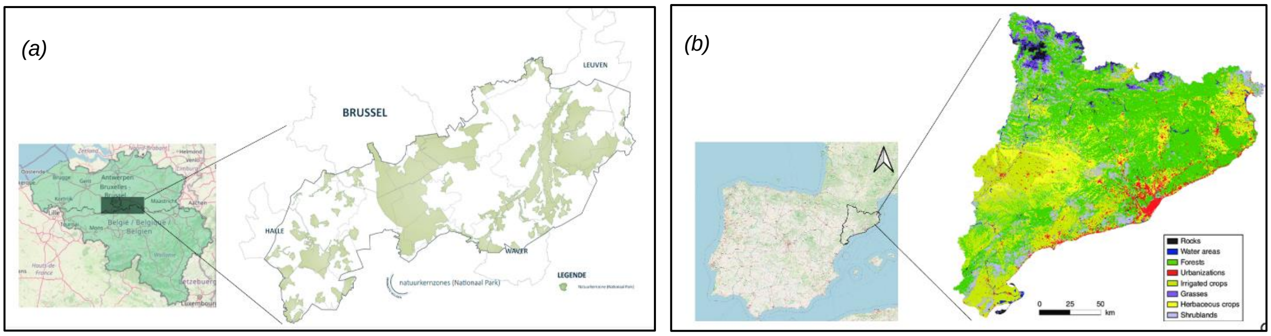


Figure II.1: Location of the study regions : (a) National Park Brabantse Wouden (Zhihan et al., 2021) and (b) the autonomous region of Catalunya (Duane et al., 2015)

2. Patch selection

The INFORMA Management Platform (IFMP) consists of a selection of managed and unmanaged patches, grouped into clusters where the patches were as similar as possible in other relevant aspects affecting ecosystem services like aspect, soil, dominant species, elevation, slope, climate and forest legacy. Each cluster contained at least one managed and one unmanaged forest patch, with the unmanaged patch remaining in an unmanaged state for at least 20 years. The IFMP consists of 32 clusters in Catalunya and 20 clusters in Belgium, within the NP BW. For each forest patch, a basic set of information parameters was available with details about the forest management, the time since abandonment of management and the dominant tree species.
A random stratified selection method was applied to make a sub-selection of these IFMP forest patches for data collection. This selection design was chosen to obtain a collection of forest patches that fitted the desired analyses and that was representative of the region, as there was not enough time to sample in all the forest patches of the database.
For the NP BW, management (managed (M)/unmanaged (UM)) and species were taken into account as strata. A species group was assigned to each forest patch based on the

dominant species, including *Fagus spp., Pinus spp*., *Quercus spp*. and ‘mixed’. As such, eight strata were obtained (table II.1). For *Quercus*, only two clusters were present so they were bundled in one stratum. Even though underrepresented, several managed patches were included in the cluster, which were still of interest for later analyses.

Table II.1: Stratification criteria for forest patch selection in NP BW (M=managed, UM=unmanaged)

Characteristics of forest patch	Stratum
Fagus - M	1
Fagus - UM	2
Pinus - M	3
Pinus - UM	4
Oak	5
Mixed- M	6
Mixed - UM	7

Within each of the managed strata, four forest patches were randomly selected with the QGIS tool ‘Randomly select from subsets’ with as subset the assigned strata. Afterward, the unmanaged patch from the same cluster was also selected (representing the according unmanaged stratum) (Table II.2)

Table II.2: Selected forest patches with cluster per stratum: NP BW

Stratum	Patch_ID	Cluster
1	BW_Son_10	Be_4
1	BW_Son_08	Be_3
1	BW_MW_14	Be_9
1	BW_MW_02	Be_5
2	BW_Son_9	Be_4
2	BW_Son_5	Be_3
2	BW_MW_13	Be_9
2	BW_MW_01	Be_5
3	BW_MW_19	Be_11
3	BW_Hal_04	Be_13
3	BW_MW_12	Be_8
3	BW_Hal_13	Be_12
4	BW_MW_17	Be_11
4	BW_Hal_03	Be_13

Stratum	Patch_ID	Cluster
4	BW_MW_1	Be_8
4	BW_Hal_12	Be_12
5	BW_Hal_11	Be_15
5	BW_Hal_09	Be_15
5	BW_MW_09	Be_7
5	BW_MW_07	Be_7
6	BW_Hev_02	Be_16
6	BW_BB_02	Be_17
6	BW_Son_02	Be_1
6	BW_BB_04	Be_18
7	BW_Hev_01	Be_16
7	BW_BB_01	Be_17
7	BW_Son_01	Be_1
7	BW_BB_03	Be_18

For the Segre-Rialb Basin, the species groups assigned were '*Pinus spp.', 'Quercus spp.'* and 'mixed'. Because of the big influence that the relief and aspect have on the environmental conditions in the patches in Catalunya, aspect was also taken into account for stratification. The digital terrain model (DTM) of Catalunya was downloaded from the ICGC plugin in 5x5m resolution and clipped on the INFORMA forest patches in QGIS (*Open ICGC — QGIS Python Plugins Repository*, z.d.). Next, the aspect was derived from the DTM with the 'Aspect' tool in QGIS, using a buffer of 10 m around the forest patches. To limit the number of strata, the aspect was classified into classes 'North' and 'South', as the dominant wind direction in Catalunya is North and this is a key factor determining the local temperature. The northness was calculated as the cosine of the aspect, classifying all patches as, on average, north- (0< northness <1) or south-facing (-1< northness <0).

There were no patches available within the IFMP-selected forests for the Quercus forests on a north-facing hill (managed or unmanaged) and the unmanaged mixed forests on the south-facing hill. These species groups were therefore only grouped in 'managed' and 'unmanaged', without making a difference in aspect (Table II.3).

Table II.3: Stratification criteria for forest patch selection in Catalunya. M=managed, UM=unmanaged, N=north-facing, S=south-facing.

Characteristics of forest patch	Stratum
Pinus – M – N	1
Pinus – M – S	2
Pinus – UM – N	3
Pinus – UM – S	4
Quercus – M – S	5
Quercus – UM – S	6
Mixed – M – S	7
Mixed – UM – S	8

Before randomly selecting a forest patch from each strata, clusters Sp_OUT_01, Sp_OUT_02, Sp_OUT_03, Sp_OUT_04, Sp_OUT_22 and Sp_OUT_23 were excluded because it was not possible to reach patches both in the most southern and the most northern region of Catalunya due to time constraints. Two patches per stratum were randomly selected similar to the selection procedure in Belgium (Table II.4).

Table II.4: Selected forest patches with cluster per stratum: Catalunya

Stratum	Patch ID	Cluster
1	SRB_OUT_14_M	Sp_OUT_14
1	SRB_OUT_21_M	Sp_OUT_21
1	SRB_OUT_09_M	Sp_OUT_09
2	SRB_04_M	Sp_04
3	SRB_OUT_14_NM	Sp_OUT_14
3	SRB_OUT_21_NM	Sp_OUT_21
3	SRB_OUT_09_NM	Sp_OUT_09
4	SRB_04_NM	Sp_04
5	SRB_OUT_08_M	Sp_OUT_08
5	SRB_OUT_15_M	Sp_OUT_15
6	SRB_OUT_08_NM	Sp_OUT_08
6	SRB_OUT_15_NM	Sp_OUT_15
7	SRB_08_Mb	Sp_08
7	SRB_OUT_02_M	Sp_OUT_02
8	SRB_08_NM	Sp_08
8	SRB_OUT_02_NM	Sp_OUT_02

3. Plot selection

To select the plots within each patch, a random stratified sampling design was used. Because there was certain prior knowledge about the IFMP forest patches, and an equal representation of the strata was required, the random stratified plot selection was appropriate (Legendre & Fortin, 1989). The random design avoids bias and creates an equal chance of a location to be selected within a plot (Taherdoost, 2016). A division in strata is necessary to allow for a homogenous design with each patch equally represented. In addition, it assumes homogeneity of the forest patches as the size of the forest patches is not taken into account, but this is assured by the IFMP. This sampling design is often chosen when there is a high amount of variation within the population (here: among clusters) and it is necessary to represent this variation (Taherdoost, 2016).

To determine the optimal number of plots in each patch, a trade-off between bias and efficiency was made, as there were limitations in time and resources (Taherdoost, 2016).

On the one hand, the bias diminishes as the number of plots increases. On the other hand, Taherdoost also states the 'law of diminishing returns', which shows that the reduction in error decreases at a lower rate with a higher number of samples. This trade-off should thus be balanced against available resources. A number of three plots was chosen per patch to be representative of the stratum. Within the IFMP, the selected patches are assumed to be relatively homogeneous in structure. Therefore, three plots per patch should be sufficient. Final plot selection was performed using the random plot selection tool in QGIS.

4. Plot size

For the plot size, a nested plot design was chosen, following the National Forest Inventory (NFI) of Belgium and Spain (Alberdi et al., 2017; Perin et al., 2018) (Figure II.2). In a nested plot design, the plot size depends on the size of the trees (Agentschap voor Natuur en Bos, 2020). In the smallest plot (A), only the smallest trees in diameter at breast height (DBH) are measured. Bigger trees are measured in a bigger plot, consequently optimizing the efficiency of the measurements in time and resources while maintaining comparability (Lin et al., 2020). Smaller trees are more time-consuming to measure while contributing less to the total biomass (Lin et al., 2020). Lin et al. (2020) stated that for measuring the stand density and basal area, a nested plot design is as accurate as a fixed plot design. All trees higher than two meters in height were measured, regardless their DBH, as the proportion of biomass stocked in the smallest trees was also of interest, and especially relevant in Catalunya (with much dense and low vegetation).

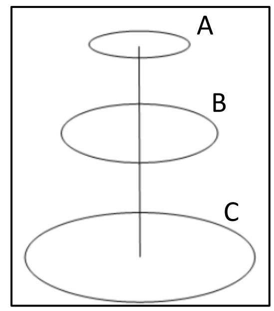


Figure II.2: Nested plot design. Only the largest trees are me-asured in level C, the smallest in level A.

For the NP BW, size limits were linked to the plot size, following the guidelines of the Flemish Forest Inventory (Table II.5) (Agentschap voor Natuur en Bos, 2020).

Table II.5: Characteristics of the trees per nesting level for NP BW

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

For Catalunya, different sizes were used, following the NFI of Spain (Alberdi et al., 2017) (Table II.6).

Table II.6: Characteristics of the trees per nesting level for Catalunya

Nesting Level	Plot radius (m)	Tree DBH (m)	Tree Height (m)
A	5	<12.5	>2
B	10	12.5-41.5	/
C	15	22.5-41.5	/
D	25	>41.5	/

For plots on a slope, the plot diameter was measured perpendicular to the slope. As the plot radius should be measured in the horizontal plane to be representative, distances to trees standing down- or uphill were measured with the '*Nikon forester pro',* measuring the horizontal distance from the plot center to the tree.

5. Data collection

5.1. General information

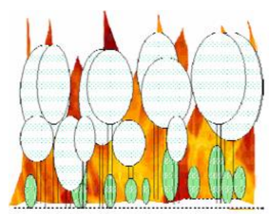
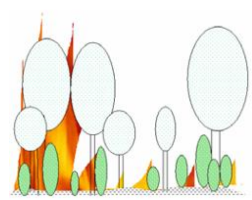
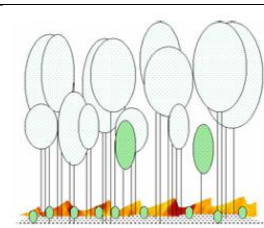
Plot coordinates were tracked in the field using a GPS type '*Garmin GPSMap 64S'*. If a river or path was going through the plot, thus disturbing the representability, the plot was replaced to a representative place as close as possible to the original coordinates. This was also the case if the plot was really not accessible or too dangerous to reach (at a cliff, close to train lines,…). This was always mentioned as a comment within the general information (Appendix 1 & 2).

For every plot, some general info was noted like the Patch ID (given by the original database), the plot ID, the date when the measurements were taken, and the coordinates of the plot center. A picture was taken of every plot. Lastly, notable observations were recorded.

5.2. Crown fire vulnerability

Crown fire vulnerability was only assessed in Catalunya because of its local relevance and relation to carbon stock. To assess the crown fire vulnerability in the field, the determination key of the Centre de la Propietat Forestal (CPF) in Catalunya was used (Piqué et al., 2011). The key was developed based on local expert knowledge, questionnaires and literature to obtain relevant silvicultural-structural variables and thresholds. They were then tested and validated in field experiments by professionals. 3 keys were used: for *Pinus halepensis,* for other *Pine spp.* and for *Quercus spp*. separately. Indicator variables are 'coverage of ladder fuel', 'thickness of ground fuel', 'distance between ground fuel and ladder fuel', 'distance between ladder fuel and tree crown' and 'crown coverage'. Visual estimates of the variables were made in the field to classify the plot following the correct key (Table II.7). Because of the low number of observations, no statistical analyses on the crown fire vulnerability were possible. However, some useful graphical analyses could indicate a trend and explain the relevance of the trade-off with carbon stock.

Table II.7: Description and characteristics of all crown fire vulnerability classes

Crown fire vulnerability class	Visual clarification	Characteristics
A : High vulnerability for crown fire		Always vertical continuity between vegetation layers
B : Middle vulnerability for crown fire		Vertical continuity and discontinuity between vegetation layers: fire will reach the crown for some trees but there is no crown fire propagation over all trees.
C : Low vulnerability for crown fire		Almost always vertical discontinuity between vegetation layers

5.3. Tree description

The tree species was defined for each tree. The diameter at breast height (DBH) was measured with a three-meter tape measure at a height of 1.5m for Belgium and a height of 1.3 m for Spain (following the respective NFI), from which the DBH was read directly. The measurements were rounded at 0.5 cm as this was the measuring limit of the measuring tape that was used.

The tree height was measured using the *Nikon Forestry Pro (*Nikon, z.d.). This hypsometer has a built-in clinometer and laser range finder. A three-point measurement mode named “the height between two points and horizontal distance” was selected in order to get the most accurate result. The “distant target priority mode” was used because of the interference of branches and leaves experienced in the field. Specification can be found in appendix 3 (Nikon, n.d.).

For multi-stem trees, both stems were noted as separate trees. Dead trees were only taken into account if they were standing, as they are still contributing to the standing biomass (Agentschap voor Natuur en Bos, 2020; Alberdi et al., 2017). For trees standing on a hill, the DBH was measured standing on the upper side of the stem (Vilppo et al., 2016).

5.4. Limitations

With this method of conventional measuring of above-ground carbon, some limitations should be mentioned. First, the biomass of non-standing dead wood was not taken into account. However, the carbon in this dead wood is an aspect that can be crucially changed by forest management and a contribution to the total above-ground biomass. Nevertheless, the dead non-standing biomass is, like soil carbon, not easily quantified through remote sensing. It was therefore chosen to limit the study to the above-ground standing biomass.

Next, dense vegetation often causes problems in measuring the tree height of all the individual trees. Therefore, a few trees were measured and from there, a visual estimation was made for the trees that could not be measured with the laser. Trees at the border of the plot were alternatively considered in and out of the plot.

6. Carbon stock calculations

6.1. National Park Brabantse Wouden

For Belgium, the carbon stock was calculated by equation II.1 (IPCC, 2003).

$$Carbon\ stock = \sum_{species} Vstem \times VEF \times WD \times CF \qquad \textbf{(Equation II.1)}$$

With Vstem = stem Volume (m^3)**,** VEF = Volume Expansion Factor (-), WD = Wood Density (t/m^3) and CF = Carbon Factor (-).

The volume expansion factor was used to convert merchantable volume to above-ground biomass and was available through the National Inventory report (2020) (Appendix 4). The wood density is also species-specific and described in the national forestry accounting plan of Belgium (Perin et al., 2018) (Appendix 4). For the carbon factor, 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 (Equation II.2). The coefficients were derived by Dagnelie et al. (1985), Berben (1983) and Quataert et al. (2011) (Appendix 4).

$$Vstem = a + b * \pi * DBH + c * (\pi * DBH)^2 + d * (\pi * DBH)^3 + e * H$$
$$+ f * (\pi * DBH) * H + g * (\pi * DBH)^2 * H \qquad \textbf{(Equation II.2)}$$

For some species however, there were no equations available so the equations of species with similar growth form could be used. This was the case for *Tilia platyphyllos, Sorbus acauparia, Salix caprea, Rhamnus frangula, Ilex aquifolium, Corylus avellana, Castanea sativa* and *Carpinus betulus.* 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 (Equation II.3- II.5):

$$V_{cone} = \frac{1}{3} * H * \frac{\pi * DBH^2}{4} \qquad \textbf{(Equation II.3)}$$

$$V_{cone\ top} = \frac{1}{3} * \frac{\pi * DBH}{H * 22} * \frac{0.22^2}{4 * \pi} \qquad \textbf{(Equation II.4)}$$

$$V_{tree} = V_{cone} - V_{cone\ top} \qquad \textbf{(Equation II.5)}$$

with DBH and h in meters. These formulas were based on the National Inventory of Belgium, in coordination with the Institute for Nature and Forest Research (INBO).

6.2. Catalunya

For Catalunya, the allometric equations to calculate the above-ground biomass were available through the *AllometrApp*, developed by the Laboratori Forestal Català under the Center of Ecological Investigation and Forest Applications (CREAF, z.d.) (Equation II.6):

$$AGB = a * DBH^{b} * H^{c} \qquad \textbf{(Equation II.6)}$$

The parameters a, b and c are species-specific, DBH is entered in cm and height (H) in m (Appendix 5). From the above-ground biomass (tons/ha), the carbon was calculated with a species-dependent percentage from the CPF in Catalunya (Cervera et al., 2022) (Appendix 5).

7. Remote Sensing data

7.1. Data retrieval

7.1.1. Sentinel-2

The Sentinel-2 mission is part of the Copernicus program, launched by the European Space Agency (ESA) (European Space Agency, z.d.-b). The mission consists of two identical satellites: Sentinel-2A, launched in 2015, and Sentinel-2B, launched in 2017 (ESA, z.d.). The mission produces high-resolution passive optical remote sensing data for monitoring the earth's surface. Spectral images are produced at 13 spectral bands with a spatial resolution of 10, 20 or 60 m (depending on the spectral band). Sentinel-2 has a revisit time of 5 days and measures at a 290 km wide swath (ESA, z.d.). Via Google Earth Engine (GEE), freely available Sentinel-2 data was retrieved at level 2A; observations at the bottom of the atmosphere with an atmospheric correction (European Space Agency, 2022; Gorelick et al., 2017). The spectral images were thus already corrected for scatter of air molecules, absorption and scattering of atmospheric gases and aerosol particles.

Data was 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. Sentinel-2 data was filtered for the sampled forest patches and the temporal mean was calculated. Different time intervals were tested (1 week, 1 month, 2 months, 3 months) and the time interval of three months gave the best result: between 1/7/2023 and 1/9/2023 (the same summer months as all field data was collected). To calculate the carbon sequestration, Sentinel-2 data was also downloaded for 2017-2022, each year in these same three months.

7.1.2. GEDI

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). A laser altimeter makes detailed structural footprints of ground vegetation with a footprint resolution of 25 meters. The high accuracy and detailed measurements of the canopy structure offer many opportunities. However, the measurements are in discrete footprints and thus lack the full coverage of passive optical remote sensing missions such as Sentinel-2. A high-resolution canopy height model of the earth (10x10m) was recently developed by the Eidgenössische Technische Hochschule Zürich (ETH), using a probabilistic deep learning model to fuse height data from the GEDI mission and optical satellite images from Sentinel-2 (Lang et al., 2022, 2023). It combines the accuracy of LiDAR data with the full coverage of passive optical remote sensing. The height measurements date from 2020, but the data was only published last year. The product was directly downloaded for the study regions and no preprocessing was needed.

7.1.3. Sentinel-1

Sentinel-1 is a 2-satellite constellation with identical, polar-orbiting satellites that were launched in 2014 and 2016 respectively (European Space Agency, z.d.-c). When operating together, they work at a repeat cycle of six days. Like Sentinel-2, Sentinel-1 is part of the ESA Copernicus program. It is a C-band synthetic aperture radar (SAR) that can thus produce imagery regardless of the time of the day and the weather (an advantage compared to Sentinel-2). C-band missions measure wavelengths between 3.8 and 7.5 cm. Sentinel-1 produces products in four acquisition modes, but for this study the level-1 Interferometric Wide swath (IW) was used. IW with dual polarization (VV and VH) is the primary conflict-free mode over land and additionally the main operational mode (European Space Agency, z.d.-d). The level-1 Ground Range Detected products were downloaded via GEE at 10m resolution ('High resolution'). Data acquired in both ascending and descending directions were used.

7.2. Preprocessing and data preparation

7.2.1. Sentinel-2

A cloud masking was performed in GEE and further preprocessing was done in R with the *terra* package (Hijmans et al., 2023). For the cloud masking, a pixel percentage of 60% cloud cover and 40% probability was used as a threshold. Cloud shadows were identified as dark NIR pixels (threshold 0.15) that were not water and that followed the expected shadow direction. Sentinel bands B5, B6, B7, B11 and B12 were resampled with the *resample* function, applying the nearest neighbor method, from 20 m to 10 m spatial resolution. The majority of the bands were already provided at 10 m resolution and this scale was preferred to work on forest stand-level. Because of the scarcity of the field data, model calibration was performed at plot level. The plots were loaded in R as geometric circles with a radius of 18m (for the NP BW) or 25m (for Catalunya) with the *sf* package, based on the radius of the highest plot nesting level (Pebesma, 2023). In the attribute table, the plot ID was linked to the calculated above-ground carbon stock per hectare. Mean values of the Sentinel bands were then calculated for each plot, using the *extract* function. The overlap of each pixel with the patch was considered by weighting the percentage of overlap in the mean values calculation and only pixels with more than 90% coverage were considered.

7.2.2. Sentinel-1

The Sentinel-1 data as downloaded from GEE was already radiometrically calibrated, ortho-corrected and thermal noise was already removed. In GEE, an additional speckle filter was applied to remove speckle noise on the images, using the widely applied Lee filter (Yommy et al., 2015). The temporal mean was taken from the 1st of July until the 30th of September (analogous to Sentinel-2 data) and resulting images of VV and VH were downloaded. For deciduous forests, VV and VH values vary throughout the year: in the leaves-on season (June up to October), the volumetric scattering and water content increase. The correlation with AGB was therefore also found to be higher in the summer season by Laurin et al. (2018), whereas it remains the same throughout the year for evergreen forest. Data was collected during the summer season for this study and the obtained VV and VH values were thus rather highly correlated with AGB. In R, both images were resampled with the nearest neighbor method to the same pixels as the Sentinel-2 data and similarly as described above, the mean value per plot was calculated.

7.3. Vegetation indices Sentinel-2

An exploration of important literature studies lead to a selection of vegetation indices, derived from Sentinel-2, that have been proven useful for above-ground biomass (AGB) modeling (Table II.8) (Chen et al., 2019a; Forkuor et al., 2020a; Mngadi et al., 2021; Moradi et al., 2022). All vegetation indices were calculated in R. The mean of each vegetation index per plot was calculated identically to the mean Sentinel band values calculation.

Table II.8: Vegetation indices derived from Sentinel-2 spectral bands with source 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)

8. Data analysis: Modeling

In figure II.3, the workflow of the modeling process is depicted, as can be followed throughout this section. First, Sentinel-2 imaging bands and vegetation indices were used to model above-ground carbon stock. Only in the 'Model optimization' (Section 8.4), Sentinel-1 and the GEDI height product were added to assess the added value of multi-sensor remote sensing modeling.

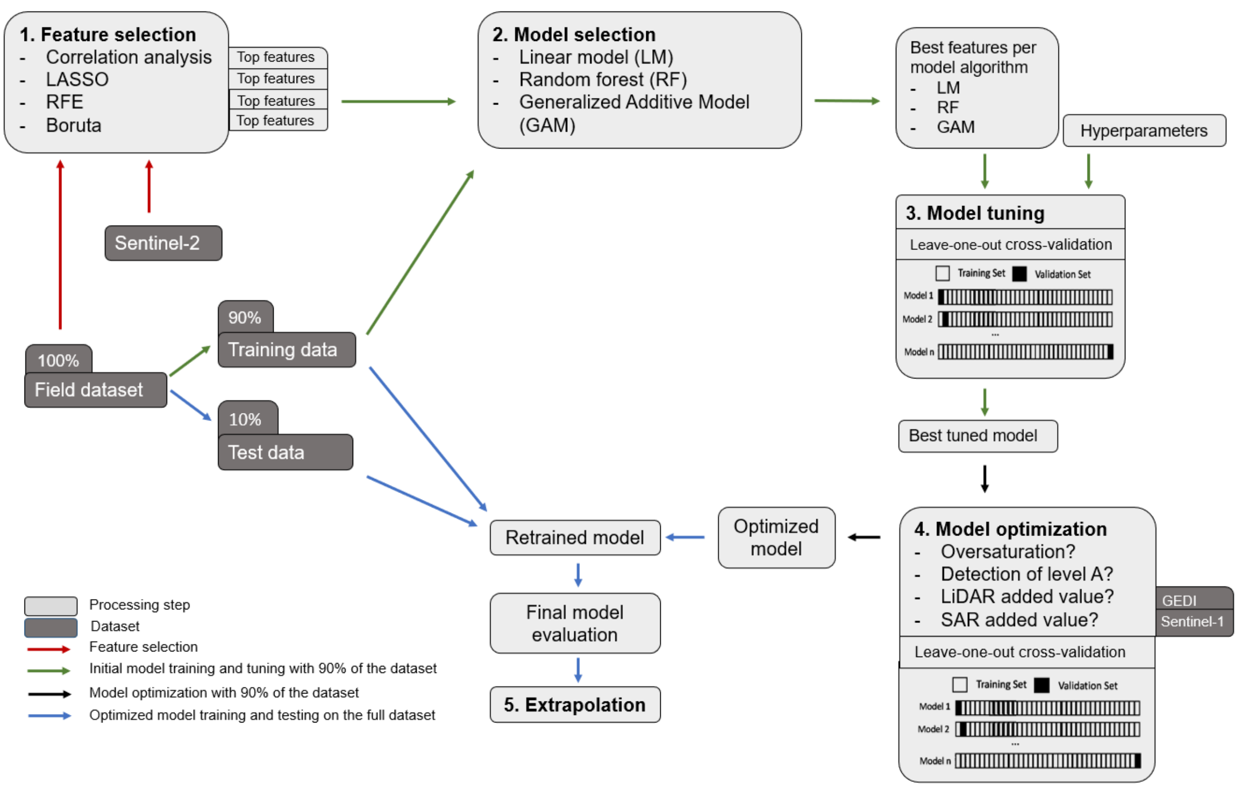


Figure II.3: Workflow of the modeling process

8.1. Data exploration

First, an outlier- and correlation analysis provided more insight in the data. A correlation matrix was constructed to identify highly correlated variables (Appendix 6). The carbon stock, calculated from the field measurements, was plotted with all variables and outliers were identified with *cooks.distance* function of the *stats* package (Bolar, 2019). The cause of outliers was checked in the plot description, management comments and *Google Earth* (*Google Earth*, z.d.). The distribution of the measured carbon stock was observed in a histogram.

8.2. Feature selection

The number of observations (and thus the degrees of freedom) was limited and a selection of the predictive variables (vegetation indices and sentinel bands) was needed to avoid overfitting. A large feature set often leads to lower accuracies, especially in small datasets (M. Kursa & Rudnicki, 2010). An exploration of different feature selection methods was performed, selecting the predictive features from the full dataset of measured plots. From each method, the resulting set of selected features was evaluated in the model selection (Section 8.3), to continue with the best performing set of features. First, the most basic method was based on the correlation analysis, where variables that were highly correlated with carbon stock while showing no multi-correlation with each other, were chosen.

Second, the Least Absolute Shrinkage and Selection Operator (LASSO) combines feature selection with regularization to avoid overfitting (Prabhakaran, 2018). To use LASSO, all variables were standardized. LASSO can be used to fit a regression model, or only to select features. It was programmed with the *glmnet* package in R (Friedman et al., 2023). The regularization can be controlled with the *alpha* parameter, where lower values indicate less regularization, leading to a higher number of features that is kept. *Alpha* was set to one, allowing variable coefficients to reach zero for a strict feature selection (given the small dataset and high quantity of features) (Teixeira-Pinto, 2021). *Lambda* is the second tuning parameter and determines the penalty term that is given to features that have little value in the regression. The optimal *lambda* value was selected using cross-validation built in the *cv.glmnet* function.

As the third feature selection method, the *caret* package provided a function *rfe* for recursive feature elimination (Bulut, 2021; Kuhn et al., 2023). This is a commonly used method in predictive modeling and machine learning and uses a backward selection process. The importance of each feature is calculated and rank-ordered. The least important features are then iteratively removed from the model (Bulut, 2021; Darst et al., 2018). Random forest was used as the evaluation algorithm of choice and was combined with 5 repeats of 10-fold cross validation.

Lastly, Boruta is a promising feature ranking and selection algorithm based on the random forest algorithm which can be performed with the *Boruta* package in R (M. B. Kursa & Rudnicki, 2022). It is a wrapper method, meaning that the method focuses on optimizing one specific machine learning model (in this case random forest) by iteratively selecting and evaluating a combination of features (M. Kursa & Rudnicki, 2010; Muhandisin, 2023). Features are ranked as 'important', 'tentative' or 'not important'.

8.3. Model selection

Different models were tested to find the best fit on the data, with the best set of features that resulted from the feature selection (section 8.2). Leave-one-out cross-validation (LOOCV) was performed to tune each candidate model. A training dataset of 90% of all data points was used in this process, reserving 10% for the evaluation of the final model (cfr. 8.4) (Figure II.3). LOOCV is a resampling method where the model is trained on all the samples in the training dataset, but one (Picard & Cook, 1984). The performance of the model is then evaluated based on the prediction of the left-out sample. This process is repeated until all observations are used as the test data point and the mean performance is reported. LOOCV helps to prevent overfitting in small datasets like in this study. Disadvantages such as a high computational cost and low scalability are mostly problematic for large datasets. However, extra attention to outliers is crucial as LOOCV is outlier-sensitive (Picard & Cook, 1984). The root mean square error (RMSE), the mean absolute error (MAE) and the coefficient of determination (R^2) were chosen as validation metrics and used as output from LOOCV to compare the results of different models. The *Metrics* package offers the necessary functions in R (Hamner et al., 2018). The R^2-value indicates the fit between the modeled values and the real values, using the training dataset (Goos, 2017) (Equation II.7). The RMSE and MAE measure the prediction errors. Both are valuable metrics, but the RMSE is more sensitive to outliers and to obtain this complementary information, they were both evaluated. The RMSE is calculated as the square root of the average of the squared differences between the actual and the predicted values (Goos, 2017) (Equation II.8). The MAE is calculated as the average of the absolute differences between the actual and the predicted values (Equation II.9). RMSE and MAE are both reported in the units of the data, so they are easy to interpret: the lower the RMSE and MAE, the better the prediction accuracy.

$$R^2 = 1 - \frac{\sum(y_i - \hat{y_i})^2}{\sum(y_i - \bar{y})^2}$$ **(Equation II.7)**

$$RMSE = \sqrt{\sum_1^n \frac{(y_i \sum \hat{y_i})^2}{n}}$$ **(Equation II.8)**

$$MAE = \sum_1^n \frac{|y_i - \hat{y_i}|}{n}$$ **(Equation II.9)**

where $\hat{y_i}$ is the estimated above-ground carbon stock, y_i is the measured above-ground carbon stock,$\bar{y}$ is the mean of all measured carbon stocks and n is the number of observations (plots).

Initially, a multiple generalized linear model (glm) was applied to the data using the glm function in the R stats package, accommodating the gamma distribution of the response variable (carbon stock) through appropriate transformation. All variables were scaled and the model was evaluated with and without interaction terms. There are four assumptions made when using a glm: 1) there is a linear relationship between the transformed response variable (carbon stock) and the selected features, this could be tested with a scatterplot, 2) the residuals of the regression analysis are independent, 3) multicollinearity may not occur between the predictive variables, which was verified by a Pearson correlation matrix and 4) there are no influential outliers, which was checked with the *cooks.distance* function. As this is the simplest and most comprehensive model, the results were used as a baseline to improve with other modeling techniques.

Secondly, the random forest algorithm was chosen as a promising tool to model above-ground biomass, using the *randomForest* package in R (Cutler & Wiener, 2022). Random forest is a robust and user-friendly modeling technique that has been proven to be successful in many study areas, among which above-ground biomass modeling (Chen et al., 2019; Liaw & Wiener, 2002a; Torre-Tojal et al., 2022). Random forest is a machine learning method, where trees are constructed using a bootstrap sample of the data. At each node, a random subset of predictors is chosen and the best-performing subset is the split that is chosen. Because of the random component, it is less prone to overfitting than other algorithms such as decision trees. Moreover, it is flexible, non-sensitive to outliers and the distribution of the data is not important. A disadvantage however is the lack of interpretability, as is the problem for many machine learning algorithms ('black-box algorithm'). Compared to other machine learning algorithms, Random Forest is less sensitive to tuning of the hyperparameters. Sample size and node size are two hyperparameters that have a minor influence on the performance, and these parameters are thus mostly not tuned (Probst et al., 2019). *Ntree* and *mtry* are two hyperparameters that were tuned (Liaw & Wiener, 2002b). *Ntree* bootstrap samples are taken from the given dataset. For each of the samples, a random sample *mtry* of predictors is chosen at each node and the best split is chosen from these variables. Lower *mtry* values are associated with higher stability but may also relate with a lower performance (Probst et al., 2019). By aggregating predictions of the *Ntree* trees, new data is predicted. In the default values, *mtry* is set at 1/3 of the predictor variables and *Ntree* is set at 500. Tuning was done manually and through the use of the *caret* package (Kuhn et al., 2023). In the manual selection, values between 50 and 500 at intervals of 50 were tested for *Ntree*, and values of 1 up to 25 were tested for m*try*, following the recommendations of Liaw & Wiener (2002). The *caret* package can only tune *mtry*, using a random search or a grid search with repeated cross-validation. The incorporated tuning in the randomForest package was avoided because this was signaled to lead to bias (Probst et al., 2019). Manual tuning gave the highest R^2-value and was thus used as a final tuning method. As no Random Forest model was found that gave satisfactory results, generalized additive models (GAMs) offered alternative possibilities, following the findings of Aertsen et al. (2010).

A GAM consists of the sum of smooth functions of the predictive variables and serves as a non-parametric extension of GLMs (generalized linear models) (Hastie & Tibshirani, 1986). The smooth functions make GAMs flexible while maintaining interpretability, a significant advantage compared to the Random Forest models (Wood, 2006). They allow variation in the effect of the predictor variable over its range. However, they also introduce the main challenge in GAMs: finding the optimal degree of smoothness. GAMs can only be used under several assumptions. First, the relationship between the predictor and the mean of the response variable is assumed to be correctly specified by the link function. Next, the effects of each predictor variable are assumed to be additive on the response. Additionally, the smoothness assumption ensures that there are no abrupt jumps or discontinuities in the relationships between the predictors and the response. Moreover, no multicollinearity may be present and the observations must be independent of each other. This last assumption may be problematic, as three different plots are taken in each patch (and are thus in a way related to each other). To (at least partly) take into account this dependency, a species variable was introduced, specifying the species group present in each plot (*pine, oak, mixed, beech)*. The *mgcv* package in R, including the *gam* function, was used (S. Wood, 2023). The *family* and *link function* were specified in the *gam* function from the distribution of the response variable, which was evaluated on a histogram. The *species* variable was introduced as a random intercept, using factor coding and a random effect smoother (Pedersen et al., 2019). The *gam.check* function generates a QQ-plot, a histogram of the residuals, a scatterplot of the residuals versus the predictions and a scatterplot of the response versus the fitted values. These allow for an evaluation of the model assumptions and model fit. Partial plots are generated with the *plot.gam* function and include the 95% confidence interval limits (Wood, 2006).

Tuning the GAM, several parameters were optimized. The dimension *k* represents the maximum number of base functions used to build a smooth term, and the default value is 10 for every predictor. It sets the maximum allowed degrees of freedom (*k-1)* to be used fitting the smooth function on each predictor. Hence, If *k* was close to the degrees of freedom used for each predictor, the model was constrained too much by *k*. This was not the case, so the default *k* value sufficed. If the effective degrees of freedom (edf) were 1, the relationship between the predictor and the response is linear and it was not necessary to estimate a smooth function. Higher edf indicates a higher degree of smoothness and non-linearity. *Gamma* is a parameter used in the incorporated generalized cross-validation of the gam function to minimize the prediction error. The default value is set to

1, but Wood (2006) demonstrated that a value of 1.4 can largely correct for overfitting without compromising the model fit. Lastly, the smoothing parameter estimation method was optimized. By default, generalized cross-validation (GCV) is used in the *gam* function, but restricted maximum likelihood (REML), marginal likelihood (ML) and neighborhood cross-validation (NCV) have several computational advantages, as discussed by Wood (2011). These smoothing parameter estimation methods were compared in accuracy, again using LOOCV.

From all models, the GAM in combination with the feature selection resulting from RFE resulted in the best values of R^2, RMSE and MAE. Model optimization continued only with this tuned GAM.

8.4. Model optimization

Due to the limited number of observations, we employed Leave-One-Out Cross-Validation (LOOCV) once more on the same 90% training dataset during model optimization to identify the most suitable model. To optimize the tuned GAM, the model performance was evaluated in different scenarios:

1. Oversaturation was assessed by only using data with a biomass of more than 450 tons/ha (which equals a higher carbon stock than 225 tons/ha). A known limitation of passive optical remote sensing is signal saturation for forests with high complexity and biomass (Rodríguez-Veiga et al., 2017b). This may lead to deviating spectral values that are detected, which may negatively affect the model performance.
2. The influence of the small trees in nesting level A was assessed as small trees are more difficult to detect by passive optical remote sensing, which may not benefit a predictive model. The model with all diameter classes was compared with a model containing only levels B and C (and D for Catalunya) (Figure II.2).
3. The introduction of height estimates as a new variable, obtained from the ETH product, was assessed.
4. The added value of VV and VH as indicators of above-ground carbon stock, downloaded from the Sentinel-1 mission, was assessed.

The final model was then constructed using the 90% training data and tested on the remaining 10% that was isolated in the beginning and remained unseen in the cross-validation process.

8.5. Model extrapolation

Sentinel-2 and Sentinel-1 data were downloaded for all patches of the IFMP for July until September, following the same data retrieval and processing in GEE and R as described in 7.1-7.2. The selected features were calculated in R. The extra *height* and *species* variable were then introduced. Only pixels with more than 90% coverage were kept, to ensure a pure representation of the forest stand.

All remote sensing data was visually evaluated in QGIS, outliers were identified and the cause for deviation was checked in *Google Earth.* However, the outlying pixels were kept in the extrapolation, as they represented biomass variation across the stand and may relate to management practices. The final model as finetuned during model optimization was now trained on the full dataset of the measured patches (*mgcv* package) (S. Wood, 2023). The carbon stock was predicted for every pixel of the new patches with the *predict* function in the *stats* package, including the standard error of prediction (Bolar, 2019). The mean predicted carbon stock was then calculated for each forest patch and the standard error of the mean (SEM) was calculated. The standard error of prediction indicates the uncertainty in each estimate, while the SEM indicates the deviation of the estimated sample mean from the real sample mean (Goos, 2017).

9. Statistical analyses

Subsequent statistical analyses were conducted at the patch level, given that the SEM is notably reduced compared to the standard error at pixel level. Moreover, this study prioritizes examining between-patch variability in carbon stock rather than within-patch variability. Comparing statistical tests conducted at the pixel level versus at the patch level yielded consistent conclusions, suggesting that any loss of statistical power and information associated with aggregation was not determinative. Lastly, the interpretability of the results is higher at patch level.

9.1. Comparison of carbon stock

The difference in carbon stock between unmanaged and managed patches was calculated per cluster. In the case of triplets (e.g. two managed patches and one unmanaged patch), the mean of the managed patches was considered as the carbon stock to be compared with the carbon stock in the unmanaged patch in a graphical analysis.

Generalized Linear Mixed Modeling (GLMM) offered the best opportunities to assess if management had significant effects on carbon stock (S. N. Wood, 2006). The R package *lme4* with the *glmer* function was used for this purpose (Bates et al., 2024). Carbon stock can only reach positive values and is therefore gamma-distributed (Thom, 1958). This could be incorporated in a GLMM, while a linear mixed model (LMM) is only appropriate for normally distributed response variables. The mean carbon stock per patch was the response variable, management was the fixed effect and the cluster was incorporated as random effect. A separate statistical analysis was performed for the measured plots and for the carbon stocks estimated by the model at patch level. For the analysis of the measured plots, the patch was nested in the cluster as a random variable.

9.2. Comparison of carbon sequestration

Height estimates from the ETH product were only available for 2020. To compare predicted carbon stocks in time, it was therefore not useful to include these height estimates and a second GAM was obtained for predicting carbon stock across several years. To obtain consistent predictions, new carbon stock estimates were also made for 2023, using this same model without the height variable. Data from Sentinel-2 is available from 2017 on, so the carbon stock could be estimated per patch for each year from 2017 up to 2022.

A similar statistical analysis as explained in section 9.1 was performed for the carbon stock and carbon sequestration between 2017 and 2023. The year was included as an extra crossed random effect. Carbon sequestration can reach negative values and was normally distributed, so the *lmer* function to model linear mixed models (LMM) could be used instead of *glmer* (generalized lmm).

Finally, the results were compared with existing data products. The Climate Change Initiative (CCI) of the European Space Agency published global maps of above-ground carbon stock for 2017-2020 (European Space Agency, z.d.-a). This product combines information of several microwave radars, optical remote sensing radars and spaceborne LiDAR. Given the convenient time range and recent development, the predicted carbon stocks were compared to the estimates of the CCI (using the same carbon factor of 0.5 as in equation II.1).

III. Results

This chapter presents the findings from all analyses in both study areas. Section 1 will offer a comparative analysis of the field data, while section 2 will present an analysis of the obtained models. Sections 3 and 4 will then delve into the statistical analysis of carbon stock (section 3) and carbon sequestration (section 4) in managed and unmanaged forest patches.

1. Analysis of the field data

1.1. General plot description

In table III.1, a comprehensive overview is given of the key attributes of all plots that were visited during the field survey. Several opposite trends occur in Catalunya compared to the National Park Brabantse Wouden (NP BW). In the NP BW, the difference in tree count between managed and unmanaged plots is noteworthy, a difference that is mostly reflected in trees from diameter class A (figure II.2). A contrasting pattern emerges in Catalunya, where the smallest trees are most abundant in unmanaged plots. Secondly, there is a higher tree density of the largest diameter class (C) in the unmanaged plots. The opposite occurs in Catalunya (diameter class C). Where in general, higher and larger trees are measured in unmanaged plots in NP BW, managed plots house higher and larger trees in Catalunya.

Table III.1: Comprehensive summary of the characteristics of the visited field plots. A distinction is made between the two study regions (NP BW= 'BW', Catalunya='Cat') and between managed ('M') and unmanaged ('UM') plots.

	BW_M	BW_UM	Cat_M	Cat_UM
n° of plots	39	39	25	24
n°of trees	1348	884	1067	1753
Species richness	18	19	26	24
mean DBH (cm)	20	35	13	9
mean H (m)	13	22	8	6
mean density A (stems/ha)	2717	580	2572	6584
mean density B (stems/ha)	323	322	479	444
mean density C (stems/ha)	89	104	101	83
mean density D (stems/ha)	NA	NA	2	3

1.2. National Park Brabantse Wouden

Overall, the carbon stock is gamma-distributed, only reaching positive values and following a bell-shaped curve (Figure III.1). The measured plots have a carbon stock that fluctuates between 20 tons/ha and 325 tons/ha with a mean of 170.09 ± 61.16 tons/ha. The unmanaged plots are characterized by a higher variation in carbon stock than in managed plots, where the density curve is negatively skewed (Figure III.2). There are no outliers detected on the boxplots.

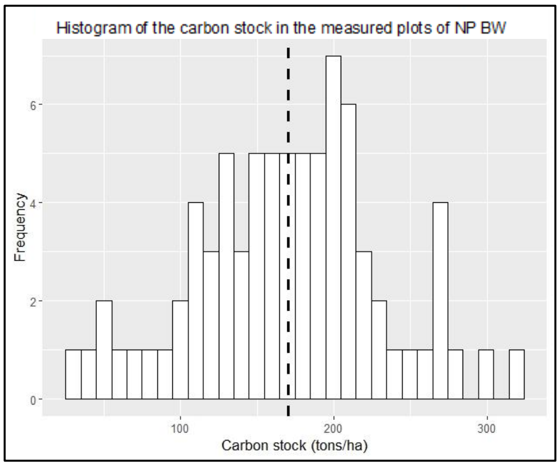


Figure III.1: Carbon stock distribution of all plots in NP BW.

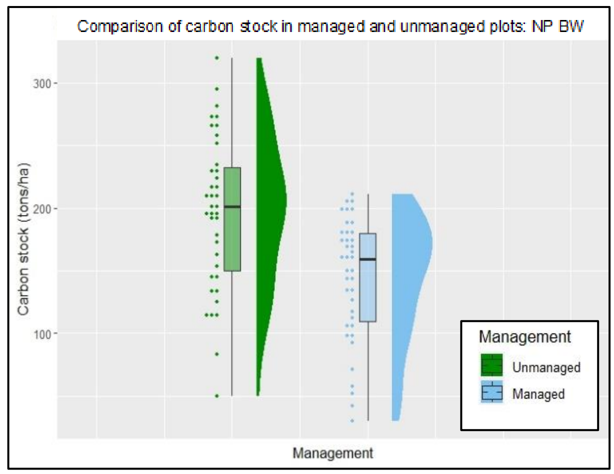


Figure III.2: Comparison of the carbon stock in managed and unmanaged plots in NP BW

For most clusters, carbon stock was higher in the unmanaged forest patch compared to the managed forest patch. The difference fluctuates between 10 and 180 tons/ha. Only in cluster Be_9 and Be_18, the obtained mean carbon stock of the managed patch is higher than of the unmanaged patch (Figure III.3). The difference in carbon stock is smallest in forests dominated by *Fagus sp.* (Figure III.4). The variance in unmanaged patches is markedly larger than in unmanaged patches in mixed forests or forests dominated by *Fagus sp.*

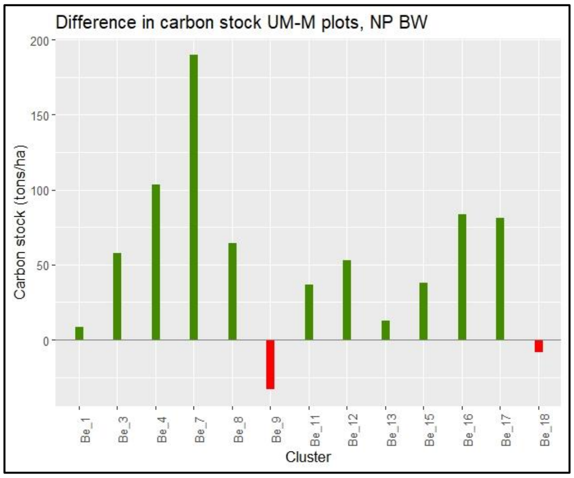


Figure III.3: Difference in carbon stock (unmanaged minus managed plots), measured in NP BW.

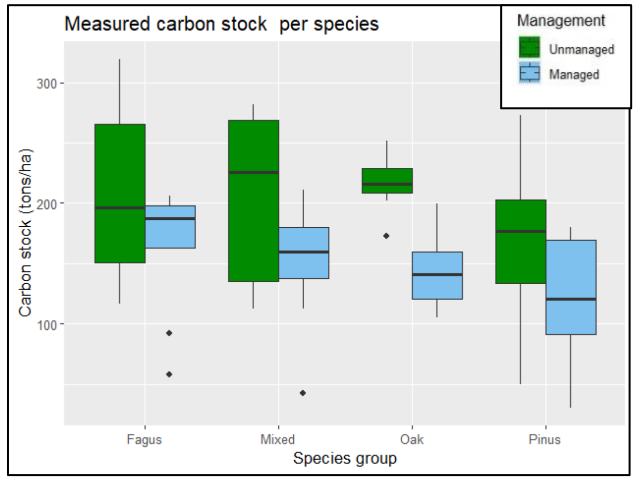


Figure III.4: The measured carbon stock per species group, for managed and unmanaged plots in NP BW

A glmm confirms the graphical results that management has a significant effect on carbon stock, with a significance level of 0.05 (Equation III.1).

Carbon ~ Management + (1 | Cluster/Patch) **(Equation III.1)**

Managed patches have a lower carbon stock than unmanaged patches (p-value=0.011, effect size -0.33). No statistical analysis on the interaction between management and the species group was possible due to the limited amount of samples per species group.

1.3. Catalunya

The histogram of the carbon stocks in all measured plots are gamma-distributed and positively skewed (Figure III.5). The same can be said for the density distributions of all managed and unmanaged plots (Figure III.6). There is a high variation in carbon stocks across plots, and a few outliers are present with a remarkably higher carbon stock. The carbon stock in the measured plots reaches values between 5 tons/ha and 82 tons/ha with a mean of 23.58 $\pm$ 16.46 tons/ha.

For most clusters, no pronounced difference in carbon stock between managed and unmanaged patches is detected (Figure III.7). However, for cluster SRB_OUT_21, the unmanaged patch stocks almost 60 tons/ha more carbon than the managed patch. This is especially remarkable given the low carbon stocks in the region (mean carbon stock = 24.39 tons/ha). The unmanaged patch of cluster SRB_OUT_21 was measured by two plots located in very dense regeneration of *Pinus halepensis,* explaining the high biomass. Thinnings performed in the managed patches of that same cluster avoid such situations. Only in clusters SRB_04 and SRB_OUT_09, the managed patch has a higher carbon stocked than the unmanaged forest patch.

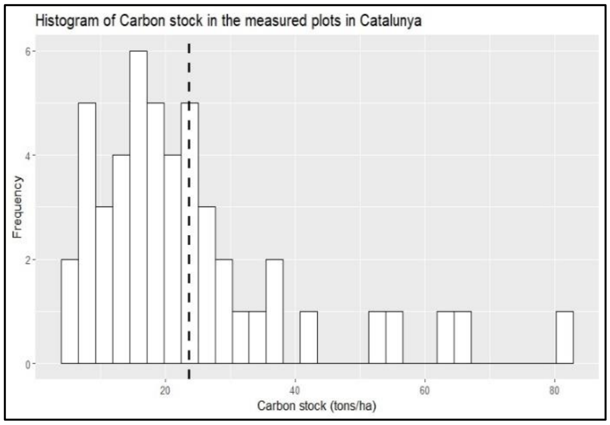


Figure III.5: Carbon stock distribution of all plots in Catalunya.

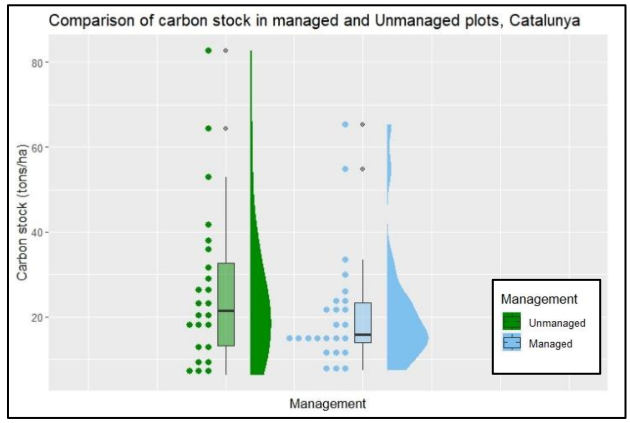


Figure III.6: Comparison of the carbon stock in managed and unmanaged plots in Catalunya

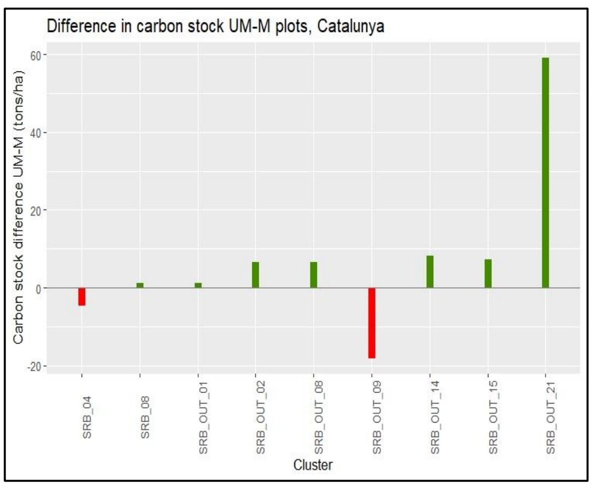


Figure III.7: Difference in carbon stock (unmanaged minus managed plots), measured in Catalunya.

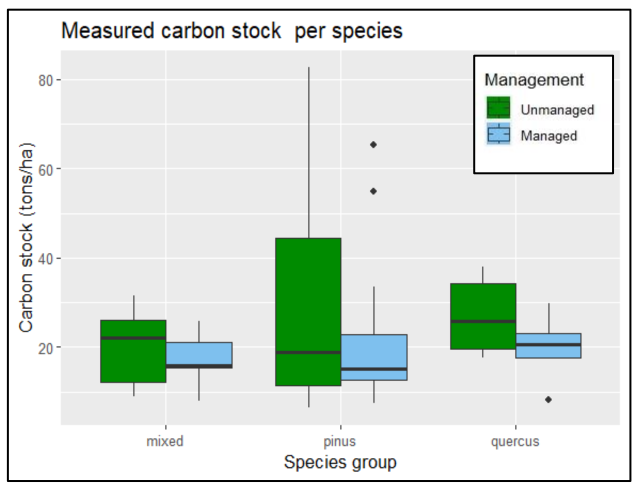


Figure III.8: The measured carbon stock per species group, for managed and unmanaged plots in Catalunya

No significant effect of management among the measured plots is detected in a generalized linear mixed model with significance level of 0.05 (Equation III.2) ($p=0.327$).

$$\text{Carbon} \sim \text{Management} + (1 \mid \text{Cluster/Patch}) \qquad \textbf{(Equation III.2)}$$

No general trends can be concluded from the crown fire vulnerability analysis due to the limited number of plots, especially in class A (highest crown fire vulnerability). The qualitative results of a crown fire analysis in Catalunya show that most managed plots are classified with a low fire vulnerability (class C) (Figure III.9 a). In the highest vulnerability class, only unmanaged plots are found. No clear relationship with carbon stock is inferred, mainly because of the lack of plots in class A (Figure III.9 b). Lastly, there is a high variation in carbon stock among the plots of class C. However, disregarding one outlier in class C, a general positive relationship is inferred with the carbon stocked in level A (smallest diameter class) (Figure III.9 c).

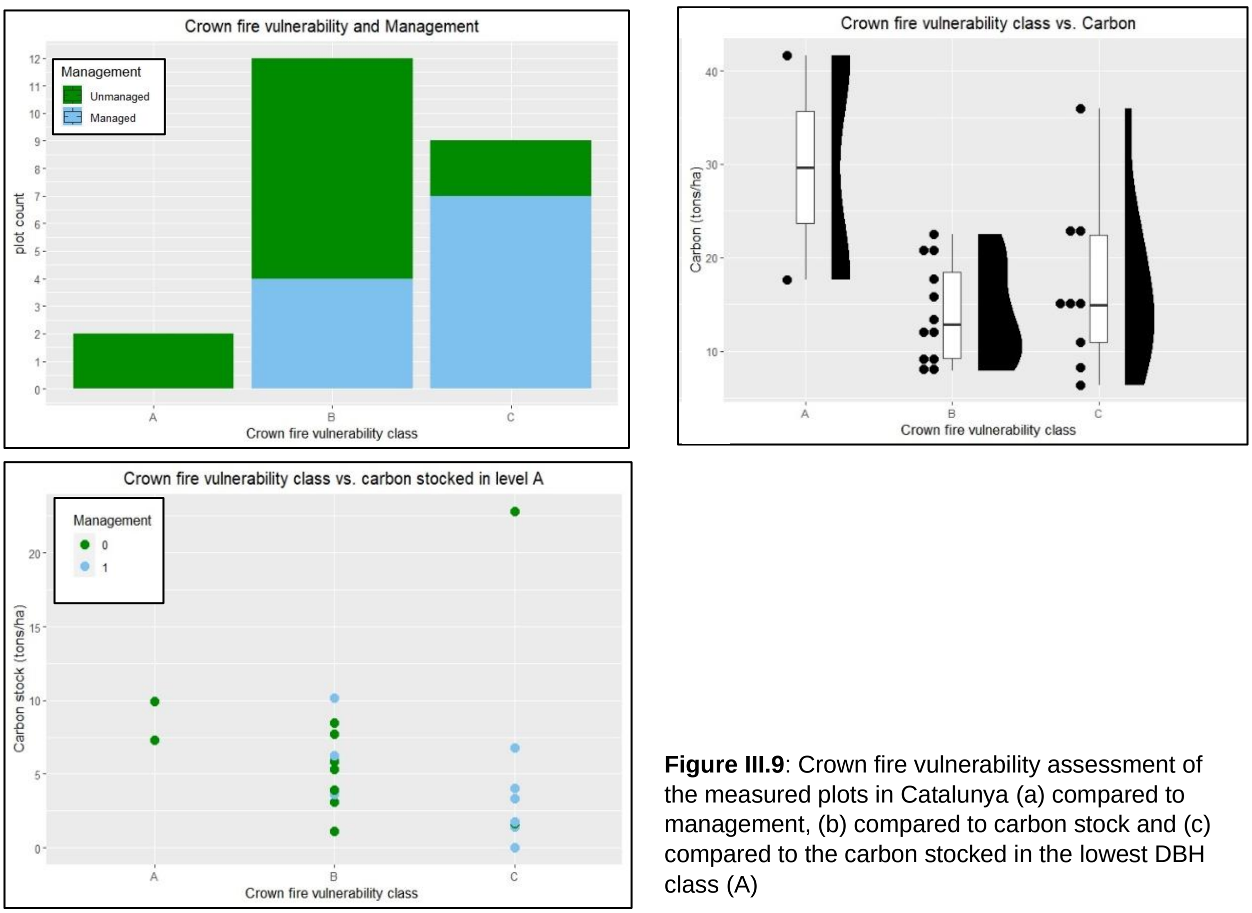


Figure III.9: Crown fire vulnerability assessment of the measured plots in Catalunya (a) compared to management, (b) compared to carbon stock and (c) compared to the carbon stocked in the lowest DBH class (A)

2. Modeling results

2.1. National Park Brabantse Wouden

2.1.1. Feature selection

First, a correlation plot of all Sentinel-2 variables indicated multicollinearity between variables (Appendix 6). Multi-correlated variables were removed in the feature selection (correlation >0.75). As such, IPVI, ARVI and B8 were removed from the selected features resulting from the correlation analysis. The features selected by different feature selection methods is shown in table III.2.

Table III.2: Results of the different feature selection methods for NP BW

Feature selection method	Feature 1	Feature 2	Feature 3	Feature 4	Feature 5
Correlation analysis	GNDVI	B7	RVI	SAVI	STVI2
LASSO	GNDVI	MCARI	/	/	/
RFE	GNDVI	MCARI	B12	B5	STVI3
Boruta	GNDVI	MCARI	B12	IRECI	MTCI

2.1.2. Model selection and tuning

The Recursive Feature Elimination (RFE) method was chosen for further analysis and applied in a Generalized Additive Model (GAM). The features selected through this approach yielded the most favorable validation parameters (R^2, RMSE, MAE) (Table III.2). Additionally, one outlier was removed from the dataset; during data collection, recent road construction activities were observed on plot 8, identified by the patch ID BW_Hal_15, both through satellite imagery and on-site inspection.

The distribution of carbon stock data was found to closely follow a gamma distribution, as evidenced by the histogram (Figure III.1). Accordingly, the model specified the family and link function (log link function) to accommodate this distribution, and Neighbourhood 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. Notably, for features B5, STVI3, and GNDVI, a linear relationship was observed, eliminating the need for a smooth function.

2.1.3. Model optimization

Before model optimization, the validation parameters to be optimized were R^2=0.56, RMSE=99.44, and MAE=91.40.

1) Disregarding all plots with a carbon stock >450 tons/ha did not result in a better fit (R^2=0.36, RMSE=100.15, MAE=68.027). Only the MAE decreased remarkably. No significant oversaturation can be detected for the patches in NP BW.
2) Only modeling carbon stock in levels B and C did not result in a better fit for all three validation parameters (R^2=0.54, RMSE=116.12, MAE=99.14). Trees in level A were sufficiently detected by passive optical remote sensing in the NP BW or

there was not a crucial amount of biomass in level A to affect the total biomass estimations.

3) Incorporating GEDI data for height estimates enhanced both the model's fit and predictive capabilities slightly (R^2=0.58, RMSE=98.056, MAE=90.21). Although ETH_height was integrated into the GAM, no smoothing was necessary due to the linear relationship observed with carbon stock.
4) The introduction of both VV and VH significantly improved the model fit and predictive power. Both variables were included in GAM, but only VH was included as a smooth term (R^2=68.2, RMSE=56.35, MAE=50.07). Derivatives of both raw metrics (VV/VH, VH/VV, VV+VH, VH-VV) were tested but did not outperform the raw bands.

The model optimization resulted in a final model, used for extrapolation (Equation III.3, Table III.3).

$$\text{Carbon} \sim \text{MCARI} + \text{B5} + \text{STVI3} + \text{B12} + \text{GNDVI} + 1|\text{Species} + \text{ETH\_height} + \text{VH} + \text{VV} \quad \textbf{(Equation III.3)}$$

Only MCARI, B12, VH and the Species variable were smoothed (Table III.4).

Table III.3: Obtained validation metrics of the final model for NP BW

R^2 (%)	68.2
R^2adj (%)	61
RMSE (tons/ha)	56.35
MAE (tons/ha)	50.07

Table III.4: All smoothed variables with k value and effective degrees of freedom (edf) from the final GAM for NP BW

Predictor	**k'**	**edf**
s(MCARI)	9.00	2.75
S(B12)	9.00	2.01
S(Species)	4.00	1.08
S(Sen1_VH)	9.00	4.46

The partial effect plots for all smoothed variables with residuals and the partial plots of all variables can be consulted in appendix 7, illustrating the goodness of fit for each variable.

The fit of the final model is graphically depicted in figure III.10 and the predictive ability in figure III.11. A point of saturation is situated around 200 tons/ha of carbon stock. Before this point, the model makes a slight overestimation, whereas beyond this threshold, it rather underestimates carbon stock. Two slight outliers are noted in the test dataset, which are severely underestimated. Plot 36 has deviating values for B5, B12, GNDVI and ETH_Height. During field measurements, it was noted that a thinning was in progress and a towing path was made through the plot, which could explain the underestimation of the model. For plot 48, no special comments were made, though values for B12 and GNDVI were slightly lower. Nothing remarkable was noticed on satellite images, so no direct explanation was found. Overall, the fit and prediction are satisfactory.

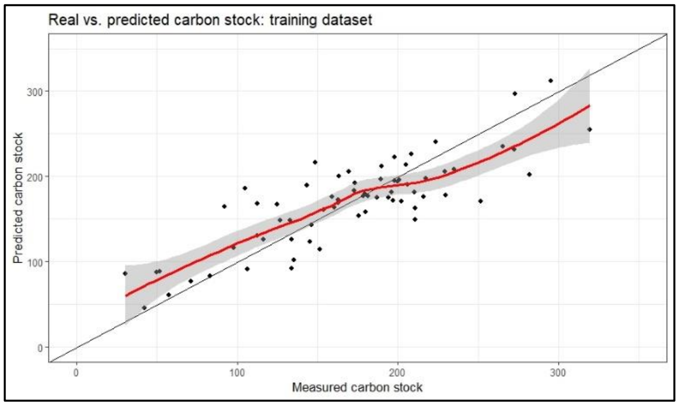


Figure III.10: Measured versus predicted carbon stock values for the 90% training dataset of the final GAM for NP BW, with a 95% confidence interval (shaded area) and the bissectrice of perfect prediction

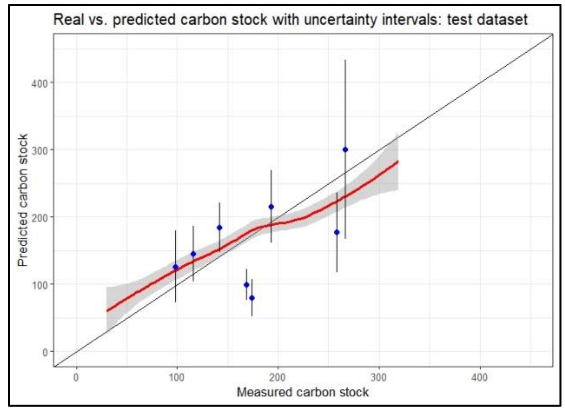


Figure III.11: Measured versus predicted carbon stock values with 95% confidence intervals and the bissectrice of perfect prediction for the 10% test dataset of the final GAM for NP BW

2.2. Catalunya

2.2.1. Feature selection

Identical to the NP BW, a correlation plot indicated the multicollinearity between several variables selected from Sentinel-2 (correlation> 0.75) (Appendix 6). These were taken into account in the feature selection. For RFE and Boruta, EVI was excluded from the feature selection because of its high correlation with LAI.

Table III.5: Results of the different feature selection methods for Catalunya

Feature selection method	Feature 1	Feature 2	Feature 3	Feature 4	Feature 5
Correlation analysis	REDNDVI	STVI1	B2	B7	B11
LASSO	NDI45	GNDVI	IRECI	LAI	/
RFE	GNDVI	LAI	B2	STVI2	/
Boruta	GNDVI	LAI	NDI45	ARVI	/

2.2.2. Model selection and tuning

Variable selection using RFE was employed for further analysis with the GAM. The features selected through this method yielded the best validation parameters (R^2, RMSE, MAE). Plots 22 and 23 were identified as outliers and subsequently removed from the dataset before model calibration. These plots showed dense forestation at the lowest vegetation level (level A). The abundance of small trees in this dense forest may have posed challenges for optical remote sensing, potentially accounting for the outlier parameters.

The response variable followed a positively skewed gamma distribution (Figure III.3). Here, the ‘inverse’ link function appeared optimal and REML was selected as the most successful smoothing parameter estimation method. Gamma was fixed at a value of 1.4, and it was not necessary to adjust the *k* values. For the features *B2, STVI2* and *GNDVI*, a linear relationship was detected and no smooth function was needed.

2.2.3. Model optimization

Before model optimization, the validation parameters to be improved were R^2=0.22, RMSE=29.19, MAE=18.33.

1) There were no plots measured with biomass higher than 450 tons/ha, so oversaturation was not an issue for prediction.
2) Only modeling carbon stock in levels B, C and D did result in a better fit (R^2=0.40, RMSE=9.81, MAE=8.039). However, high variation between the plots regarding the biomass stocked in level A was present. Often, a large proportion or even all of the biomass is stocked in level A, leading to a systematic underestimation by the final model if disregarding level A. Hence, level A is included in the final model. It is however important to know that the low vegetation is not well detected by remote sensing.
3) The height estimates (ETH) from the inclusion of GEDI data improved the fit of the model, however with a slight reduction of the predictive power (R^2=0.44, RMSE=31.74, 23.31). ETH was included in GAM, applying a smoothing function.
4) By adding Sentinel-1 VV and VH variables as raw bands or derivatives, the model fit was improved, selecting VV for the highest improvement in fit and prediction accuracy (R^2=0.47, RMSE=15.38, MAE=14.82). VV was added as a linear term (edf=1).

A final model was obtained (Table III.6, Equation III.4), only introducing ETH_height and Species as smoothed variables:

Carbon ~ GNDVI + B2 + LAI + STVI2 + ETH + VV+ 1|Species, **(Equation III.4)**

Table III.6: Obtained validation metrics of the final model for Catalunya

R^2 (%)	51.68
R^2adj (%)	44.90
RMSE (tons/ha)	14.18
MAE (tons/ha)	13.42

Table III.7: All smoothed variables with k value and effective degrees of freedom (edf) from the final GAM for Catalunya

Predictor	**k'**	**edf**
S(ETH_height)	9.00	3.09
S(Species)	3.00	1.73

The model fit of the continuous smoothed predictor variable (only ETH_height) can be consulted in appendix 8.

The fit of the final model is graphically depicted in figure III.12 and the predictive ability in figure III.13. A point of saturation is already situated around 22 tons/ha of carbon stock. Before this point, the model makes an overestimate while beyond this threshold, a serious underestimation is made, leading to low predictive power (Figure II.13). It was decided to not continue with extrapolation for Catalunya, as the predictions and thus the conclusions would be too unreliable, especially in these outer ranges. Hence, the following paragraphs only include the results for NP BW.

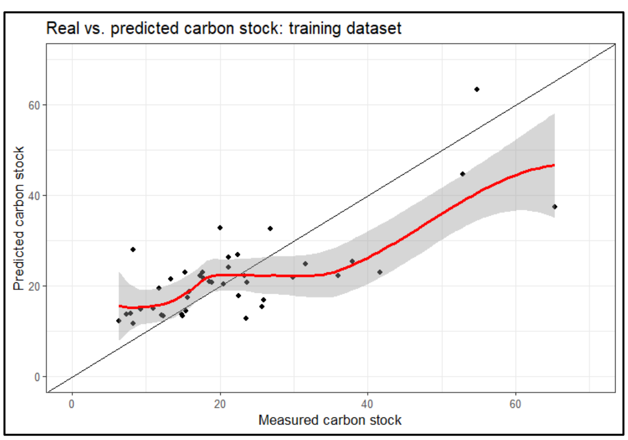


Figure III.12: Measured versus predicted carbon stock values for the 90% training dataset of the final GAM for Catalunya, , with a 95% confidence interval (shaded area) and the bissectrice of perfect prediction

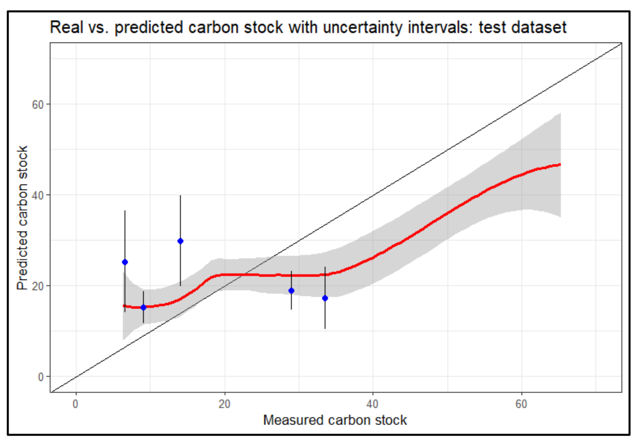


Figure III.13: Measured versus predicted carbon stock values with 95% confidence intervals and the bissectrice of perfect prediction for the 10% test dataset of the final GAM for Catalunya

3. Statistical analysis of carbon stock (NP BW)

The mean carbon stock for the unmanaged patches was 165.89 $\pm$ 26.46 tons/ha, for managed patches this was 166.8 $\pm$ 32.28 tons/ha. On average, the SEM was 1.27 tons/ha and the maximal SEM was 5.94 for the smallest patch that only contained 130 pixels. The managed patches have a higher variability in carbon stock compared to the unmanaged patches (Figure III.14). For some clusters, almost no difference in carbon stock between the unmanaged and the managed patches is observed (Figure III.15). For other clusters a difference up to 40 tons/ha is estimated. However, there does not seem to be a consequent difference between managed and unmanaged patches.

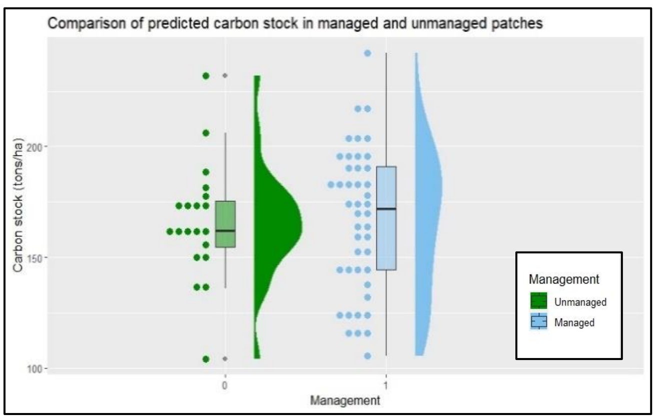


Figure III.14: Comparison of the carbon stock in managed and unmanaged patches, as predicted for NP BW

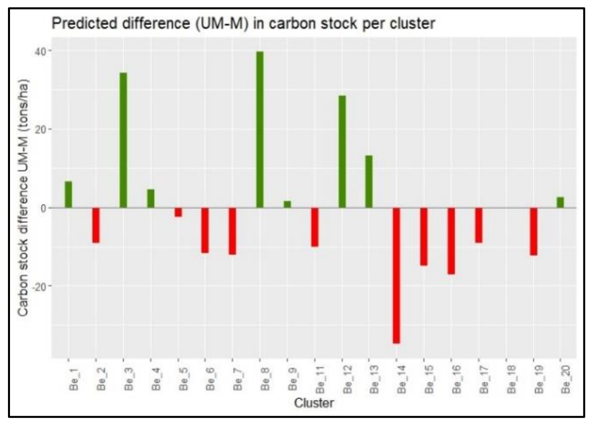


Figure III.15: Predicted difference in carbon stock (unmanaged minus managed patches) in NP BW

With a generalized linear mixed model, management was found to be non-significant with a significance level of 0.05 (p=0.61) (Equation III.5). From a boxplot analysis however, an interaction between management and the carbon stock in the species group *Pinus* is suspected (Figure III.16). This is the only species group where unmanaged patches have a higher estimated above-ground carbon stock, with an average difference of 21.79 tons/ha. No statistical analysis was possible due to the limited number of observations (degrees of freedom) to statistically confirm this suspicion.

Carbon ~ Management + (1 | Cluster) **(Equation III.5)**

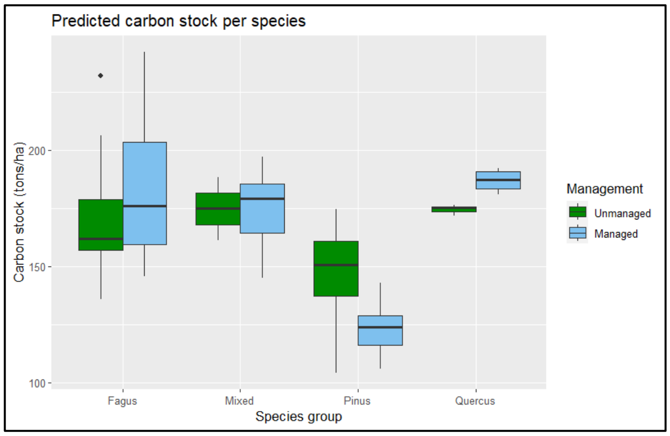


Figure III.16: The predicted carbon stock per species group, for managed and unmanaged patches in NP BW

4. Statistical analysis of carbon sequestration (NP BW)

4.1. Carbon stock over the years

No clear trend is deduced when evaluating the modelled carbon stock in managed and unmanaged patches over the years (since 2017) in NP BW (Figure III.17). In 2017 and 2019, more variation among all estimated patches can be observed compared to the other years.

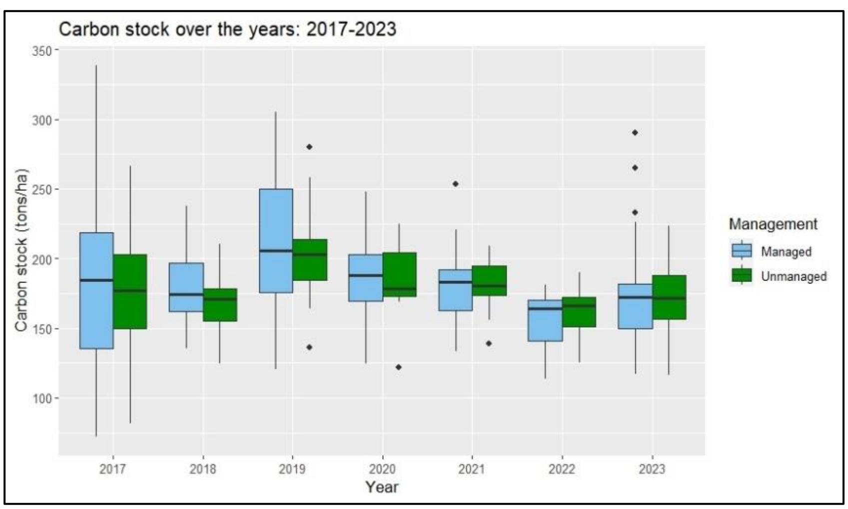


Figure III.17: The predicted carbon stock from 2017 to 2023, for managed and unmanaged patches in NP BW

The graph showed that there wasn't any clear difference between managed and unmanaged patches, and this was confirmed by the GLMM analysis (p=0.29) (Equation III.6). There is no statistically significant impact of management on carbon stock over several years, at a significance level of 0.05. There is also no significant effect of management on carbon stock for one specific species group.

$$\text{Carbon} \sim \text{Management} + (1|\text{Cluster}) + (1|\text{Year}) \qquad \textbf{(Equation III.6)}$$

4.2. Carbon sequestration over the years

The difference in carbon sequestration between unmanaged and managed patches fluctuates for all clusters around zero, without a consistent positive difference for some clusters and a negative difference for others (Figure III.18). The managed and unmanaged patches follow a similar pattern, as do all patches dominated by *Fagus*, *Quercus* or mixed species (Figure III.19, Figure III.20). Patches dominated by *Pinus* have the highest carbon sequestration from 2017 to 2018 and from 2019-2020, but only for this species a general decreasing trend is detected between 2017 and 2022.

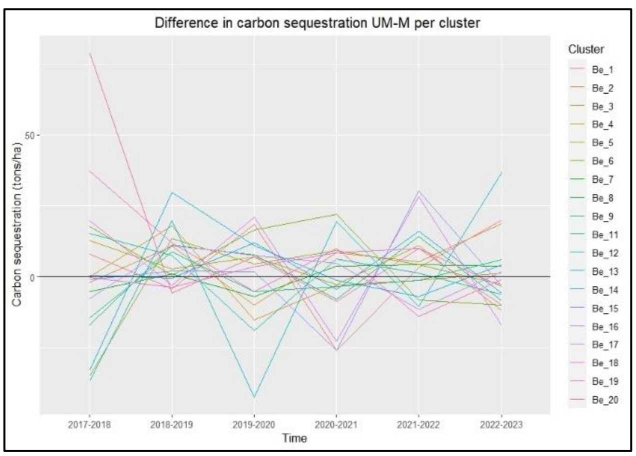


Figure III.18: The difference in carbon sequestration (unmanaged minus managed patches) per cluster between 2017 and 2023 in NP BW

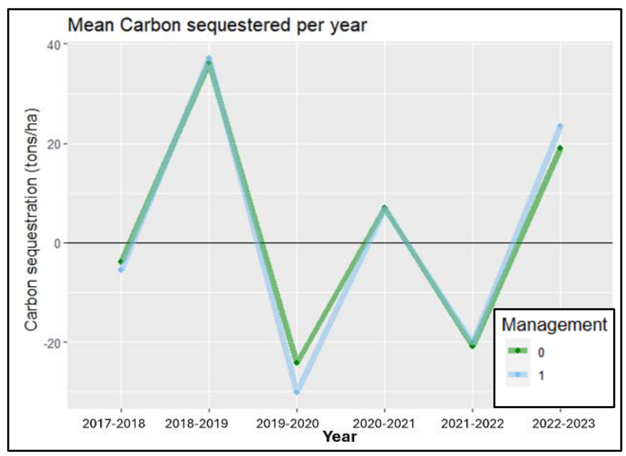


Figure III.19: The mean carbon sequestered per year between 2017 and 2023 by managed (1) and unmanaged (0) patches in NP BW

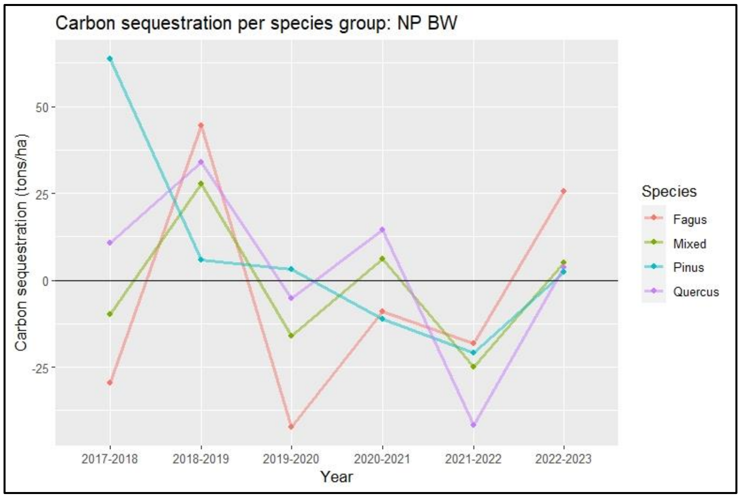


Figure III.20: The mean carbon sequestered per year between 2017 and 2023 per species group in NP BW

Again, the effect of management was confirmed by the lmm (Equation III.7). When the carbon sequestration is calculated between all subsequent years, no significant difference between managed and unmanaged patches is detected (p=0.91). No interaction effect with the dominant species could be tested due to limited data.

$$\text{Carbon sequestration} \sim \text{Management} + (1|\text{Cluster}) + (1|\text{Year}) \qquad \textbf{(Equation III.7)}$$

4.3. Comparison with CCI product

The developed model in this study gives consistently higher carbon stock estimates than the estimates obtained from the CCI (Figure III.21). In both predictions, no clear trend over the years is observed.

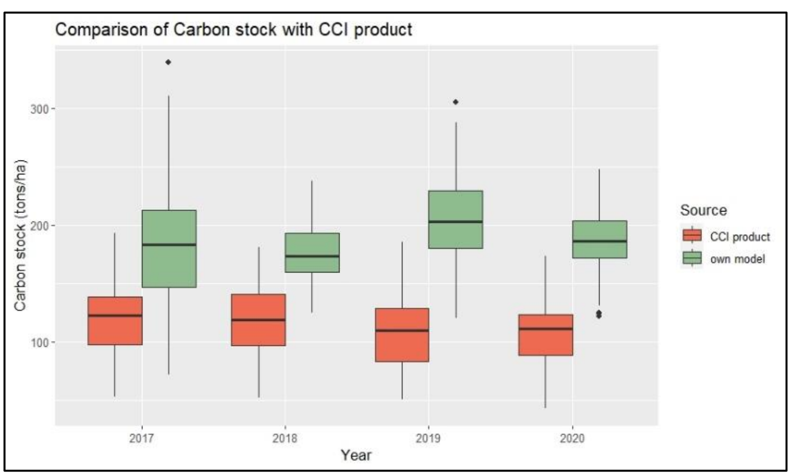


Figure III.21: Comparison of the carbon stocks estimated by CCI and by the GAM method for NP BW between 2017 and 2020

IV. Discussion

Forests play a crucial role in mitigating climate change by sequestering and storing carbon dioxide from the atmosphere. However, the impact of forest management practices on carbon stocks and sequestration rates remains a topic of significant scientific inquiry. This discussion will focus on the results of a pairwise comparison analysis of managed and unmanaged forests in two distinct study regions: the National Park Brabantse Wouden (Flanders, Belgium) and the autonomous region of Catalunya (Spain). First, methodological insights into remote sensing techniques and modeling approaches used to estimate carbon stocks and assess sequestration rates will be provided. Subsequently, the results of the carbon stock analysis will be presented, comparing managed and unmanaged forests, followed by the results of the carbon sequestration analysis. Additionally, findings from a qualitative crown fire vulnerability analysis in relation to carbon stock and forest management will be discussed. Finally, the limitations of the study will be acknowledged, and perspectives for future research to advance understanding of the complex interactions between forest management and carbon dynamics will be outlined.

1. Methodological insights

1.1. Remote sensing evaluation

The variables selected by recursive feature elimination for the Generalized Additive Model (GAM) represent different photosynthetic and structural characteristics. For the NP BW, these were: B5, B12, GNDVI, STVI3, and MCARI. Measurements from B5 at the red-edge wavelength are utilized for detecting vegetation density and type, whereas B12 captures short-wave infrared wavelengths, enabling sensitivity to variations in chlorophyll content, leaf structure, and the overall health of vegetation. Hence B5 is an indicator of the quantity of biomass and B12 of the photosynthetic (and thus carbon sequestration) capacity, therefore relevant for carbon stock assessments. Next, GNDVI (Green Normalized Difference Vegetation Index) is a chlorophyll index and indicates the nitrogen and water uptake by the plant (Otsu et al., 2019). GNDVI is primarily applied to mature crops and forests, unlike the traditionally used NDVI, which is typically more effective during early development stages (Otsu et al., 2019). As the GNDVI is more sensitive to these high chlorophyll concentrations than NDVI, it is more accurate to assess chlorophyll content at the tree crown level, according to the findings of Chen et al. (2019). Even though GNDVI does not fully solve saturation issues encountered by the regular NDVI, it slightly mitigates it. STVI3 was the fourth selected variable: a STress-related Vegetation Index, calculated with B4, B8, and B11. The selection of this index demonstrates the application potential of combining near and middle infrared bands for estimating above-ground biomass, confirming the findings of Forkuor et al. (2020). Lastly, MCARI is the Modified Chlorophyll Absorption Ratio Index; it measures the depth of chlorophyll absorption and has been proven useful in biomass assessments as an indicator of carbon sequestration capacity (Chen et al., 2019b; Nagler et al., 2000).

Different vegetation indices were selected for Catalunya. This underscores the importance of local model calibration and feature selection. In Atlantic forests, saturation issues pose the main remote sensing problems, while the heterogeneous vegetation and steep topography are problematic factors in the Mediterranean forests of Catalunya. This local context may lead to different optimal vegetation indices for carbon stock estimations and local feature selection is thus crucial. For NP BW as well as for Catalunya, recursive feature elimination scored best among the different feature selection methods tested. This method is therefore recommended for similar future research in other study areas as well. GNDVI and a different stress-related index (STVI2) recur in both study regions. The other selected variables for Catalunya are LAI and B2. LAI or the Leaf Area Index measures the amount of leaf material in the canopy, defining the size of the interface for photosynthesis (Weiss & Baret, 2016). It is therefore an indicator of plant health and biomass. B2 measures blue wavelengths in the optical spectrum, which is a wavelength at which light is absorbed during photosynthesis.

All optical remote sensing variables are indirect indicators of biomass, whereas GEDI can directly measure the tree height, which is also what is measured in the field with conventional methods. The model fit and predictive accuracy of the GAM in this study was only slightly improved. However, LiDAR proved especially useful for biomass prediction at high forest AGB values, by buffering the saturation problems of optical remote sensing. Canopy height is a morphological variable that cannot be measured by Sentinel-2, thus adding useful information to the model. NASA published a level-4 product with global above-ground biomass density estimates from GEDI. Nevertheless, similar to the lower-level GEDI products, the sparsity of data points remained problematic. Therefore, a processed tree-height product developed by ETH was used to overcome the low spatial resolution and geographical gaps of the original GEDI data. It was developed with a focus on detecting tall canopies, which also typically have large carbon stocks (explaining the buffering of saturation problems). 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 in the tropics (Lang et al., 2021) and again proved useful in our study. Our findings align with previous research combining LiDAR and Sentinel-2 for 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 as a third element. 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 reflects surface roughness and water content, VH backscatter is rather sensitive to volumetric scattering (Laurin et al., 2018). The amount of backscatter depends on the structural attributes of forest canopies and interactions between the surface and the volume of vegetation, which are both indicators of AGB.

Derivatives of Sentinel-1 bands, such as VV/VH, VH/VV, VV+VH, and VH-VV, are often favored over raw bands (VV, VH) because they have the advantage of reducing topographic and structural heterogeneity effects and they are not affected by calibration errors, as noted by Sarker et al. (2013). However, in our study, raw backscatter values were prioritized over derivatives due to the limited number of observations, preventing the inclusion of all indices for overfitting. Surprisingly, the raw backscatter values outperformed derived indices based on the resulting validation metrics. 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.

Sentinel-1 operates at C-band microwaves and is more attuned to detecting leaves and needles than trunks and branches (as opposed to P- and L-bands) (Rüetschi et al., 2018). The shorter wavelength interacts more with smaller vegetation elements and a higher water content. 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). Possibilities to improve predictions even more may lie in multifrequency remote sensing. Integrating C-band with L-band SAR can enhance the detection of texture features, vegetation diversity, and density (Laurin et al., 2018).

From this 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., 2019b; David et al., 2022; Forkuor et al., 2020b; Hoscilo et al., 2018; Nuthammachot et al., 2022). Tamiminia et al. (2024) performed a similar study in the state of New York (USA), using a canopy height map generated by Sentinel-2 and GEDI in combination with Sentinel-2 and Sentinel-1 for above-ground biomass prediction. Their obtained validation metrics (R^2 =65.00% and RMSE = 39.46 tons/ha) are in similar ranges as this study. The spectral attributes of the crown, as detected by passive optical remote sensing, are influenced by factors such as microclimate, water conditions, or the overall health status of the forest; the addition of LiDAR and SAR offers possibilities for more accurate detection of such local differences while also reducing signal saturation effects.

1.2. Model evaluation

The GAM proved successful in this study for modeling above-ground biomass carbon stock in NP BW, in line with the results of Soriano-Luna et al. (2018) and Rosas-Chavoya et al. (2023) in temperate forests in Mexico. In Flanders and Catalunya, GAM methods were already used for other purposes in ecological research, and are praised for their flexibility and interpretability (Aertsen et al., 2010; Wen et al., 2022). However, no earlier studies were found using GAM for above-ground carbon stock prediction in Atlantic and Mediterranean forests in Europe. In several recent above-ground biomass modeling studies, Random Forest was preferred over other modeling algorithms (Chen et al., 2019b; Forkuor et al., 2020b; Hoscilo et al., 2018; Torre-Tojal et al., 2022b). This contradicts the findings of this study, where Random Forest was outperformed by the GAM. The GAM showed high potential for further research in this area, offering higher interpretability compared to the Random Forest while allowing complex interactions between the response and the predictor variables and imposing fewer model assumptions than the linear model.

However, no successful modeling technique was found for Mediterranean forests (Catalunya). Even though a moderately good model fit was achieved (R^2=51.68%), the predictions on the test dataset were not sufficiently accurate (RMSE=14.18 tons/ha, MAE=13.42 tons/ha). When only the measured carbon stocks in diameter classes B, C, and D were used to calibrate the GAM, a highly improved predictive accuracy was obtained. As such, especially biomasses in the lowest diameter class are difficult to detect by remote sensing, as was expected. Mediterranean pine and mixed forests are typically strongly layered with pines in the upper-canopy layer, several under-canopy layers of shade-tolerant broadleaves (e.g. *Quercus ilex*) and shrubs (e.g. *Buxus sempervirens*) in the lowest layer (Morsdorf et al., 2010; Puletti et al., 2021). The signal is obstructed by many vegetation layers in higher diameter classes and the complex structure of the lower vegetation (Tuanmu et al., 2010). Optical remote sensing is known to have difficulties in accurately measuring AGB in mountainous areas, and the low water content and heterogeneous vegetation aggravate signal distortion, as earlier studies show (Delalay et al., 2019; Kycko et al., 2022). Steep slopes and high variation in topography and microclimate result in a high variation in carbon stock across the region (Figure III.6). To correctly model this variation, a higher number of field plots is necessary in the future (Lu et al., 2012). Moreover, the addition of SAR detectors in L-band has proven useful to capture above-ground biomass in Catalunya by Olivares-Cabello et al. (2021) and may help to obtain a successful model, detecting more structural variation in the lowest diameter class.

Overall, the obtained standard errors on the carbon stock estimates at the patch level for NP BW were acceptable (0.43-5.94 tons/ha). This model uncertainty arose from the prediction error of the GAM, but also other sources of uncertainty were present in the data collection and processing steps. Measurement errors in the field are inherent to the conventional method, particularly regarding height measurements. The laser signal frequently encountered obstruction from surrounding vegetation, posing challenges to accurate measurements. Smaller errors in the DBH may have occurred for irregular tree stems. Unfortunately, a high number of sample plots is necessary for such a thorough uncertainty analysis, which was not possible due to limitations in time and resources. Small uncertainties during biomass calculations (e.g. biomass conversion factors) and preprocessing (e.g. geometrical and radiometric correction) are expected to have minimal effects on the final results (Lu et al., 2012). Nevertheless, awareness of these uncertainties is necessary for the correct interpretation of the results.

The first research question is thus answered by agreeing with the research hypothesis: multisource remote sensing is superior over the use of only passive optical remote sensing for estimating above-ground biomass carbon stock.

2. The effect of forest management on carbon stock

In this section, the two study regions will be discussed separately because they are characterized by different modeling difficulties, remote sensing indicators and forest types, leading to different conclusions.

2.1. National Park Brabantse Wouden

From the measured carbon stocks in the field, a significant difference between managed and unmanaged forest patches was detected in NP BW. Surprisingly, the tree density was higher in managed plots and this difference could be assigned to the lowest diameter class (A). A few plots were situated in dense regeneration, and unmanaged plots on average thus had fewer but larger trees (in height and diameter). Older trees can continue growing without being harvested in unmanaged plots, leading to a higher biomass and carbon stock. No conclusion could be made about specific management techniques, given the low number of patches per management type. Decisions on thinning intensity, thinning type, rotation period, and harvesting operations may have positive or negative effects on carbon stock (Ruiz-Peinado et al., 2017b). The results of the measured carbon stock corroborate with Chatterjee et al. (2009), Garcia-Gonzalo et al. (2007), and Gurung et al. (2015) and do not reject the research hypothesis.

The mean carbon stock for managed plots was 143.68 ± 48.90 tons/ha, for unmanaged patches this was 196.50 ± 61.28 tons/ha. This is a rather high carbon stock, compared to the findings of Vanhellemont et al. (2024). On silt soils in Flanders, they found on average 119.8 ± 72.1 tons/ha of carbon stock, and 152.7 ± 39.9 tons/ha in set-aside forest reserves (unmanaged), where this was 93.8 ± 54.7 and 112.8 ± 37.7 tons/ha respectively on sandy silt soils. The NP BW is situated on highly fertile silt and sandy silt soils, among the most favorable of Flanders, which can explain the relatively high carbon stock. Moreover, the bigger forest complexes in NP BW, compared to other regions in Flanders, may serve as a buffer against disturbances such as air pollution and storms, which leads to lower mortality. Additionally, the data used by Vanhellemont et al. (2024) dates from 2009 to 2018, and as they report positive carbon sequestration, the carbon stock has probably increased since then. While non-standing dead wood is not taken into account in this study, all diameters are considered, and the opposite was true in the study of Vanhellemont et al. (2024) which could also explain some differences in the results.
The species richness was approximately the same in managed (18) and unmanaged (19) plots. Conversely to other species, *Fagus* stands had a similar carbon stock for managed and unmanaged patches (Figure III.4). An explanation may be that the unmanaged *Fagus* stands are characterized by low undergrowth. These areas have only remained unmanaged for a limited time, and the high canopy closure limits undergrowth, which typically occurs in naturally regenerated unmanaged stands. Thus, the lack of undergrowth that persists in unmanaged beech forests explains the similarity to managed stands. This confirms the findings of Stiers et al. (2018), who found that structural complexity does not increase in the first 30 years after abandonment of beech forests. According to Jandl et al. (2017), species with a higher wood density (broadleaf) have a higher biomass production and thus a higher carbon stock. This was confirmed, as the lowest above-ground carbon stock was detected for *Pinus* stands compared to broadleaf and mixed stands. *Pinus* species typically exhibit faster growth rates than broadleaves. As a result, the wood of *Pinus* species tends to have a lower density, which contributes to their lower biomass and carbon stock.

The results derived from the measured plots thus revealed significant differences, whereas the GAM, extrapolated over the entire study area at pixel level using remote sensing data, did not detect any significant differences. Moreover, the obtained estimated differences in mean carbon per patch did not fully align with the differences measured on the field. For example, within cluster Be_9, the managed patch stocked 90 tons/ha more carbon than the unmanaged patch, according to field measurements. In the model predictions, however, the unmanaged patch stored about 2 tons/ha more carbon. In addition, within cluster Be_7, the unmanaged forest patch is measured to stock 182 tons/ha more carbon than the managed patch, though the model estimates a difference of 12 tons/ha in the opposite direction. Overall, carbon differences estimated by the model are smaller (between 0-40 tons/ha) than measured in the field (10-180 tons/ha). The mean carbon stock of the field-measured plots is 196.5 ± 61.3 tons/ha for unmanaged and 143.7 ± 48 tons/ha for managed plots. According to the model, this is 165.9± 26.5 tons/ha for unmanaged patches and 166.8 ± 32.3 tons/ha for managed patches. The unmanaged patches thus appear to be underestimated by the GAM when considering the conventional field method as the ground truth, and the opposite is true for managed patches. 13 out of the 15 plots with the lowest measured biomass were managed, and 14 out of the 15 plots with the highest biomass were unmanaged. First, the underestimation of high biomasses (unmanaged patches) can be assigned to oversaturation, as is common when passive optical remote sensing and SAR fail to detect complex forest structures. Oversaturation at 400 tons/ha biomass (200 tons/ha carbon stock) was noted for NP BW, in accordance with several earlier studies (Hoscilo et al., 2018; Laurin et al., 2018). Second, low biomasses (managed patches) were overestimated; this corresponds with the research of Hoscilo et al. (2018) and Zhang et al. (2023). Despite the different carbon stock ranges, the GAM was calibrated with a dataset containing both managed and unmanaged patches. As a result, the estimated carbon stock values are linked to remote sensing values that are not representative, leading to an overestimation. A solution could be to separately model managed and unmanaged patches, but more observations are then needed. Lastly, fewer plots were measured in these outer ranges, which may also lead to deviations, as well for low as for high biomasses. Nevertheless, the error decreased when adding indices from SAR and LiDAR, corresponding to the findings of Hoscilo et al. (2018), Forkuor et al (2018), and David et al. (2022).

Even though a satisfactory model fit and prediction accuracy were obtained for the NP BW according to the validation parameters, modeling with remote sensing indices did not detect the subtle differences between managed and unmanaged forests when extrapolating over the whole study area. Next to the technical limitations as described above, it is possible that the forest has not been unmanaged for long enough to detect a difference through remote sensing, while it is already detectable by field measurements. This may be the case if the extra carbon stock in unmanaged forests mostly occurs in the understory and if these smaller trees are insufficiently detected by remote sensing. However, part of the NP BW is characterized by monumental beech trees with little undergrowth and table III.1 also indicates the opposite. For these forest types, this explanation is not satisfactory. Past management intensity was defined as one of the major drivers for above-ground carbon stock in Atlantic forests by Pires Coelho et al. (2022). Hence, this similar management history may overrule the effect of current management practices in remote sensing analyses.

Despite the fact that the model detected no overall significant effect of management, the interaction between management and the species group *Pinus* was remarkable. Unmanaged *Pinus* patches had a markedly higher carbon stock than the managed patches, unlike the other species groups. Pine forests are generally more open than broadleaf forests (lower canopy closure), hence this difference may be detected more easily by remote sensing than in *Quercus* or mixed broadleaf forests with a dense canopy cover. This estimated difference coincides with the findings of Chatterjee et al. (2010) and with the measured plots, where unmanaged pine stands had a higher carbon storage in AGB than managed stands. Managed pine plots were characterized by a higher tree density in the undergrowth, caused by a lower tree density in the upper canopy layer due to continued thinnings. Nevertheless, the carbon stock was markedly higher for all three DBH-class levels in unmanaged forests. Regardless of the tree density, the difference in carbon stock was thus mostly attributed to the size of the trees, both in under- and upper canopy layers.

2.2. Catalunya

No significant difference was measured in the field between the managed and unmanaged forest patches in Catalunya. Managed plots had a mean carbon stock of 20.85 $\pm$ 13.30 tons/ha, in unmanaged plots the mean stock was 26.43 $\pm$ 18.48 tons/ha. The high standard error compared to the mean carbon stock should be noted, showing a high variation in carbon stocks among the plots. The measured mean carbon stock is however low compared to the findings of Simonson et al. (2016), who found an average carbon stock of 62.45 tons/ha in mixed forests in Catalunya, compared to 18.82 $\pm$ 7.61 tons/ha in mixed forests in this study. Ameztegui et al. (2022), and Olivares-Cabello et al. (2021) confirm the findings of Simonson et al. However, the high variation and wide range of biomasses correspond with estimates by Ispikoudis et al. (2024) in the Mediterranean forests of Greece.

While unmanaged forests had a higher tree density, managed forests were, on average, characterized by larger height and DBH measurements. The higher biomass in diameter class A in unmanaged forests, caused by a high density of young trees, is thus balanced by fewer but thicker trees in managed plots (level C+D), which is the opposite as in the NP BW. Species richness was again similar in managed (26) and unmanaged (24) plots. Even though no difference was detected from the measured plots, the effect of management is especially important in Mediterranean forests, according to the literature. Vayreda et al. (2012) mention that due to climate change, lower water availability is leading to a reduction in the carbon sink capacity of unmanaged forests, while this is more controlled in managed forests. Additionally, management is important to reduce wildfire sensitivity and protect carbon stocks (see section 4).

It should be noted that lower vegetation (< 2m) such as shrubs were not measured in this study, while they were observed in the field to be omnipresent and they may also store a significant amount of carbon. Ruiz-Peinado et al. (2017) state that 1-29% of the total above-ground carbon of Mediterranean forests is stocked in shrubs, depending on the forest type, climate, and location. Kycko et al. (2022) confirm that shrublands cover 14% of Catalunya because shrubs can withstand dry and warm conditions better than larger trees.

Given the expected significance of forest management on the amount and protection of carbon stock, further research with more observations and measurements including shrubs is recommended. Special attention to the detection of low vegetation is necessary.

The second research question can thus not be answered unambiguously. In NP BW, the carbon stock in unmanaged forests is higher than in managed forests according to field measurements, agreeing with the research hypothesis. In Catalunya however, no significant difference was found.

3. The effect of forest management on carbon sequestration

In the NP BW, managed and unmanaged forest patches both follow a fluctuating, but net-zero, trend between 2017 and 2023 regarding carbon sequestration. Forests can switch between being a carbon sink and a source of carbon depending on disturbances, management activities, and succession stages (Garcia-Gonzalo et al., 2007b). Possibly, a time horizon of seven years is not sufficient to see an overall trend. Nevertheless, these findings contradict the findings of Vanhellemont et al. (2024). Over a mean time horizon of 15 years, they reported a significant increase in carbon stock (1.3 tons.ha^{-1}yr^{-1}) in Flanders' forests, while the ecological carrying capacity was not yet reached at the end of their study (2018). They reported a significantly higher carbon stock change in set-aside (unmanaged) forests compared to the 'average' Flemish forest (managed and unmanaged), as obtained from the Flemish Forest Inventory. The non-significance of management according to our results may be explained by the fact that the unmanaged patches have only been unmanaged for a limited time (at least 20 years but never more than 50 years), and therefore do not distinguish themselves yet in detectable carbon sequestration differences. This adaptation period is confirmed by Kern et al. (2021). On the other hand, the GAM method did not successfully detect the differences in carbon stocks between managed and unmanaged patches in 2023, and the same is true for 2017-2022. As there is only field data collected from 2023, and model estimations of the difference in carbon stock between managed and unmanaged plots showed unreliable, it cannot be ruled out that there is a difference in carbon sequestration between managed and unmanaged forests.

In this study, the wood stocked in the products obtained from managed forests was not taken into account. In studies where extracted wood was considered to be stocked in sustainable products and this carbon stock was taken into account in the calculations, managed forests were found to have a higher rate of carbon sequestration (Pukkala, 2017b; Ruiz-Peinado et al., 2017b). Pukkala (2017) found that in the longer term, considering a time horizon of more than 100 years, the carbon balance in managed forests is higher when considering the substitution effect of the wood products (where carbon emissions are avoided in other industries by using wood as an alternative product). These studies, however, require complex lifecycle analyses as carbon is also lost into the atmosphere during the harvesting and processing cycle,

In 2017, a remarkably higher variation in carbon stock is estimated compared to the other years. 2017 is the first year Sentinel-2 was active in data collection and a lower data quality and initial data calibration may therefore explain the high variation in predicted carbon stocks. In 2019 as well, there was a high variation in carbon stock estimates among the managed patches. 2019 was characterized by intense heatwaves in July and August, coinciding with extreme droughts. Climate is among the most influential variables for carbon sequestration and this drought may have affected forest patches differently, depending on the microclimate and forest structure (Kern et al., 2021b). The higher structural heterogeneity in unmanaged forests may explain why this variability is not detected among the unmanaged patches. As the spring of 2019 was favorable in climate, the carbon sequestration was still positive between 2018 and 2019. Extreme droughts induce heat stress, resulting in closing leaf stomata and reduced photosynthesis (and thus reduced carbon sequestration). This reduced photosynthesis and increased tree mortality resulted in a decrease in carbon stock the next year (2020). This trend continues over the years 2019-2022. Except for 2021 (extremely wet summer), several dry years followed, slowing down forest recovery.

The lack of a clear trend in carbon stock over the years is confirmed by the estimations according to the Climate Change Initiative (CCI) product. However, the CCI product is not locally calibrated and was validated by a set of field measurements, heterogeneously spread over the world. The closest validation plots included were in the Netherlands, representing temperate oceanic forests. It therefore makes underestimations of the above-ground carbon stock compared to the model used in this study. CCI itself already obtained an underestimation in the validation results for the temperate broadleaf and mixed forests biome (Kay et al., 2019). This underestimation of the biomass by CCI and the lack of correlation to local field measurements was also reported by Bhat et al. (2023). Lastly, the spatial resolution is quite large (100m) for estimations at the forest stand level, so local variations are less accurately detected, even when only pure pixels within the forest stand are used (Bhat et al., 2023; Kay et al., 2019).

For Catalunya, no carbon sequestration could be calculated, as the predictive accuracy of the model did not suffice.

The third research question cannot be answered confidently. The model findings for NP BW do not agree with the hypothesis that managed forests sequester more carbon, as no difference was found. However, the obtained model estimates cannot be fully trusted as the management difference was not detected either for the year 2023 (when field measurements showed otherwise). For Catalunya, no carbon sequestration could be estimated.

4. Integrating wildfire resilience into the carbon budget

Catalunya is one of the most drought-sensitive regions of Europe, extremely susceptible to wildfires. Even though the number and affected area of wildfires have been reduced over the last 20 years, the intensity of the wildfires has increased (forestWISE, z.d.; gencat, 2024). This leads to more destructive and dangerous wildfires, implying more environmental, economic and human damage. Taking into account the vulnerability of forests to wildfires, and especially the most destructive and rapidly propagating crown fires, is therefore an essential aspect to include in carbon stock and management analyses in the region as it reflects the stability of the stock. Bradford et al. (2013) modeled the influence of natural disturbances on carbon stocks and found that the increase of wildfires by climate change in such regions may affect carbon stocks more than timber harvesting, partly because of the larger area that is affected. Not only above-ground biomass is directly destroyed by wildfires but also soil carbon stocks and soil quality are severely affected. This leads to a switch in vegetation type (and carbon stock) after a wildfire, as was observed in the field. In Catalunya, *Pinus halepensis* grows vigorously on burnt soils, leading to a homogenous and high-density forest stand. The amount of carbon stock was expected to positively relate to crown fire vulnerability, while management could decrease this vulnerability.

The majority of the managed plots were indeed in the lowest crown fire vulnerability class and only unmanaged plots were assigned to the highest vulnerability class. Unmanaged plots had a higher tree density, especially in the lower diameter classes, which relates to the crown fire vulnerability (Table III.1) (Dupire et al., 2019; Piqué et al., 2011). That is, low vegetation can serve as a ladder for the fire to reach the crown. Management practices such as the removal of ladder vegetation and prescribed fires at a sustainable regime may help to avoid disastrous mega-fires and protect the present carbon stock (Adame et al., 2020). Indeed, there was a positive relationship between carbon stocked in the lowest diameter class and crown fire vulnerability.

Conversely, there was no relation between crown fire vulnerability and overall carbon stock. This contradicts the research of Ruiz-Peinado et al. (2017) and Adame et al. (2020). Further research in this area, with a higher number of sample plots is therefore certainly necessary, to statistically confirm or reject the hypothesis.

The last research question can be answered (non-statistically) by agreeing with the research hypothesis on the relation between forest management and crown fire vulnerability: managed plots are generally less vulnerable to crown fires. However, no relationship with total carbon stock was found, disagreeing with the last research hypothesis.

5. Relevance, limitations and perspectives

The study is among the first to experimentally study the effect of forest management from carefully selected forest patches that are as similar as possible in climate, soil, and topography. The effect of forest management on carbon stock and sequestration could thus be extracted with minimized side effects. Carbon stock is a crucial variable in the current battle against climate change, and this study offers a deeper understanding of its distribution and dynamics across forest types, climates, and management regimes. By clarifying the differences in carbon storage and sequestration between managed and unmanaged forests, this study contributes to the development of sustainable forest management practices that guide forest managers with unambiguous decision rules into sustainable yet profitable forest management in a changing climate. Furthermore, research in this domain holds significance in the context of carbon credit schemes, where accurate assessment of carbon stocks and sequestration rates is essential for incentivizing forest conservation and restoration efforts. However, the success of the different remote sensing sources used in this study shows high dependency on the study site, forest type, and climate. The outcome of this study is therefore especially useful regarding management perspectives and further research in the NP BW and Catalunya.

Some limitations need to be noted from this study, which may also offer opportunities for further research. Accurate above-ground biomass prediction remains a challenge due to signal saturation. Even though progress is made by combining different sensors, underestimation above a standing stock threshold of 400 tons/ha biomass remains an issue. Additional SAR at P- or L-band may help to decrease this oversaturation effect even further. Another limitation of this study is the limited number of plots. Especially in Catalunya, this caused modeling difficulties. The high heterogeneity in forest structures, topography, and climatic conditions require more than 49 plots. Also in the NP BW, more plots could help to increase the model accuracy even more and detect the measured difference between managed and unmanaged forest stands.

It should be noted that more benefits can often be obtained from managed forests regarding wood and non-wood forest products and maximizing the carbon stock is not the only management goal. Other forest ecosystem services such as wildfire protection, recreation, water purification, and wood provision should be considered while maintaining a climate-robust and healthy forest. Future research should thus also consider those other ecosystem services in a local context, next to carbon stock and sequestration, and consider the trade-offs that occur between them. An example is the trade-off between forest fire vulnerability and carbon stock, which was the only ecosystem trade-off that was covered (to a limited extent) in this study. As forest area and vitality are decreasing worldwide, it is crucial to optimally manage the remaining forest ecosystems, taking social, ecological, and economic benefits and their trade-offs into account. More detailed effects of different management practices, rotation lengths, and thinning regimes on carbon stock, including the substitution effect of resulting wood products, were beyond the scope of this study but could lead to more specific management guidelines and decision rules.

V. Conclusion

In the context of a rapidly changing climate, forest degradation, and upcoming carbon credit schemes, the accurate, time- and cost-efficient quantification of carbon stocks is crucial. Moreover, a deeper understanding of the relationship between management and carbon stock as well as sequestration may lead to the development of sustainable forest management guidelines, necessary to obtain climate-smart forests and optimally benefit from the nature-based solutions they offer.

From this study, it can be concluded that the combination of passive optical remote sensing (Sentinel-2), synthetic aperture radar (Sentinel-1), and spaceborne LiDAR (GEDI) significantly improves the performance of a generalized additive model (GAM) for estimating above-ground biomass carbon stock compared to Sentinel-2 alone, thus confirming the first research hypothesis that the combination of multiple remote sensing sources improves carbon stock estimation. Generalized additive models (GAM) outperformed Random Forest and showed high potential in this research area, combining interpretability and flexibility with the ability to model complex relationships in an ecological context.

Regarding the second research question on the influence of forest management on above-ground biomass carbon stock, no unambiguous answer was found. According to the field measurements, the Atlantic forests of the National Park Brabantse Wouden (NP BW) should remain unmanaged when the intention is to maximize above-ground biomass carbon stock, while there was no significant difference measured in the Mediterranean forests of Catalunya. However, testing this hypothesis on the carbon stock estimated by the model caused difficulties. First, no satisfactory model validation parameters were obtained for Catalunya, and no extrapolation was made. Especially the lower vegetation was not successfully detected by remote sensing. Second, the final GAM obtained from remote sensing data in the NP BW did not detect the effect of management on carbon stock that was measured in the field, except for plots dominated by *Pinus* species. The open structure of pine forests compared to broadleaves may explain why the difference is detectable for these stands. In general, an underestimation was made compared to the obtained field measurements, despite the satisfactory model fit and prediction accuracy. Possibly, the similar management history and limited time of non-management restricts the detection of subtle differences in carbon stock between managed and unmanaged forests by remote sensing. Moreover, remote sensing may be characterized by inherent technical shortcomings restricting accurate measurements.

The third research hypothesis, stating an expected higher carbon sequestration for managed forests, was rejected as no difference between managed and unmanaged forest patches in carbon sequestration from 2017 up to 2023 was found for NP BW. However, the inherent deficiencies of remote sensing based information in the model of 2023 most probably also affect the estimates over the years and restrict the detection of the differences in carbon sequestration between managed and unmanaged forests. Moreover, an overall net-zero trend in carbon sequestration was observed, as opposed to earlier experimental studies in the same region. A time horizon of seven years may be too short to detect carbon stock changes, or the increasing droughts and heatwaves in the last decade might have affected the carbon sequestration capacity of Flanders' forests.

Lastly, a qualitative study on the crown fire vulnerability was performed in Catalunya. The research hypothesis that management reduces crown fire vulnerability could not be statistically tested due to a limited number of observations. Nevertheless, management indeed appeared to reduce the vulnerability to crown fires. No relation was found with above-ground biomass carbon stock, but plots with a higher carbon stock in the smallest diameter class generally had a higher crown fire vulnerability. This lower vegetation can serve as a ladder for the fire to reach the canopy, highly increasing its propagation speed and impact.

The addition of multi-frequency SAR in future research may help to reduce signal saturation and improve model prediction. Additionally, more field data should be collected, especially for Catalunya. Further research on the influence of more specific management regimes on carbon stock and sequestration and the trade-offs with other ecosystem services could lead to more specific management guidelines and decision rules.

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VII. Appendices

1. Appendix 1: overview of the plots in Catalunya

Table VII.1 All measured plots in Catalunya with location information.

Patch ID	Plot ID	date	GPS mark	latitude	longitude	aspect	slope
SRB_08_Mb	0	18/09/2023	147	42.09986111	1.1475	SW	10
SRB_08_Mb	2	18/09/2023	148	42.10069444	1.14594444	SE	25
SRB_04_NM	3	19/09/2023	149	42.06552778	1.21538889	SE	20
SRB_04_NM	4	19/09/2023	150	42.06894444	1.21655556	E	15
SRB_04_NM	5	19/09/2023	151	42.07133333	1.21355556	E	25
SRB_08_NM	6	18/09/2023	144	42.09186111	1.14655556	SW	35
SRB_08_NM	7	18/09/2023	145	42.09697222	1.1455	S	35
SRB_08_NM	8	18/09/2023	146	42.09733333	1.14769444	E	20
SRB_OUT_09_M	9	08/09/2023	125	42.30133333	2.63155556	N	25
SRB_OUT_09_M	10	08/09/2023	123	42.30038889	2.63719444	N	17.5
SRB_OUT_09_M	11	08/09/2023	124	42.29994444	2.63069444	NE	15
SRB_OUT_08_M	12	08/09/2023	126	42.31077778	2.65527778	S	20
SRB_OUT_08_M	13	09/09/2023	128	42.31516667	2.66555556	S	35
SRB_OUT_08_M	14	09/09/2023	127	42.31544444	2.67033333	S	20
SRB_OUT_15_M	15	14/09/2023	135	42.18527778	2.21455556	S	25
SRB_OUT_15_M	16	14/09/2023	137	42.18775	2.20677778	S	20
SRB_OUT_15_M	17	14/09/2023	136	42.18472222	2.21197222	S	20
SRB_OUT_21_NM	22	28/08/2023	110	41.79666667	1.76313889	N	20
SRB_OUT_21_NM	23	25/08/2023	107	41.79363889	1.7655	N	5
SRB_OUT_14_M	24	13/09/2023	133	42.160859	2.209151	SW	35
SRB_OUT_14_M	25	13/09/2023	134	42.16316667	2.20997222	NW	25
SRB_OUT_14_M	26	13/09/2023	132	42.15897222	2.20747222	NW	30
SRB_04_M	27	19/09/2023	153	42.07655556	1.21869444	E	35
SRB_04_M	28	19/09/2023	154	42.07388889	1.21880556	E	15
SRB_04_M	29	19/09/2023	152	42.07566667	1.301475	NE	30
SRB_OUT_08_NM	30	09/09/2023	129	42.31430556	2.66583333	S	15
SRB_OUT_08_NM	31	09/09/2023	130	42.31433333	2.66322222	S	30
SRB_OUT_08_NM	32	09/09/2023	131	42.31308333	2.66277778	O	25
SRB_OUT_09_NM	33	07/09/2023	121	42.32411111	2.63605556	NW	35
SRB_OUT_09_NM	34	07/09/2023	122	42.32316667	2.6355	NW	30
SRB_OUT_09_NM	35	07/09/2023	120	42.32375	2.61230556	N	35
SRB_OUT_14_NM	39	16/09/2023	143	42.18897222	2.20038889	NW	20
SRB_OUT_14_NM	40	14/09/2023	138	42.18444444	2.21030556	N	30
SRB_OUT_14_NM	41	16/09/2023	142	42.18691667	2.20025	S	20
SRB_OUT_15_NM	42	15/09/2023	140	42.18622222	2.20411111	SW	30
SRB_OUT_15_NM	43	16/09/2023	141	42.18647222	2.20022222	S	30
SRB_OUT_15_NM	44	15/09/2023	139	42.18352778	2.20575	SW	30
SRB_OUT_21_M	45	28/08/2023	107	41.78836111	1.74605556	N	25
SRB_OUT_21_M	46	28/08/2023	109	41.7905	1.75188889	N	20
SRB_OUT_21_M	47	28/08/2023	108	41.79066667	1.74575	N	15
SRB_OUT_01_NM	48	29/08/2023	113	41.35113889	1.51477778	N	15
SRB_OUT_01_M	49	29/08/2023	111	41.35022222	1.50811111	N	5
SRB_OUT_01_M	50	29/08/2023	112	41.35177778	1.51330556	N	20
SRB_OUT_02_NM	51	31/08/2023	118	41.34888889	1.02830556	N	10
SRB_OUT_02_NM	52	31/08/2023	117	41.35119444	1.02638889	S	30
SRB_OUT_02_NM	53	31/08/2023	119	41.34411111	1.02833333	N	20
SRB_OUT_02_M	54	31/08/2023	116	41.34305556	1.02405556	N	30
SRB_OUT_02_M	55	31/08/2023	114	41.34436111	1.02191667	N	30
SRB_OUT_02_M	56	31/08/2023	115	41.34386111	1.02372222	S	25

Table VII.2: Comments noted in the field per plot in Catalunya

plot_ID	comment
0	
2	Seems to be close to the border of a patch
3	
4	Managed? Some trees were cut
5	
6	Managed? Some trees were cut
7	Species different from plot 6: no pines
8	
9	a lot of dead wood
10	GPS did not function properly in the vally, check later if position was close
11	A lot of bramble. Open forest, but dense low vegetation cover.
12	Terrace plot.
13	Between 2 roads.
14	Change in vegetation 50 m downhill. Rest of the patch is Qi, while here pine dominates. Dead wood. Brambles.
15	A small path runs through plot, but this is not bigger than the distance between the trees
16	plot replaced, away from a big road
17	Plot was on big road, so was moved +- 20 m from road
22	Very, very dense. Same patch as plot_ID 23
23	Very dense forest of natural regeneration of allepo pine after wildfire
24	dense plot, difficult to access, steep slope.
25	Dense vegetation. Qgis plot was too close to cliff and train track, so a safer spot was chosen
26	The plot does not seem managed. Dead wood. Too little Ps to be classified as a Ps forest. Nikon forester is not possible to use
27	
28	
29	Plot replaced because of road and big boulders
30	
31	
32	plot next to wall, so plot was moved 10 m. Plot near river valley so denser vegetation.
33	rocks, 20 m high rock wall just behind the plot.
34	stones on the hill --> open space + dead wood DBH 7.5
35	thick litter layer, dead wood, steep hill, replaced plot to a representative part of the forest
39	Very little pine for a pine stand: more acer campestre and quercus humilis
40	a lot of beech for a pine classified forest.
41	Similar as Qh plots NM, delineation of patches is not clear. Estimation of level A done from distance as it was very difficult to get to
42	Lot of dense Corylus avelanum
43	Plot was on the road. Left: too steep & slippery (dangerous). Right: near border of pine patch. A lot of dense dead Buxus

44	Plot was replaced a little (15m), because of inaccessibility, terrace-like plot.
45	Steep terasses from old vineyard/olive tree planting. Vertex had many issues with finding respons due to branches being in the way of the top.
46	Darker than plot_ID 47.
47	Same steep terasses
48	
49	
50	2 Qi qualified for the 15 m plot (25, 28 DBH), but they were the only Qi that were present in the whole visible area and were therefore left out because of possible biased extrapolation
51	Remarkably bigger trees. Probably because in lowest point of valley
52	Moved plot because could not get through. Very steep again
53	Moved plot because the random point was in the middle of a part that they managed for an experiment. 1 dead tree on ground: DBH: 25cm & L 7m
54	Very steep slope again
55	Plot was in middle of road. So I decided to move it as it better represents the area. Steep terrain and remarkably lower trees
56	Moved a bit up the slope because point was in a river bed.

2. Appendix 2: Overview of the plots in the NP BW

Table VII.3:All measured plots in the NP BW with location information

Patch ID	Plot ID	date	GPS mark	latitude (°)	longitude (°)	aspect (N/S)	slope (%)	tree_ layers
BW_Hev_01	0	07/08/2023	105	50.830556	4.681528	0	0	2
BW_Hev_01	1	18/08/2023	37	50.83013333	4.6673	0	0	3
BW_Hev_01	2	18/08/2023	36	50.83155	4.679516667	0	0	2
BW_Hev_02	3	07/08/2023	104	50.829694	4.678222	0	0	2
BW_Hev_02	4	18/08/2023	34	50.83105	4.678316667	0	0	+
BW_Hev_02	5	18/08/2023	35	50.8307	4.676733333	0	0	2
BW_Hal_11	6	09/10/2023	178	50.70288889	4.275833333	0	0	2
BW_Hal_11	7	09/10/2023	176	50.70272222	4.27675	0	0	2
BW_Hal_11	8	09/10/2023	174	50.70166667	4.277444444	0	0	3
BW_BB_01	9	22/08/2023	46	50.88196667	4.6457	N	?	+
BW_BB_01	10	22/08/2023	47	50.8829	4.6454	E	?	+
BW_BB_01	11	22/08/2023	48	50.88203333	4.648266667	0	0	+
BW_SON_10	12	28/08/2023	73	50.78481667	4.433683333	W	?	2
BW_SON_10	13	28/08/2023	72	50.7842	4.431333333	N	?	2
BW_SON_10	14	21/08/2023	38	50.78058333	4.431816667	?	?	3
BW_BB_04	15	31/08/2023	80	50.88821667	4.635416667	0	0	2
BW_BB_04	16	31/08/2023	81	50.88345	4.638833333	0	0	2
BW_BB_04	17	31/08/2023	83	50.8838	4.6407	0	0	+
BW_BB_03	18	31/08/2023	82	50.8821	4.640883333	0	0	2
BW_BB_03	19	31/08/2023	84	50.8813	4.643416667	0	0	+
BW_BB_03	20	31/08/2023	85	50.87775	4.6418	0	0	2
BW_BB_02	21	22/08/2023	45	50.8454666667	4.640966667	SE	?	2
BW_BB_02	22	22/08/2023	44	50.88085	4.637683333	0	0	2
BW_BB_02	23	22/08/2023	43	50.88121667	4.63595	0	0	2
BW_SON_09	24	28/08/2023	70	50.78293333	4.427866667	NE	?	2
BW_SON_09	25	28/08/2023	69	50.7791	4.428833333	0	0	2
BW_SON_09	26	28/08/2023	71	50.78368333	4.426766667	0	0	2
BW_MW_19	27	23/08/2023	54	50.8038	4.6683	0	0	+
BW_MW_19	28	23/08/2023	53	50.80576667	4.672216667	0	0	+
BW_MW_19	29	23/08/2023	52	50.80535	4.674833333	0	0	3
BW_MW_14	30	30/08/2023	75	50.80631667	4.738333333	0	0	+
BW_MW_14	31	30/08/2023	74	50.80905	4.738683333	0	0	2
BW_MW_14	32	30/08/2023	76	50.8062	4.736266667	0	0	2
BW_MW_13	33	30/08/2023	79	50.80283333	4.733083333	0	0	2
BW_MW_13	34	30/08/2023	78	50.80373333	4.735933333	SW	?	1
BW_MW_13	35	30/08/2023	77	50.80435	4.7365	W	?	2
BW_MW_12	36	01/09/2023	86	50.81793333	4.727416667	0	0	2
BW_MW_12	37	01/09/2023	87	50.81821667	4.730516667	0	0	+
BW_MW_12	38	01/09/2023	88	50.81938333	4.731083333	0	0	3
BW_MW_10	39	01/09/2023	91	50.81751667	4.744933333	0	0	2
BW_MW_10	40	01/09/2023	90	50.81605	4.74365	0	0	1
BW_MW_10	41	01/09/2023	89	50.81635	4.741433333	0	0	2
BW_MW_09	42	26/08/2023	63	50.80256667	4.722616667	0	0	2
BW_MW_09	43	26/08/2023	62	50.80391667	4.720116667	0	0	+
BW_MW_09	44	26/08/2023	64	50.80163333	4.7195	S	?	2

Patch ID	Plot ID	date	GPS mark	latitude (°)	longitude (°)	aspect (N/S)	slope (%)	tree_ layers
BW_MW_07	45	26/08/2023	65	50.79798333	4.716916667	0	0	3
BW_MW_07	46	26/08/2023	66	50.80095	4.712083333	0	0	2
BW_MW_07	47	26/08/2023	67	50.79768333	4.710766667	0	0	3
BW_Hal_04	48	11/10/2023	197	50.71116667	4.306277778	0	0	+
BW_Hal_04	49	11/10/2023	199	50.71316667	4.307361111	0	0	2
BW_Hal_04	50	11/10/2023	198	50.71238889	4.306138889	0	0	2
BW_Hal_03	51	11/10/2023	200	50.71380556	4.305555556	0	0	2
BW_Hal_03	52	11/10/2023	201	50.71316667	4.305055556	0	0	2
BW_Hal_03	53	11/10/2023	202	50.71227778	4.304833333	W	10	2
BW_Hal_13	54	15/10/2023	228	50.70858333	4.285305556	0	0	2
BW_Hal_13	55	15/10/2023	226	50.70902778	4.286444444	0	0	1
BW_Hal_13	56	15/10/2023	227	50.70875	4.286027778	0	0	1
BW_Hal_12	57	15/10/2023	231	50.71972222	4.289805556	0	0	2
BW_Hal_12	58	15/10/2023	230	50.71852778	4.292166667	0	0	1
BW_Hal_12	59	15/10/2023	229	50.71819444	4.291111111	0	0	2
BW_SON_08	60	24/08/2023	59	50.75958333	4.414483333	0	0	1
BW_SON_08	61	21/08/2023	41	50.76598333	4.414483333	0	0	3
BW_SON_08	62	24/08/2023	60	50.76116667	4.407766667	0	0	1
BW_Hal_09	63	09/10/2023	182	50.70625	4.279416667	0	0	3
BW_Hal_09	64	09/10/2023	184	50.70633333	4.278888889	0	0	3
BW_Hal_09	65	09/10/2023	180	50.70477778	4.276777778	0	0	2
BW_MW_17	66	23/08/2023	51	50.80788333	4.680466667	0	0	2
BW_MW_17	67	23/08/2023	50	50.80686667	4.679783333	0	0	2
BW_MW_17	68	23/08/2023	49	50.80901667	4.682333333	0	0	2
BW_SON_01	69	21/08/2023	42	50.76431667	4.421833333	0	0	+
BW_SON_01	70	21/08/2023	40	50.76796667	4.418166667	0	0	2
BW_SON_01	71	24/08/2023	61	50.76333333	4.416883333	E	?	2
BW_SON_02	72	21/08/2023	39	50.77155	4.417516667	0	0	+
BW_SON_02	73	24/08/2023	55	50.76661667	4.423133333	0	0	2
BW_SON_02	74	28/08/2023	68	50.77493333	4.418516667	0	0	+
BW_SON_05	75	24/08/2023	56	50.75046667	4.420716667	0	0	2
BW_SON_05	76	24/08/2023	57	50.75051667	4.4232	0	0	2
BW_SON_05	77	24/08/2023	58	50.75565	4.416233333	0	0	2

Table VII.4: Comments noted in the field per plot in NP BW

plot_ID	comment
0	A lot of oaks with a high regeneration because a lot of light, below the beech trees this is a lot less
1	regeneration of Q. rubra but outside plot A, 3 big dead trees on the ground, plot measures taken alone (therefore more time)
2	
3	
4	dense regeneration of Q.rubra, limited dead wood and limiter under grow of S. acauparia and F.sylvatica + problems with hypsometer: took a lot of time
5	a lot of regeneration of Q rubra, different from the dominant trees and a lot of dead wood. Center of plot partly in a small open space in the regeneration.
6	
7	mud pool and large dead tree
8	plot was replaced because there wer road works on the plot (so no forest + not accessible)
9	dead wood
10	
11	dead wood
12	
13	regeneration of fagus sylv, dead tree trunk.
14	dead wood in the surroundings
15	dead wood, difficult to access at the border of the forest, dead wood, regeneration of fagus sylv and acer pseud.
16	upper tree layer is dominant
17	dead wood
18	a lot of regeneration of acer_pseud. Smaller than 2m. Arboreal GPS coordinates were next to this regeneration patch
19	dead wood
20	close to forest border
21	dead wood
22	old hollow path through plot, dead wood
23	dead wood, regeneration of acer pseudoplatanus, very dense vegetation, very difficult to access plot and surroundings
24	
25	a small path runs through the plot, plot is in a small vally with a (now dry) river running through
26	a lot of grass
27	next to playing ground in the forest. i
28	
29	small path of grass (not on QGIS) goes through center of the plot.
30	next to regeneration of fagus sylv.
31	dead wood
32	regeneration of fagus sylv, dead wood
33	
34	

35	dead tree trunk, small slope
36	they just made a thinning in the stand, and a towing path cut through the plot
37	plot put 18m from the road
38	
39	at the bottom of a hill
40	at the top of a valley
41	
42	regeneration of acer pseudoplatanus.
43	partly in regeneration of carpinus betulus & fagus sylvatica, GPS was not accurate
44	dead wood, plot center in small valley
45	dead wood
46	dead wood, regeneration of fagus and acer. iPad plots was shifted to the north, not in middle midle of regeneration
47	dead wood
48	
49	
50	Plot moved away from big walking trail
51	Close to forest border, dead wood
52 - 53	
54	in regeneration plot (<2m) of carpinus betulus
55	Plot is under castanea sativa, while outside the plot, the rest of the patch is pinus sylvestris. A path runs trhough the 18m plot border
56	ferns
57	close to open space
58	beech forest
59	next to open space
60	plot center is in the middle of an open fern field (+/- 40m diameter) with only 2 big trees within the plot on the edge.
61	iPad: Height of 44 m?
62	regeneration of quercus robur on 60% of the plot, other 40% are ferns with only 1 big dead tree (measured in the rain, difficult accessible)
63 -64	/
65	dead wood
66	
67	part of the plot is in the heterogeneous border vegetation of the pine patch
68	
69	plot between small paths that are not on the map.
70	a lot of small regeneration of acer pseudoplatanus
71	dead wood, rain.
72	dead wood
73	dead wood
74	dead wood
75	

76	dead tree trunk + little mud pool.
77	

3. Apppendix 3: Nikon Forester Pro specifications

Table VII.5: Specifications of the Nikon Forester Pro, used for height measurements

Measuring system	
Measuring distance	10 – 500 m
Angle range	± 89 °
Accuracy	
Internal display	
Linear distance	0.5 m (< 100 m) 1.0 m (≥ 100 m)
Horizontal distance	0.2 m (< 100 m) 1.0 m (≥ 100 m)
Height	0.2 m (< 100 m) 1.0 m (≥ 100 m)
Angle	0.1° (< 10 °) 1.0 ° (≥ 10 °)
External display	
Linear distance	0.5 m
Horizontal distance	0.2 m
Height	0.2 m
Angle	0.1 °
Optical system	
Type	Roof- prism monocular
Laser classification	IEC60825-1: Class 1M/Laser Product FDA/21 CFR Part 1040.10: Class 1 Laser Product
Wavelength [nm]	870
Pulse duration [ns]	14
Output [W]	15
Beam divergence [mrad]	Vertical: 2.5, Horizontal: 0.025

4. Appendix 4: Coefficients for carbon calculations in Belgium

Table VII.6: Coefficients used in allometric equations for carbon stock calculations in the NP BW. For the volume calculations, the DBH should be implemented in m in the equations of Quataert et al. The respective species are Carpinus betulus, Castanea sativa, Fagus sylvatica, Quercus petraea and Quercus robur. In the equations developed by Berben et al. and Dagnelie et al., the DBH should be implemented in cm (all the other species). The height is always in m. VEF= Volume expansion factor, WD=wood density, CF = carbon factor

	a	b	c	d	e	f	g	VEF (-)	WD (t/m³)	CF (-)
Acer pseudoplatanus	1.0343E-02	-1.4341E-03	3.4521E-05	-1.3053E-07	7.7115E-04	0	3.0231E-06	1.4	0.52	0.5
Betula pendula	-1.1392E-02	-1.0010E-04	2.8290E-05	-1.8695E-07	-5.9573E-04	0	3.0811E-06	1.29	0.53	0.5
Carpinus betulus	0.1645	-0.5612	0.2910	0	-0.00725	0.025	0.0230	1.4	0.52	0.5
Castanea sativa	-0.01115	0	-0.08560	-0.04996	0	0.00256	0.03633	1.4	0.52	0.5
Corylus avellana	-3.9083E-02	1.9935E-03	-1.6148E-05	-6.4188E-09	-9.8341E-04	0	3.8373E-06	1.4	0.52	0.5
Fagus sylvatica	-0.01115	0	-0.08560	-0.04996	0	0.00256	0.03633	1.42	0.59	0.5
Fraxinus excelsior	-3.9083E-02	1.9935E-03	-1.6148E-05	-6.4188E-09	-9.8341E-04	0	3.8373E-06	1.29	0.56	0.5
Ilex aquifolium	-3.9083E-02	1.9935E-03	-1.6148E-05	-6.4188E-09	-9.8341E-04	0	3.8373E-06	1.4	0.52	0.5
Larix decidua	-3.0880E-02	1.4885E-03	-4.9257E-06	-1.2313E-07	-1.1638E-03	0	4.1134E-06	1.3	0.46	0.5
Picea abies	-1.0929E-02	1.3945E-03	-9.5965E-06	-2.5164E-07	-2.7922E-03	0	4.8985E-06	1.3	0.38	0.5
Pinus nigra var Corsicana	-2.8460E-03	0	- 2.2785E-07	0	- 2.4768E-04	0	3.9082E-06	1.23	0.42	0.5
Pinus sylvestris	-3.9836E-02	1.5505E-03	-6.1835E-06	4.8022E-08	7.3997E-05	0	2.9607E-06	1.23	0.42	0.5
Prunus serotina	-2.3110E-03	-3.7474E-04	1.5103E-05	-2.5175E-08	3.3282E-04	0	3.1943E-06	1.4	0.52	0.5
Pseudotsuga menziesii	-1.9911E-02	5.9559E-04	1.2901E-05	-1.8587E-07	7.1591E-04	0	3.9892E-06	1.29	0.43	0.5
Quercus petraea	0.1645	-0.5612	0.2910	0	-0.00725	0.025	0.0230	1.39	0.56	0.5
Quercus robur	0.1645	-0.5612	0.2910	0	-0.00725	0.025	0.0230	1.39	0.56	0.5
Quercus rubra	-2.1490E-02	9.5069E-04	-4.3068E-06	-7.0329E-08	-7.4299E-04	0	3.7969E-06	1.4	0.52	0.5
Rhamnus frangula	-3.9083E-02	1.9935E-03	-1.6148E-05	-6.4188E-09	-9.8341E-04	0	3.8373E-06	1.4	0.52	0.5
Salix caprea	-1.1392E-02	-1.0010E-04	2.8290E-05	-1.8695E-07	-5.9573E-04	0	3.0811E-06	1.4	0.52	0.5
Sorbus acauparia	-2.1490E-02	9.5069E-04	-4.3068E-06	-7.0329E-08	-7.4299E-04	0	3.7969E-06	1.4	0.52	0.5
Tilia platiphyllus	-2.1490E-02	9.5069E-04	-4.3068E-06	-7.0329E-08	-7.4299E-04	0	3.7969E-06	1.4	0.52	0.5
Tsuga heterophylla	-0.01991	0.000596	0.000012901	-1.86E-07	0.000716	0	3.99E-06	1.4	0.40	0.5
Ulmus sp.	-3.4716E-02	1.3586E-03	-1.3402E-05	-5.6980E-08	1.6516E-04	0	3.8818E-06	1.4	0.52	0.5

5. Appendix 5: Allometric equations for Catalunya

Table VII.7: parameters a, b and c to enter in the allometric equations for biomass calculations in Catalunya. C% gives the species-dependent percentage of biomass to calculate the carbon stock.

Species	param_a	param_b	param_c	C%
Acer campestre	0.07796081	2.063987855	0.505025137	50.0
Acer monspessulanum	0.07796081	2.063987855	0.505025137	50.0
Acer opalus	0.07796081	2.063987855	0.505025137	50.0
Amelanchier ovalis	0.07796081	2.063987855	0.505025137	50.0
Arbutus unedo	0.083016401	1.937864793	0.747854151	50.0
Aria edulis	0.083016401	1.937864793	0.747854151	50.0
Buxus sempervirens	0.083016401	1.937864793	0.747854151	50.0
Castanea sativa	0.07796081	2.063987855	0.505025137	48.4
Cornus sp	0.07796081	2.063987855	0.505025137	50.0
Corylus avellana	0.07796081	2.063987855	0.505025137	50.0
Crataegus monogyna	0.07796081	2.063987855	0.505025137	50.0
Erica arborea	0.114507313	2.079071003	0.418516947	50.0
Erica scoparia	0.114507313	2.079071003	0.418516947	50.0
Fagus sylvastica	0.053988224	1.822005675	0.947204319	48.6
Ilex aquifolium	0.083016401	1.937864793	0.747854151	50.0
Juniperus communis	0.05961788	2.045368554	0.539718594	50.0
Juniperus phoenica	0.05961788	2.045368554	0.539718594	50.0
Malus sylvestris	0.07796081	2.063987855	0.505025137	50.0
Phillyrea latifolia	0.083016401	1.937864793	0.747854151	50.0
Pinus halepensis	0.083798189	1.955447787	0.519203298	49.9
Pinus nigra	0.042742703	2.154838364	0.537661105	50.9
Pinus pinea	0.053994811	2.382540049	0.107570536	50.8
Pinus sylvestris	0.055393345	2.046940791	0.557689006	50.9
Populus tremula	0.026084996	2.021729352	0.974375216	48.3
Prunus avium	0.07796081	2.063987855	0.505025137	50.0
Prunus spinosa	0.07796081	2.063987855	0.505025137	50.0
Quercus faginea	0.084670619	1.974907524	0.55005669	48.0
Quercus humilis/cerroides	0.077967606	2.076014613	0.510466871	48.0
Quercus ilex	0.114507313	2.079071003	0.418516947	47.5
Rhamnus alaternus	0.083016401	1.937864793	0.747854151	50.0
Sorbus aucuparia	0.07796081	2.063987855	0.505025137	50.0
Sorbus torminalis	0.07796081	2.063987855	0.505025137	50.0
Tilia cordata	0.07796081	2.063987855	0.505025137	50.0
Ulmus laevis	0.118856439	1.862621215	0.55832565	50.0
Viburnum lantana	0.083016401	1.937864793	0.747854151	50.0

6. Appendix 6: Correlation plots between Sentinel-2 variables

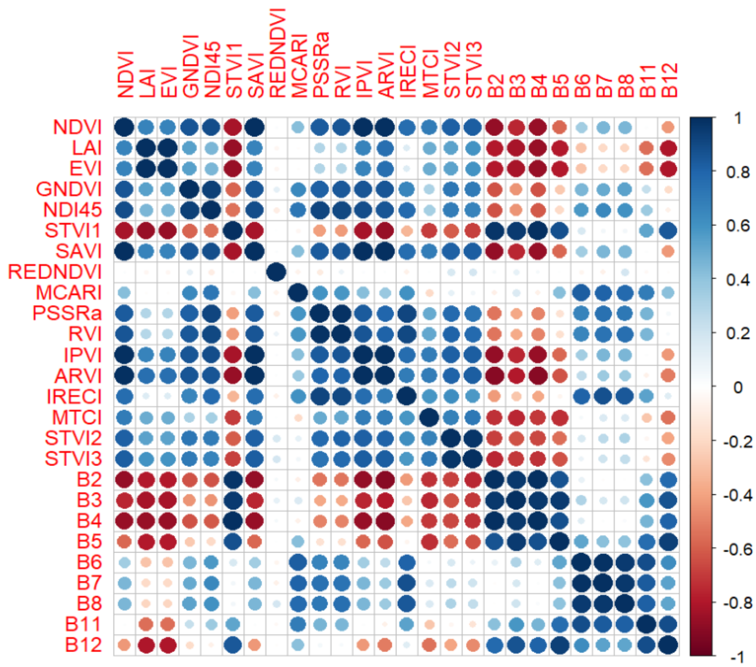

Figure VII.1: Correlation plot of all Sentinel-2 variables with each other for NP BW. The color, intensity and size of the circles represent the Pearson correlation coefficient

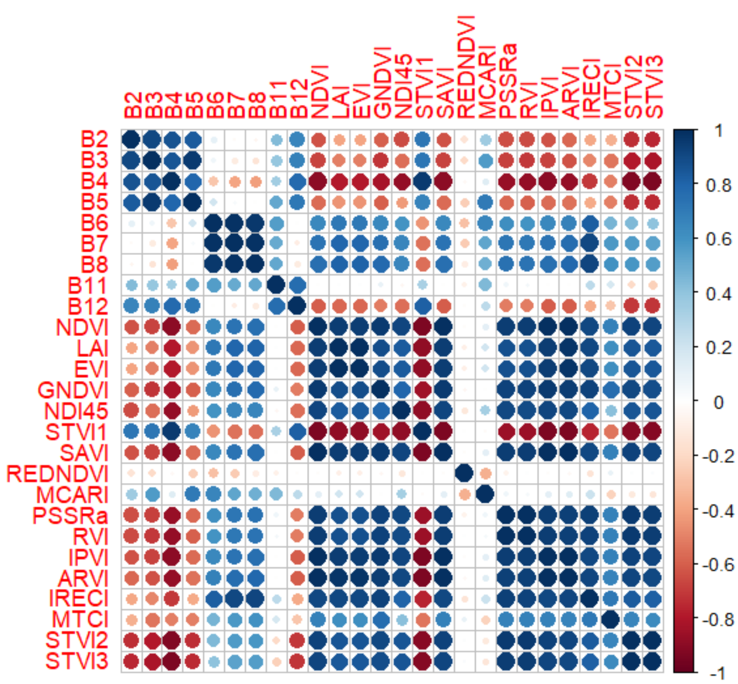

Figure VII.2: Correlation plot of all Sentinel-2 variables with each other for Catalunya. The color, intensity and size of the circles represent the Pearson

7. Appendix 7: Partial plots final GAM NP BW

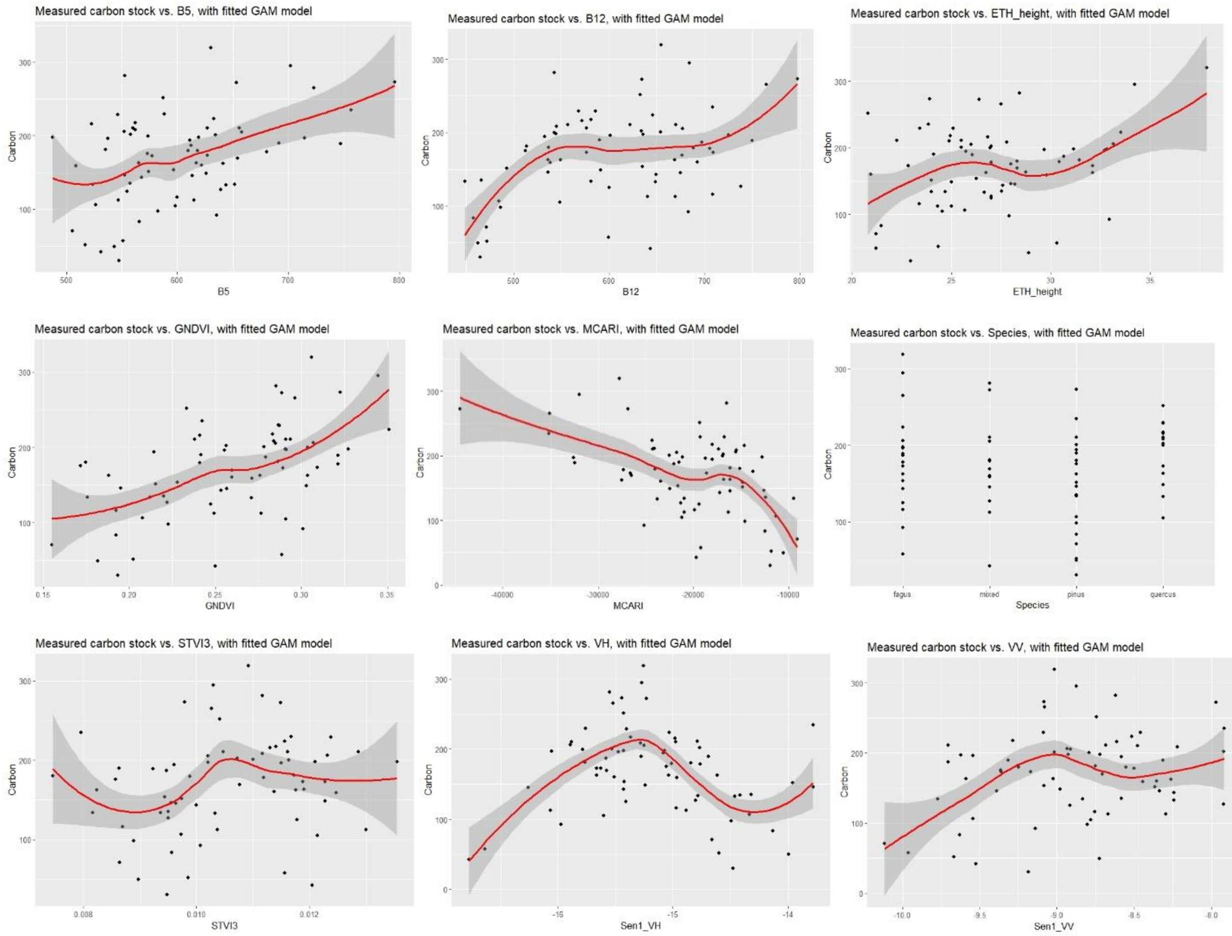

Figure VII.3: Partial plots for all variables included in the final GAM in NP BW. On the y-as, the carbon stock is plotted, and the variable values are represented on the x-axis. The red curve is the fitted GAM, and the grey shade the 95% confidence interval. From left to right and top to bottom: B5, B12, Height, GNDVI, MCARI, Species, STVI3, VH, VV.

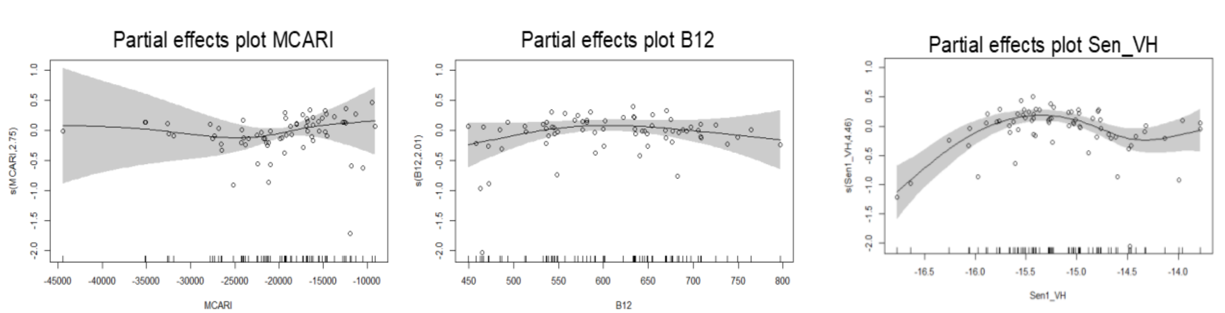

Figure VII.4: Partial effects plots of all continuous smoothed predictor variables in NP BW. Each response curve depicts the additive influence of its respective variable, employing non-parametric smoothing techniques. On the y-axis the component effect of the smoothed variable is plotted, adding up to the overall prediction, with the edf indicated between brackets. On the x-axis, the original variable is plotted. The shaded zone illustrates the 95% prediction interval. Dots show the sample distribution across that variable.

8. Appendix 8: Partial plots final GAM Catalunya

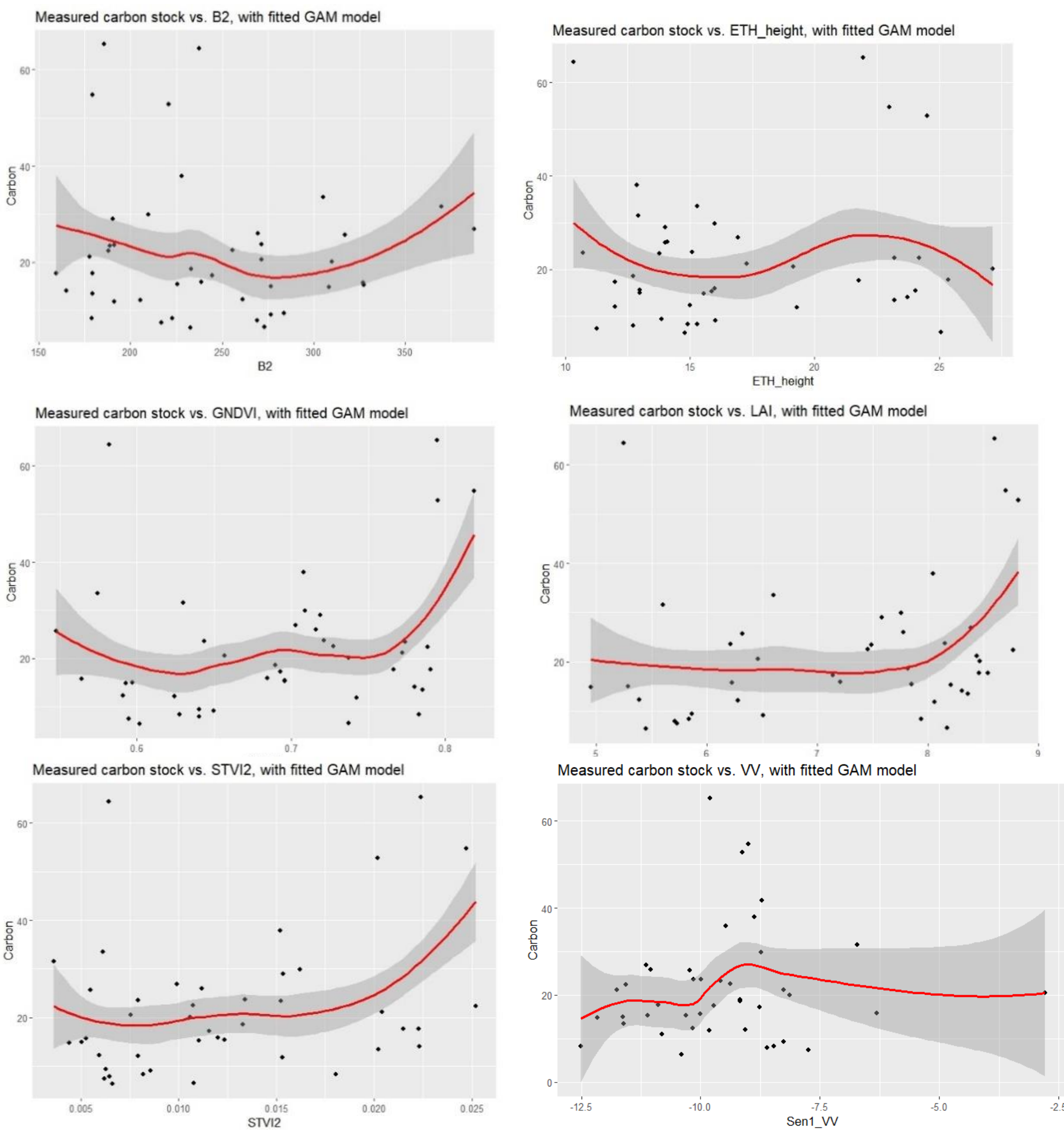

Figure VII.5: Partial plots for all variables included in the final GAM mode in Catalunyal. On the y-as, the carbon stock is plotted, and the variable values are represented on the x-axis. The red curve is the fitted GAM, and the grey shade the 95% confidence interval. From left to right and top to bottom: B2, Height, GNDVI, LAI, STVI2, VV

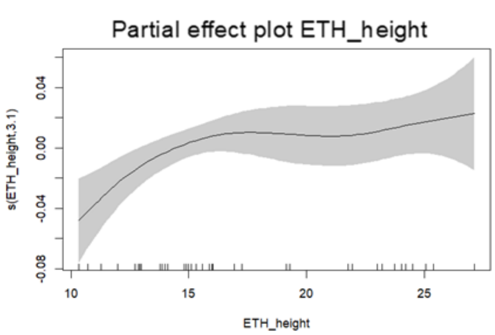

Figure VII.6: Partial effects plots of the only smoothed predictor variables in Catalunya: Height. The response curve depicts the additive influence of height, employing non-parametric smoothing techniques. On the y-axis the component effect of the smoothed variable of height is plotted, adding up to the overall prediction, with the edf indicated between brackets. On the x-axis, the original variable is plotted. The shaded zone illustrates the 95% prediction

VIII: Vulgariserende samenvatting

Om te groeien zetten bomen koolstofdioxide (CO_2) om in biomassa met behulp van energie die ze halen uit licht (fotosynthese). Dit proces wordt ook wel koolstofvastlegging genoemd en zo absorberen bossen zo'n 27% van de jaarlijkse wereldwijde uitstoot van fossiele brandstoffen. CO_2 is een broeikasgas dat warmte vasthoudt en door een enorme stijging in onnatuurlijke uitstoot in de laatste decennia, zoals door industrialisatie en ontbossing, is het een cruciale factor in klimaatverandering. Bomen absorberen niet enkel koolstof uit de lucht, ze houden die ook vast voor een erg lange tijd, bijvoorbeeld in hun boven- en ondergrondse biomassa. Zo'n 45% van de koolstof op aarde is opgeslagen in bossen. Daarom bieden bossen veelbelovende toepassingen in de wereldwijde initiatieven tegen klimaatopwarming. Het beheer van deze bossen speelt hierin een sleutelrol, maar wetenschappers zijn het nog niet eens of het in deze context juist beter is om bossen wel of niet te beheren. In deze thesis werden geavanceerde teledetectie-technieken gebruikt om de bovengrondse koolstofvoorraden in een Atlantisch (Nationaal Park Brabantse Wouden, Vlaanderen, België) en Mediterraan (Catalonië, Spanje) studiegebied te modelleren, gebaseerd op veldmetingen die als referentie dienden. Paren en tripletten van beheerde en onbeheerde bossen werden vergeleken om vier onderzoeksvragen te beantwoorden: 1) Is de combinatie van meerdere teledetectie-bronnen superieur voor het schatten van de bovengrondse koolstofvoorraad? 2) Wat is het effect van bosbeheer op de koolstofvoorraad? 3) Wat is het effect van bosbeheer op koolstofvastlegging? 4) Wat is het effect van de koolstofvoorraad en het bosbeheer op de kwetsbaarheid voor kruinbranden? De combinatie van verschillende teledetectiebronnen bleek voordelig om koolstofopslag te voorspellen, vooral voor hoge biomassa's. Uit de veldgegevens in België bleek vervolgens dat onbeheerde bossen een hogere koolstofopslag hebben dan beheerde bossen. Hoewel het bekomen model accuraat genoeg voorspellingen maakte, werd dit verschil echter niet succesvol gedetecteerd door het teledetectie-model, o.a. door saturatie bij signaaldetectie. In Spanje werd geen verschil in koolstofopslag gemeten, en werd geen succesvol model verkregen. Het gevarieerde reliëf, het tekort aan observaties en de technologische tekortkomingen bieden hiervoor een verklaring. Vervolgens werd de koolstofopslag in België geschat voor alle jaren tussen 2017 en 2023 volgens het finale model, om vervolgens de koolstofvastlegging doorheen de tijd te berekenen. Hierbij werd geen verschil gevonden tussen beheerde en onbeheerde bossen, mogelijks omdat ze nog niet lang genoeg onbeheerd waren of het verschil niet gedetecteerd werd door teledetectie. Klimaatrampen zoals bosbranden vormen een grote bedreiging voor de koolstofopslag in bossen, zeker in droogtegevoelige regio's zoals Spanje. In dit studiegebied werd een kwalitatieve analyse gedaan naar het verband tussen koolstofopslag, bosbeheer, en de gevoeligheid voor kruinbranden (waarbij het vuur zich via de kruin aan hoge snelheid verspreidt). Beheerde bossen zijn over het algemeen minder gevoelig voor kruinbranden, maar er werd geen verband gevonden met de totale koolstofopslag. Echter, hoe meer biomassa in kleine bomen opgeslagen is, hoe gevoeliger, omdat het vuur via deze lage vegetatie de kruin kan bereiken. Verder onderzoek naar de invloed van concrete beheersrichtlijnen kan leiden tot meer specifieke beheersrichtlijnen.

To grow, trees convert carbon dioxide (CO_2) into biomass using light energy from the sun (photosynthesis). This process is also called carbon sequestration, and this way, forests absorb about 27% of annual global fossil fuel emissions. CO_2 is a gas that has heat-trapping properties (so-called greenhouse gas), and a huge increase in unnatural emissions in recent decades, such as from industrialization and deforestation, makes it a crucial factor in climate change. Trees not only absorb carbon from the air, they also retain it for a very long time, for example in their above- and below-ground biomass. Some 45% of the Earth's carbon is stored in forests. Therefore, forests offer promising applications in the global combat against climate change. The management of these forests is then an important factor, but scientists do not yet agree on whether it is better to manage forests in this context or leave them unmanaged. In this thesis, advanced remote sensing techniques were used to model aboveground carbon stocks in an Atlantic (Brabantse Wouden National Park, Flanders, Belgium) and Mediterranean (Catalonia, Spain) study area, based on field measurements serving as a reference. Pairs and triplets of managed and unmanaged forests were compared to answer four research questions: 1) Is the combination of multiple remote sensing sources superior for estimating aboveground biomass carbon stock? 2) What is the effect of forest management on this carbon stock? 3) What is the effect of forest management on carbon sequestration? 4) What is the effect of carbon stock and forest management on vulnerability to crown fires? The combination of different remote sensing sources proved advantageous in predicting carbon sequestration, especially for high biomasses. Field data in Belgium then showed that unmanaged forests have a higher carbon stock than managed forests. However, although the obtained model had an acceptable prediction accuracy, this difference was not successfully detected by the remote sensing model, in part due to saturation in signal detection. In Spain, no difference in carbon storage was measured, and no successful model was obtained. The varied relief, lack of observations, and technological shortcomings explain this. Carbon storage in Belgium was then estimated for all years between 2017 and 2023 according to the final model, and then carbon sequestration through time was calculated. Here, there was no difference between managed and unmanaged forests, possibly because they had not been unmanaged long enough or the difference was not detected by remote sensing. Climate disasters such as forest fires are a major threat to forest carbon stock, especially in drought-prone regions such as Spain. In this study area, a qualitative analysis was done on the relationship between carbon storage, forest management, and susceptibility to crown fires (where fire spreads through the crown at high speed). Managed forests are generally less susceptible to crown fires, but no relationship was found with the total carbon storage. However, the more biomass is stored in small trees, the more vulnerable, as fire can reach the crown through this low vegetation. Further research on the influence of more specific management regimes on carbon stock and sequestration and the trade-offs with other ecosystem services could lead to unambiguous management guidelines and decision rules.

IX. Gebruik van Generatieve Artificiële Intelligentie (GenAI)

Naam student: Sofie Van Winckel
Studentennummer: r0788791

Geef met "X" aan of het gaat om een cursusopdracht, een BIG-project of een masterproef:

X Dit formulier heeft betrekking op mijn masterproef.
Titel masterproef: Assessing the effect of forest management on carbon stock and sequestration by remote sensing
Promotor: Bart Muys

O Dit formulier heeft betrekking op een BIG-project.
Titel BIG-project: ...
Promotor: ...

O Dit formulier heeft betrekking op een cursusopdracht.
Cursusnaam: ...
Cursusnummer: ...

Geef met "X" aan:

o Ik heb geen GenAI tool gebruikt.
X Ik heb wel een Gen AI tool gebruikt. Geef in dat geval aan welke (bv. ChatGPT/GPT-4/...): ChatGPT

Geef met "X" aan (mogelijk meerdere keren) op welke manier je de Gen AI tool hebt gebruikt:

- X **Als taalassistent voor het herwerken of verbeteren van zelf geschreven teksten zonder nieuwe inhoud toe te voegen.** (Dit gebruik is gelijk aan spelling- en grammaticacheckers en hoef je niet expliciet te vermelden.)
- o **Als zoekmachine om eerste informatie te krijgen over een onderwerp of voor een eerste aanzet om op zoek te gaan naar literatuur.** (Deze toepassing is gelijkaardig aan het gebruik van een gewone zoekmachine bij de uitwerking van een persoonlijk werkstuk. Als student ben je verantwoordelijk voor het controleren en verifiëren van de afwezigheid of correctheid van referenties. Ga dus vervolgens zelf op zoek naar wetenschappelijke referenties en voer zelf een analyse van de brondocumenten. Interpreteer, analyseer en verwerk de verkregen informatie; kopieer ze niet zomaar. Indien je vervolgens eigenhandig een tekst opstelt, hoef je het gebruik niet te vermelden.)
- o **Om tekstblokken te genereren.** (Wanneer je tekstblokken van GenAI output letterlijk overneemt, dan vermeld je de GenAI bronnen en citeer je, m.a.w. je meldt duidelijk dat het item via GenAI is aangemaakt d.m.v. citatie/referentie.)
- o **Om grafieken of figuren te genereren.** (Wanneer je grafieken/figuren van GenAI output letterlijk overneemt, dan vermeld je de GenAI bronnen en citeer je, m.a.w. je meldt duidelijk dat het item via GenAI is aangemaakt d.m.v. citatie/referentie.)
- X **Om code te laten genereren als deelaspect binnen een grotere opdracht.** (Let op, dit mag enkel als de docent hier EXPLICIET toestemming voor heeft gegeven.)
- o **Anders** (Neem contact op met de docent van de cursus of de promotor van de thesis of het BIG-project. Leg uit hoe je voldoet aan artikel 84 van het examenreglement. Leg uit wat het nut of de toegevoegde waarde van het gebruik van GenAI.)