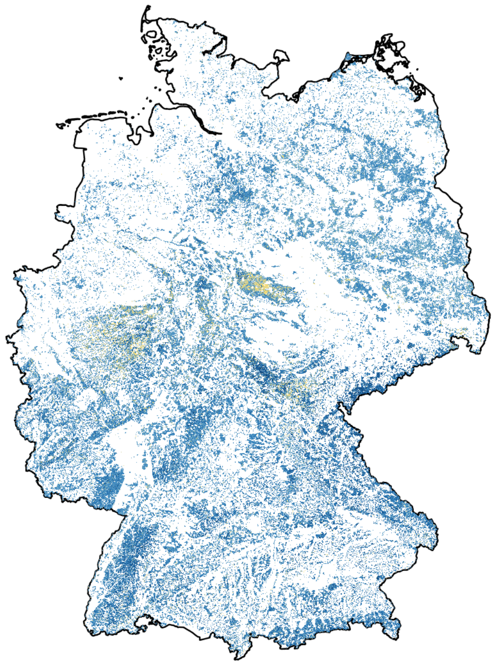

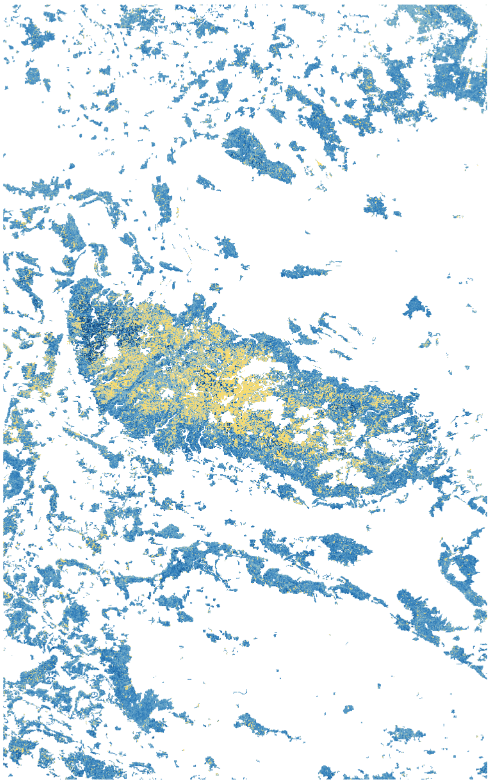

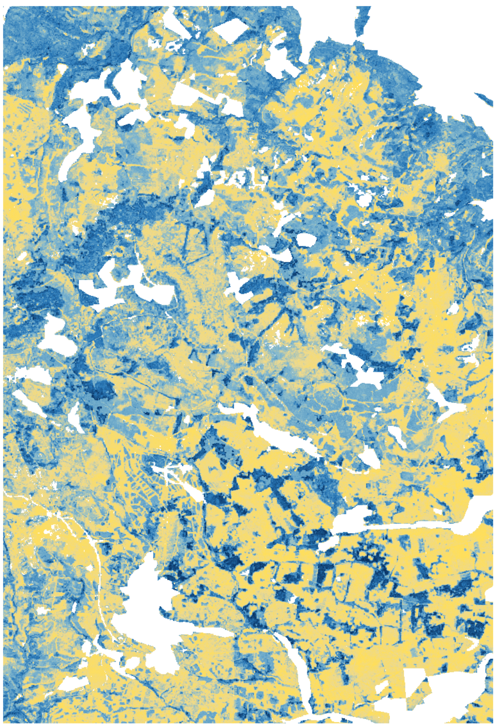

Multi-Sensor Remote Sensing of Forest Biodiversity

Novel Earth Observation Techniques for Forest Structure Analyses and Multi-Scale Characterization of Forests

Dissertation zur Erlangung der Doktorwürde der Philosophischen Fakultät der Julius-Maximilians-Universität Würzburg

vorgelegt von

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Titelbild:
Darstellung der Waldstruktur in Deutschland basierend auf Daten von der Global Ecosystem Dynamics Investigation (GEDI), Sentinel-1 und Sentinel-2 (Kacic et al., 2023). Die Darstellungen zeigen die Waldhöhen im Sommer 2023 für Deutschland (oben), den Harz (mittig) und den Nationalpark Harz (unten). Hohe Wälder sind in blau dargestellt, wohingegen gelbe Bereiche niedrige Waldhöhen zeigen.

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Deutsches Zentrum für Luft- und Raumfahrt
German Aerospace Center

"What you do makes a difference,
and you have to decide what kind of difference you want to make."
Jane Goodall

English Summary

About one third of the Earth's land surface is covered by forest providing habitats for numerous animals and plants. Forests are present in many different biomes, such as the tropical, subtropical, temperate, and boreal biome. Carbon sequestration, water filtration, as well as habitat creation are exemplary ecosystem functions of forests. The provision of those ecosystem functions is depending on structural characteristics of forests, e.g. vertical and horizontal properties, fragmentation, and temporal continuity. Temperature buffering, water storage, and recreational purposes are selected ecosystem services for human well-being, resulting from the interplay of ecosystem functions.

In Central Europe, more than three centuries of forest management have altered the natural structure of forests. In Germany, about 95% of the forests are managed for forestry purposes. In several regions, silvicultural management has led to a structural homogenization: few dominant tree species, age-class structures, as well as deadwood scarcity are typical characteristics. Furthermore, homogeneous forests are specifically susceptible to natural disturbances. Continuous information on forest structure at the national scale for multiple attributes of forest structure and several years is missing to better characterize the recent forest structure dynamics in Germany during times of large-scale disturbance events. In addition, the monitoring of novel forest management techniques aiming to enhance the structural complexity of forests is of high relevance for the development of more natural, biodiverse and resilient forests. The topic of this dissertation addresses those knowledge gaps by assessing recent forest structure changes in Germany at high spatial resolution for multiple years in the context of forest biodiversity.

High spatio-temporal observations derived from Earth observation (EO) data enable the monitoring of the Earth's surface dynamics. EO data comprises spaceborne derived information from different sensors, such as radar (e.g. Sentinel-1), multispectral (e.g. Sentinel-2), or Light detection and ranging (Lidar) (e.g. Global Ecosystem Dynamics Investigation (GEDI)), to quantify forest structure and biodiversity. A systematic literature review on forest biodiversity monitoring with a focus on EO data, as part of this dissertation, showed that previous research mostly integrated single-sensor observations from multi-

spectral satellites. In addition, the studies were often limited to sub-national data on forests. Furthermore, the potential of multi-sensor analysis of forests, as well as the integration of long time-series remains understudied.

A novel machine-learning workflow making use of multi-sensor EO data was developed to model forest canopy height, total canopy cover, and above-ground biomass from 2017 to 2023 in 10 meter (m) spatial resolution for Germany. More precisely, satellite time-series from Sentinel-1 and Sentinel-2 serve as predictor variables for sampling data on forest structure attributes derived from GEDI in order to generate annual products. Both at the national and regional level, forest structure change dynamics were quantified. For two hotspots of forest canopy cover loss in Germany, namely the Harz and Thuringian forest, a reduction in canopy height of more than 20 m, total canopy cover exceeding 50 %, and above-ground biomass density of up to 200 megagrams per hectare (Mg/ha) was assessed.

In the context of an integrative research project funded by Deutsche Forschungsgemeinschaft (DFG), BETA-FOR, experimental silvicultural treatments were implemented in German broad-leaved forests to assess forest structure-biodiversity relationships. Different arrangements of cuttings (aggregated: gap felling, distributed: selective removal) in combination with various deadwood structures were created to diversify the light conditions and habitats. The implementation of those small-scale treatment patches (50 m x 50 m) results in abrupt forest structure changes. A new methodological framework was set up to identify change points in Sentinel-1 and Sentinel-2 time-series. Based on a comprehensive catalog, various spectral indices were calculated and aggregated per patch and time-step as spatial statistics. Metrics (combination of spectral index and spatial statistic) from Sentinel-1 (n = 98) and Sentinel-2 (n = 903) were evaluated in order to identify metrics best assessing the change in forest structure (implementation of experimental silvicultural treatment). Overall, aggregated treatments were best assessed for both sensors using heterogeneity statistics. Only few distributed treatments could be identified, with benefits for Sentinel-2 metrics. Sentinel-1 vertical transmit, horizontal receive (VH) polarization and Sentinel-2 Normalized Multi-band Drought Index (NMDI) determined the most treatment implementations accurately.

By integrating forest structure heterogeneity information based on modeled attributes of forest structure, as well as satellite time-series metrics of Sentinel-1 and Sentinel-2, correlation analyses were carried out to in-situ remotely sensed forest structure indicators. Mobile Laser Scanning (MLS) and Terrestrial Laser Scanning (TLS) observations hold sub-canopy perspectives which are complementary to the top-of-canopy measurements of spaceborne sensors. The correlation analyses were conducted in the context of the experimental silvicultural treatments of the BETA-FOR project. Although different attributes of forest structure are quantified by the spaceborne and in-situ indicators, namely canopy cover and openness, structural heterogeneity, and structural complexity, strong correlations ($|r| > 0.7$) were identified among MLS box dimension, MLS canopy cover, TLS Canopy Openness Index (COI), Sentinel-1 VH, Sentinel-2 NMDI, and modeled GEDI total canopy cover. Both spaceborne and in-situ indicators of forest structure can accurately delineate among control (unaltered forest structure) and aggregated treatments, but not consistently among control and distributed treatments. Furthermore, a sensitivity towards the presence of standing deadwood in aggregated treatments was found for spaceborne, as well as in-situ indicators.

Forest structure-biodiversity relationships were quantified by integrating forest structure heterogeneity indicators based on Sentinel-1 and Sentinel-2 time-series, as well as modeled attributes of forest structure from GEDI data. The indicators of forest structure consistently characterize the main difference in forest structure heterogeneity of control to aggregated treatments, and to a minor extent the structural differences among control and distributed treatments. Taxonomic diversity data of bats, birds, gastropods, hoverflies, insects, moths, spiders, and trees serves as biodiversity reference data. Linear correlations were calculated among forest structure heterogeneity indicators and biodiversity measurements reaching values greater than 0.4 for several taxa: birds, gastropods, hoverflies, insects, and tree species.

To sum up, multi-sensor spaceborne data have a great potential for the multi-annual characterization of forest structure change dynamics at the national scale. Both radar and multispectral time-series are suited for the monitoring of novel experimental silvicultural treatments when conducted as gap felling. Correlation analyses among spaceborne and in-situ indicators of forest structure demonstrated the alignment of several metrics, thus confirming the potential of spaceborne indicators to up-scale in-situ remotely sensed indicators in space and time. Several forest structure-biodiversity relationships were identified based on spaceborne multi-sensor data and in-situ biodiversity measurements, suggesting a deeper integration of EO in ecology to better inform forest management for biodiversity preservation.

Deutsche Zusammenfassung

Etwa ein Drittel der Landoberfläche der Erde ist von Wäldern bedeckt, die Lebensraum für zahlreiche Tiere und Pflanzen bieten. Wälder sind in vielen verschiedenen Biomen zu finden, z. B. in den Tropen, Subtropen, gemäßigten Breiten und im borealen Klima. Die Kohlenstoffbindung, Wasserfilterung und Schaffung von Lebensräumen sind beispielhafte Ökosystemfunktionen der Wälder. Die Bereitstellung dieser Ökosystemfunktionen hängt von den strukturellen Merkmalen der Wälder ab, z. B. von den vertikalen und horizontalen Eigenschaften, der Fragmentierung und der zeitlichen Kontinuität. Kühlung, Wasserspeicherung und Erholungsfunktion sind ausgewählte Ökosystemleistungen für das menschliche Wohlbefinden, die sich aus dem Zusammenspiel der Ökosystemfunktionen ergeben.

In Mitteleuropa haben mehr als drei Jahrhunderte der Waldbewirtschaftung die natürliche Struktur der Wälder verändert. In Deutschland werden etwa 95 % der Wälder für forstwirtschaftliche Zwecke bewirtschaftet. In mehreren Regionen hat die waldbauliche Bewirtschaftung zu einer strukturellen Homogenisierung geführt: wenige dominante Baumarten, Altersklassenstrukturen sowie Totholzarmut sind typische Merkmale. Außerdem sind homogene Wälder besonders anfällig für natürliche Störungen. Kontinuierliche Informationen über die Waldstruktur auf nationaler Ebene für mehrere Attribute der Waldstruktur und über mehrere Jahre hinweg fehlen, um die rezente Waldstrukturdynamik in Deutschland in Zeiten großflächiger Störungsereignisse besser zu charakterisieren. Darüber hinaus ist die Überwachung neuartiger Waldbewirtschaftungstechniken, die darauf abzielen, die strukturelle Komplexität von Wäldern zu erhöhen, von großer Bedeutung für die Entwicklung natürlicherer, biodiverser und resilienter Wälder. Das Thema dieser Dissertation adressiert diese Wissenslücken, indem es die jüngsten Veränderungen der Waldstruktur in Deutschland mit hoher räumlicher Auflösung über mehrere Jahre im Kontext der Waldbiodiversität untersucht.

Aus EO-Daten (Earth Observation) abgeleitete Beobachtungen mit hoher räumlichen und zeitlichen Auflösung ermöglichen die Überwachung der Dynamik der Erdoberfläche. EO-Daten umfassen aus dem Weltraum abgeleitete Informationen von verschiedenen Sensoren wie Radar (z. B. Sentinel-1), Multispektral (z. B. Sentinel-2) oder Lidar (z. B. GEDI), um die Waldstruktur und Biodiversität zu quantifizieren. Eine systematische Literaturrecherche über die Überwachung der biologischen Vielfalt in Wäldern mit Schwerpunkt auf EO-Daten im Rahmen dieser Dissertation ergab, dass die bisherige Forschung meist Einzelsensorbeobachtungen von Multispektralsatelliten integriert. Darüber hinaus beschränkten sich die Studien häufig auf subnationale Daten über Wälder. Darüber hinaus ist das Potenzial der Multisensor-Analyse von Wäldern sowie die Integration langer Zeitreihen noch nicht ausreichend erforscht.

Ein neuartiger machine-learning-Workflow, der Multisensor-EO-Daten nutzt, wurde entwickelt, um die Höhe, den Bedeckungsgrad und die oberirdische Biomasse der Wälder von 2017 bis 2023 in 10 m räumlicher Auflösung für Deutschland zu modellieren. Genauer gesagt dienen Satellitenzeitreihen von Sentinel-1 und Sentinel-2 als Prädiktorvariablen für Stichprobendaten zu Waldstruktureigenschaften, die von GEDI abgeleitet werden, um jährliche Produkte zu erzeugen. Sowohl auf nationaler als auch auf regionaler Ebene wurde die Dynamik der Waldstrukturveränderung quantifiziert. Für zwei Regionen mit starken Verlusten des Kronendachs in Deutschland, nämlich dem Harz und dem Thüringer Wald, wurde eine Verringerung der Höhe um mehr als 20 m, Reduktion des Bedeckungsgrads von mehr als 50 % und eine Abnahme der oberirdischen Biomasse von bis zu 200 Mg/ha ermittelt.

Im Rahmen des von der DFG geförderten integrativen Forschungsprojekts BETA-FOR wurden experimentelle waldbauliche Maßnahmen in deutschen Laubwäldern durchgeführt, um die Beziehungen zwischen Waldstruktur und Biodiversität zu untersuchen. Unterschiedliche Hiebsatzanordnungen (aggregiert: Lückenhieb, verteilt: selektive Entnahme) in Kombination mit verschiedenen Totholzstrukturen wurden geschaffen, um die Lichtverhältnisse und Lebensräume zu diversifizieren. Die Umsetzung dieser kleinräumigen Interventionen (50 m x 50 m) führt zu abrupten Veränderungen der Waldstruktur. Es wurde ein neuer methodischer Ansatz entwickelt, um Veränderungspunkte in den Zeitreihen von Sentinel-1 und Sentinel-2 zu identifizieren. Auf der Grundlage eines umfassenden Katalogs wurden verschiedene Spektralindizes berechnet und als räumliche Statistiken pro Fläche der Intervention und Zeitschritt aggregiert. Die Metriken (Kombination aus Spektralindex und räumlicher Statistik) von Sentinel-1 (n = 98) und Sentinel-2 (n = 903) wurden ausgewertet, um die Metriken zu ermitteln, die die Veränderung der Waldstruktur (Durchführung einer experimentellen waldbaulichen Behandlung, d.h. Interventionen) am besten erfassen. Insgesamt wurden aggregierte Interventionen für beide Sensoren mit Hilfe von Heterogenitätsstatistiken am besten identifiziert. Es konnten nur wenige verteilte Interventionen identifiziert werden, mit Vorteilen für die von Sentinel-2 abgeleiteten Metriken. Mit der

Sentinel-1 VH Polarisation und dem Sentinel-2 NMDI Spektralindex wurden die meisten Interventionen genau bestimmt, d.h. in den Zeitreihen als Veränderung der Waldstruktur quantifiziert.

Durch die Integration von Informationen über die Heterogenität der Waldstruktur, die auf modellierten Attributen der Waldstruktur beruhen, sowie von Satelliten-Zeitreihenmetriken von Sentinel-1 und Sentinel-2 wurden Korrelationsanalysen zu den in-situ Naherkundungs-Waldstrukturindikatoren durchgeführt. MLS- und TLS-Beobachtungen bieten Perspektiven unterhalb der Baumkronen, die die Messungen der weltraumgestützten Sensoren oberhalb der Baumkronen ergänzen. Die Korrelationsanalysen wurden im Zusammenhang mit den experimentellen waldbaulichen Behandlungen des BETA-FOR-Projekts durchgeführt. Obwohl die weltraumgestützten und die In-situ-Indikatoren unterschiedliche Attribute der Waldstruktur quantifizieren, nämlich Bedeckungsgrad und Offenheit, strukturelle Heterogenität und strukturelle Komplexität, wurden starke Korrelationen ($|r| > 0,7$) zwischen MLS box dimension, MLS canopy cover, TLS COI, Sentinel-1 VH, Sentinel-2 NMDI und modellierten GEDI Bedeckungsgrad festgestellt. Sowohl weltraumgestützte als auch In-situ-Indikatoren für die Waldstruktur können eine genaue Abgrenzung zwischen Kontrollflächen (unveränderte Waldstruktur) und aggregierten Interventionen vornehmen, jedoch nicht konsistent zwischen Kontrollflächen und verteilten Interventionen (selektive Entnahme). Darüber hinaus wurde sowohl für die weltraumgestützten als auch für die In-situ-Indikatoren eine Sensitivität gegenüber dem Vorhandensein von stehendem Totholz in aggregierten Interventionen festgestellt.

Die Beziehungen zwischen Waldstruktur und biologischer Vielfalt wurden durch die Integration von Indikatoren für die Heterogenität der Waldstruktur auf der Grundlage von Sentinel-1- und Sentinel-2-Zeitreihen sowie von modellierten Attributen der Waldstruktur aus GEDI-Daten quantifiziert. Die Indikatoren für die Waldstruktur charakterisieren durchweg den Hauptunterschied in der Heterogenität der Waldstruktur zwischen den Kontrollflächen und den aggregierten Interventionen und in geringem Maße die strukturellen Unterschiede zwischen den Kontrollflächen und den verteilten Interventionen. Taxonomische Diversitätsdaten von Fledermäusen, Vögeln, Schnecken, Schwebfliegen, Insekten, Motten, Spinnen und Bäumen dienen als Referenzdaten für die biologische Vielfalt. Es wurden lineare Korrelationen zwischen den Indikatoren für die Heterogenität der Waldstruktur und den Messungen der biologischen Vielfalt berechnet, die für mehrere Taxa - Vögel, Gastropoden, Schwebfliegen, Insekten und Baumarten - Werte von über 0,4 erreichten.

Zusammenfassend lässt sich sagen, dass weltraumgestützte Multisensordaten ein großes Potenzial für die mehrjährige Charakterisierung der Dynamik von Waldstrukturveränderungen auf nationaler Ebene haben. Sowohl Radar- als auch multispektrale Zeitreihen eignen sich für die Überwachung neuartiger experimenteller waldbaulicher Behandlungen, wenn diese als Lückenschlag (aggregierte Intervention) durchgeführt werden. Korrelationsanalysen zwischen weltraumgestützten und in-situ-Indikatoren für die Waldstruktur zeigten die Übereinstimmung mehrerer Metriken und bestätigten damit das Potenzial weltraumgestützter Indikatoren zur räumlichen und zeitlichen Aufwertung von in-situ-Indikatoren aus der Fernerkundung. Auf der Grundlage von weltraumgestützten Multisensordaten und In-situ-Biodiversitätsmessungen wurden mehrere Beziehungen zwischen Waldstruktur und Biodiversität identifiziert, die auf eine tiefere Integration der Erdbeobachtung in die Ökologie hindeuten, um die Waldbewirtschaftung im Hinblick auf die Erhaltung der Biodiversität zu verbessern.

Anglické Shrnutí

Přibližně třetinu zemského povrchu pokrývají lesy, které poskytují životní prostor mnoha živočichům, rostlinám a mikroorganismům. Lesy jsou součástí mnoha různých biomů v tropickém, subtropickém, mírném a boreálním pásmu. Mezi důležité ekosystémové funkce lesů patří sekvestrace uhlíku, stabilizace vodního režimu, filtrace vody a podpora biodiverzity . Poskytování těchto ekosystémových funkcí závisí na strukturálních vlastnostech lesů, např. na vertikální a horizontální stratifikaci, fragmentaci a časové kontinuitě v lesním porostu. Stabilizace teplotních výkyvů, retence vody a využití lesa pro rekreační účely jsou vybrané ekosystémové služby důležité pro kvalitu lidského života, které jsou však výsledkem vzájemného působení jeho komplexních ekosystémových funkcí.

Více než tři století intenzivního lesního hospodaření ve střední Evropě změnila přirozenou strukturu lesů. V Německu je přibližně 95 % lesů obhospodařováno pro lesnické účely. V mnoha regionech vedlo lesnické hospodaření ke strukturální homogenizaci lesů. Typickými znaky jsou: lesní porosty dominované limitovaným počtem druhů dřevin, nízká diverzita věkových tříd a také nedostatek přirozeně tlejícího mrtvého dřeva. Homogenní lesy jsou navíc více náchylné k rozsáhlým přírodním disturbancím. K tomu, abychom dostatečně charakterizovali nedávnou dynamiku vývoje lesů v Německu chybí vícerozměrné informace v čase o jejich struktuře v národním měřítku. Kromě toho je pro rozvoj přirozenějších, biologicky rozmanitějších a odolnějších lesů velmi důležité sledování nových technik lesního hospodaření zaměřených na zvýšení strukturní komplexity porostů. Téma této disertační práce řeší tyto mezery ve znalostech tím, že hodnotí nedávné změny struktury lesů v Německu s experimentálně zvýšeným prostorovým rozlišením za několik let v kontextu lesní biodiverzity.

Časoprostorová pozorování z dat dálkového průzkumu Země (EO, Earth Observation) umožňují sledovat dynamiku zemského povrchu. Data EO zahrnují informace získané z různých typů senzorů, jako je radar (např. Sentinel-1), multispektrální senzory (např. Sentinel-2) nebo lidar (např. GEDI), a umožňují kvantifikovat strukturu a biologickou rozmanitost lesů. Systematický přehled literatury o monitorování biodiverzity lesů se zaměřením na data EO, který je součástí této disertační práce, ukázal, že předchozí výzkumy většinou používaly pouze pozorování z multispektrálních satelitních senzorů. Kromě toho se studie často omezovaly na dílčí strukturální údaje. Potenciál multisenzorových přístupů a integrace dlouhodobých časových řad, tak zůstává dosud nedostatečně využitý.

V rámci této práce byl vyvinut nový pracovní postup využívající strojové učení a multisenzorová EO data k modelování výšky lesního porostu, pokryvnosti korun a množství nadzemní biomasy v lesích Německa v letech 2017 - 2023. Modelování probíhalo v prostorovém rozlišení 10 m a využívalo časové řady družic Sentinel-1 a Sentinel-2 jako prediktory pro referenční data struktury lesa odvozená z misí GEDI. Výsledkem jsou roční informace o struktuře lesa, které umožnily kvantifikovat změny na národní i regionální úrovni. Například v regionech s rozsáhlým úbytkem lesních porostů, jako jsou Harz a Durynský les, byly zaznamenány výrazné poklesy výšky korun (>20 m), změny v pokryvnosti korun (>50 %) a současná množství nadzemní biomasy dosahující 200 Mg/ha.

V rámci integrativního výzkumného projektu BETA-FOR financovaného DFG, zaměřeného na vztahy mezi strukturou lesa a biodiverzitou v listnatých lesích, byly realizovány experimentální lesnické zásahy. Tato ošetření kombinovala různá uspořádání těžby (agregované – kácení ve skupinách; distribuované – výběrové odstranění jednotlivých stromů) s úpravami objemu mrtvého volně tlejícího dřeva, s cílem diverzifikovat světelné podmínky a mikrostanoviště. Výsledkem byly náhlé strukturální změny na maloplošných experimentálních plochách (50 m × 50 m), které byly sledovány pomocí nově vyvinutého metodického rámce pro detekci změn na základě časových řad Sentinel-1 a Sentinel-2. Pro každý časový krok byly vypočteny různé spektrální indexy a prostorové statistiky na základě dat z Sentinel-1 (n = 98) a Sentinel-2 (n = 903), které byly následně vyhodnoceny z hlediska citlivosti na změny struktury lesa po experimentálním lesnickém zásahu. Pomocí statistiky heterogenity byla nejlépe hodnocena agregovaná ošetření. Pouze několik málo distribuovaných ošetření bylo možné identifikovat s důrazem na hodnoty ze Sentinel-2. Celkově byly nejúspěšnější pro určení typu experimentálního zásahu polarizace Sentinel-1 VH a index NMDI (Sentinel-2).

Dále byly EO metriky porovnány s in-situ indikátory struktury lesa získanými metodami mobilního (MLS) a terestrického (TLS) laserového skenování. Zatímco vzdálená data poskytují pohled na horní část lesního porostu, MLS/TLS zachycují strukturu pod korunami, čímž se obě perspektivy doplňují. V kontextu experimentálních lesnických zásahů projektu BETA-FOR byly provedeny základní korelační analýzy. Ačkoli kvantifikují satelitní a in-situ indikátory y různé atributy struktury lesa, konkrétně pokryvnost a otevřenost korun, strukturní heterogenitu a strukturní komplexitu, byly mezi nimi zjištěny silné korelace ($|r| > 0,7$), zvláště mezi box dimension MLS, canopy cover MLS, COI TLS, VH Sentinel-1, NMDI Sentinel-2 a celkovou pokryvností korun modelovaných GEDI. Jak satelitní, tak in-situ indikátory struktury lesa dokáží přesně rozlišit kontrolní neovlivněné porosty a porosty s agregovanými změnami, ne však se stejnou přesností rozdíly mezi kontrolními a distribuovaně aplikovanými zásahy. Dále byla u obou typů indikátorů zaznamenána citlivost na přítomnost stojícího mrtvého dřeva v agregovaných ošetřeních.

Integrací modelovaných atributů struktury lesa a EO časových řad byly dále analyzovány vztahy mezi strukturální heterogenitou lesa a biologickou rozmanitostí. Referenční data pro hodnocení biodiverzity zahrnovala více různých taxonomických skupin (např. netopýři, ptáci, plži, členovci, hmyz, rostliny). U několika taxonů – konkrétně ptáků, plžů, stromů a vybraného hmyzu – byly zjištěny lineární korelace mezi strukturálními indikátory a biodiverzitními ukazateli přesahující hodnoty 0,4. V případě lesních druhů byly tyto korelace obzvlášť výrazné.

Tato disertační práce ukazuje, že multisenzorová data dálkového průzkumu Země představují silný nástroj pro kontinuální a dlouhodobé sledování změn ve struktuře lesa na národní úrovni. Radarová a multispektrální časová řada umožňují efektivně detekovat experimentální lesnické zásahy, především ve formě mezernatých sečí. Výsledky korelačních analýz mezi satelitními a in-situ indikátory dále potvrzují potenciál EO dat pro široké využití ve sledování prostorové a časové rozmanitosti ve struktuře lesa. Identifikované vztahy mezi strukturou lesa a biodiverzitou podtrhují rostoucí význam integrace EO do ekologického výzkumu s cílem informovat dopadu lesního hospodářství na biodiverzitu lesa as cílem podpořit biologicky udržitelné lesní hospodaření.

Resumen en Español

Alrededor de un tercio de la superficie terrestre está cubierta por bosques que sirven de hábitat a numerosos animales y plantas. Los bosques están presentes en muchos biomas diferentes como el tropical, el subtropical, el templado y el boreal. El secuestro de carbono, la filtración de agua y la creación de hábitats son funciones ejemplares de los ecosistemas forestales. La provisión de esas funciones ambientales depende de las características estructurales de los bosques, por ejemplo, las propiedades verticales y horizontales, la fragmentación y la continuidad temporal. La amortiguación de la temperatura, el almacenamiento de agua y los fines recreativos son servicios ambientales seleccionados para el bienestar humano, resultado de la interacción de las funciones de los ecosistemas.

En Europa Central, más de tres siglos de gestión forestal han alterado la estructura natural de los bosques. En Alemania, cerca del 95 % de los bosques se gestionan con fines silvícolas. En varias regiones, la gestión silvícola ha conducido a una homogeneización estructural: pocas especies arbóreas dominantes, estructuras de clases de edad, así como escasez de madera muerta son características típicas. Además, los bosques homogéneos son especialmente susceptibles a las perturbaciones naturales. A escala nacional falta información continua sobre múltiples atributos de la estructura forestal y para varios años que permitirían caracterizar mejor la reciente dinámica de la estructura forestal en Alemania durante épocas de eventos de perturbación a gran escala . Además, el seguimiento de nuevas técnicas de gestión forestal dirigidas a mejorar la complejidad estructural de los bosques es de gran relevancia para el desarrollo de bosques más naturales, con alta biodiversidad y más resilientes. El tema de esta tesis aborda este déficit de conocimiento mediante la evaluación de los cambios recientes en la estructura forestal en Alemania y los analiza a alta resolución espacial durante varios años en el contexto de la biodiversidad forestal.

Las observaciones a alta resolución espaciotemporal derivadas de datos de teledetección permiten vigilar la dinámica de la superficie terrestre. Los datos de observación de la Tierra incluyen información obtenida desde el espacio a partir de diferentes sensores, como radares (por ejemplo, Sentinel-1), multiespectrales (por ejemplo, Sentinel-2) o Lidar (por ejemplo, GEDI), para cuantificar la estructura y la biodiversidad de los bosques.

Una revisión sistemática de la bibliografía sobre el seguimiento de la biodiversidad forestal centrada en los datos de observación de la Tierra, como parte de esta tesis, mostró que las investigaciones anteriores integraban principalmente observaciones de un solo sensor procedentes de satélites multiespectrales. Además, los estudios se limitaban a menudo a datos subnacionales sobre los bosques. Por otra parte, el potencial del análisis multisensorial de los bosques, así como la integración de largas series temporales, sigue sin estudiarse suficientemente. Se ha desarrollado un novedoso flujo de trabajo de aprendizaje automático que hace uso de datos EO (Earth Observation) multisensorales para modelar la altura del dosel forestal, la cobertura total del dosel y la biomasa por encima del suelo de 2017 a 2023 en una resolución espacial de 10 m para Alemania. Más concretamente, las series temporales de los satélites Sentinel-1 y Sentinel-2 sirven como variables predictoras para los datos de muestreo sobre los atributos de la estructura forestal derivados de GEDI con el fin de generar productos anuales. Tanto a nivel nacional como regional, se cuantificó la dinámica de cambio de la estructura forestal. Para dos puntos críticos de pérdida de cobertura forestal en Alemania, los bosques de Harz y Turingia, se evaluó una reducción de la altura de las copas de más de 20 m, una cubierta total de copas superior al 50 % y una densidad de biomasa por encima del suelo de hasta 200 Mg/ha.

En el contexto de un proyecto de investigación integrativo financiado por la DFG, BETA-FOR, se aplicaron tratamientos silvícolas experimentales en bosques alemanes de frondosas para evaluar la relación entre la estructura forestal y la biodiversidad. Se crearon diferentes disposiciones de las cortas (agregadas: tala en hueco, distribuidas: eliminación selectiva) en combinación con diversas estructuras de madera muerta para diversificar las condiciones de luz y los hábitats. La aplicación de esos parches de tratamiento a pequeña escala (50 m x 50 m) produce cambios bruscos en la estructura del bosque. Se estableció un nuevo marco metodológico para identificar los puntos de cambio en las series temporales de Sentinel-1 y Sentinel-2. Basándose en un catálogo exhaustivo, se calcularon varios índices espectrales y se agregaron por parcela y paso temporal como estadísticas espaciales. Se evaluaron las métricas (combinación de índice espectral y estadística espacial) de Sentinel-1 (n = 98) y Sentinel-2 (n = 903) para identificar las métricas que mejor evaluaban el cambio en la estructura del bosque (aplicación de un tratamiento silvícola experimental). En general, los tratamientos agregados se evaluaron mejor para ambos sensores utilizando estadísticas de heterogeneidad. Sólo pudieron identificarse unos pocos tratamientos distribuidos, con beneficios para las métricas de Sentinel-2. La polarización VH de Sentinel-1 y el NMDI de Sentinel-2 determinaron con precisión el mayor número de implementaciones de tratamientos.

Mediante la integración de información sobre la heterogeneidad de la estructura forestal basada en atributos modelizados de la estructura forestal, así como en métricas de series temporales de satélite de Sentinel-1 y Sentinel-2, se llevaron a cabo análisis de correlación con indicadores de estructura forestal obtenidos in situ mediante teledetección. Las observaciones MLS y TLS ofrecen perspectivas del dosel inferior que complementan las mediciones del dosel superior de los sensores espaciales. Los análisis de correlación se realizaron en el contexto de los tratamientos silvícolas experimentales del proyecto BETA-FOR. Aunque los indicadores espaciales e in situ cuantifican diferentes atributos de la estructura forestal, como la cubierta y la apertura del dosel, la heterogeneidad estructural y la complejidad estructural, se identificaron fuertes correlaciones ($|r| > 0{,}7$) entre MLS box dimension, MLS canopy cover, el COI TLS, el VH Sentinel-1, el NMDI Sentinel-2 y la cubierta total del dosel modelada por GEDI. Tanto los indicadores espaciales como los in situ de la estructura forestal pueden delimitar con precisión entre el control (estructura forestal inalterada) y los tratamientos agregados, pero no de forma consistente entre el control y los tratamientos distribuidos. Además, tanto los indicadores espaciales como los in situ son sensibles a la presencia de madera muerta en pie en los tratamientos agregados.

La relacione entre la estructura forestal y la biodiversidad se cuantificaron integrando indicadores de heterogeneidad de la estructura forestal basados en las series temporales de Sentinel-1 y Sentinel-2, así como atributos modelados de la estructura forestal a partir de datos de GEDI. Los indicadores de estructura forestal caracterizan de forma consistente la principal diferencia en la heterogeneidad de la estructura forestal de los tratamientos de control a los agregados, y en menor medida las diferencias estructurales entre los tratamientos de control y los distribuidos. Los datos de diversidad taxonómica de murciélagos, aves, gasterópodos, revoloteadores, insectos, polillas, arañas y árboles sirven como datos de referencia de la biodiversidad. Se calcularon correlaciones lineales entre los indicadores de heterogeneidad de la estructura forestal y las medidas de biodiversidad, alcanzando valores superiores a 0,4 para varios taxones: aves, gasterópodos, revoloteadores, insectos y especies arbóreas.

En resumen, los datos espaciales multisensorales tienen un gran potencial para la caracterización plurianual de la dinámica de cambio de la estructura forestal a escala nacional. Tanto el radar como las series temporales multiespectrales son adecuados para el seguimiento de nuevos tratamientos silvícolas experimentales cuando se llevan a cabo como talas en hueco. Los análisis de correlación entre los indicadores espaciales e in situ de la estructura forestal demostraron la alineación de varias métricas, confirmando el potencial de los indicadores espaciales para aumentar la escala de los indicadores de teledetección in situ en el espacio y el tiempo. Se identificaron varias relaciones entre estructura forestal y biodiversidad a partir de datos de multisensores espaciales y mediciones de biodiversidad in situ, lo que sugiere una integración más profunda de la EO en ecología para informar mejor la gestión forestal para la preservación de la biodiversidad.

Résumé en Français

Environ un tiers des terres émergées de la planète sont couvertes de forêts, et servent d'habitat à de nombreux animaux et plantes. Les forêts sont présentes dans de nombreux différents biomes, tels que le biome tropical, le biome subtropical, le biome tempéré et le biome boréal. La séquestration du carbone, la filtration de l'eau et la création d'habitats sont des fonctions écosystémiques essentielles des forêts. L'apport de ces fonctions écosystémiques dépend des caractéristiques structurelles des forêts, c'est-à-dire de leurs propriétés verticales et horizontales, de leur fragmentation et de la continuité de leur évolution temporelle. La régulation des températures, le stockage de l'eau et les activités récréatives sont des services écosystémiques profitant au bien-être de l'homme, et qui résultent de l'interaction des fonctions écosystémiques.

En Europe centrale, plus de trois siècles de gestion forestière ont modifié la structure naturelle des forêts. En Allemagne, environ 95 % des forêts sont gérées à des fins sylvicoles. Dans plusieurs régions, la gestion sylvicole a conduit à une homogénéisation structurelle caractérisée par peu d'essences dominantes, des structures par classes d'âge, ainsi que par la rareté du bois mort. Par ailleurs, les forêts homogènes sont particulièrement sensibles aux perturbations naturelles. Le manque d'informations continues et historiques sur la structure forestière à l'échelle nationale limite une meilleure caractérisation de la dynamique récente de la structure forestière en Allemagne pendant les périodes de perturbations à grande échelle. En outre, l'évaluation de nouvelles techniques de gestion forestière visant à améliorer la complexité structurelle des forêts est d'une grande importance pour le développement de forêts plus naturelles, biodiversifiées et résilientes. Le sujet de cette thèse aborde ces lacunes de connaissances en évaluant les changements récents de la structure forestière en Allemagne à haute résolution spatiale sur plusieurs années en relation avec la biodiversité forestière.

Les observations spatio-temporelles à grande échelle dérivées des données d'Observation de la Terre (OT, ou EO, Earth Observation) permettent de surveiller la dynamique de la surface de la Terre. Les données d'OT peuvent être dérivées de différents capteurs montés sur satellites, tels que des données radar (par exemple issues

du satellite Sentinel-1), multispectrales (par exemple issues du satellite Sentinel-2) ou Lidar (par exemple issues du satellite GEDI), et permettent de quantifier la structure et la biodiversité des forêts. Une analyse systématique de la littérature menée dans le cadre de cette thèse sur le suivi de la biodiversité des forêts s'appuyant sur les données d'observation de la Terre, a révélé que la plupart des études précédentes ont utilisé des observations à capteur multispectral unique De plus, les études se limitaient souvent à des données infranationales sur les forêts. Par conséquent, le potentiel de l'analyse de données multi-capteurs issues de différents satellites, ainsi que l'intégration de longues séries temporelles restent sous-étudiés.

Toujours dans le cadre de cette thèse, un nouveau processus d'apprentissage automatique utilisant ainsi des données d'observation de la Terre multi-capteurs a été développé pour modéliser la hauteur du couvert forestier, l'étendue totale du couvert et la biomasse de surface entre 2017 et 2023 avec une résolution spatiale de 10 m pour l'Allemagne. Plus précisément, les séries temporelles satellitaires de Sentinel-1 et Sentinel-2 servent de variables prédictives pour les données d'échantillonnage sur les attributs de la structure forestière dérivées de GEDI afin de générer des produits annuels. Les dynamiques de changement de la structure forestière ont été quantifiées tant au niveau national que régional. Deux régions hautement impactées par la perte de couvert forestier en Allemagne, à savoir le Harz et la forêt de Thuringe, ont été évaluées montrant une réduction de la hauteur du couvert de plus de 20 m, un déclin dans l'étendue totale du couvert supérieur à 50 % et une densité de biomasse aérienne allant jusqu'à 200 Mg/ha.

Dans le cadre d'un projet de recherche intégré financé par le DFG, BETA-FOR, des traitements sylvicoles expérimentaux ont été mis en œuvre dans des forêts de feuillus allemandes afin d'évaluer les relations entre la structure de la forêt et la biodiversité. Différentes dispositions de coupes (agrégées : abattage par trouées, réparties : abattage sélectif) combinées à diverses structures de bois mort ont été créées pour diversifier les conditions de lumière et les habitats. La mise en œuvre de ces parcelles de traitement à petite échelle (50 m x 50 m) entraîne de brusques changements dans la structure de la forêt. Afin d'identifier les points de changement dans les séries temporelles de Sentinel-1 et Sentinel-2, un nouveau cadre méthodologique a été mis en place. Une collection exhaustive de divers indices spectraux a été calculée et agrégée temporellement et spatialement par parcelle. Les mesures (statistiques d'hétérogénéité spatiales calculées sur combinaison d'indices spectraux) de Sentinel-1 (n = 98) et de Sentinel-2 (n = 903) ont été comparées afin d'identifier celles qui permettent le mieux d'évaluer le changement dans la structure de la forêt à la suite de la mise en œuvre d'un traitement sylvicole expérimental. Dans l'ensemble, les statistiques d'hétérogénéité ont présenté de meilleures performances d'évaluation pour les traitements agrégés pour les deux satellites. Seuls quelques traitements distribués ont pu être identifiés, grâce à des mesures provenant de Sentinel-2. La polarisation VH de Sentinel-1 et le NMDI de Sentinel-2 ont permis de déterminer avec précision la plupart des traitements mis en œuvre.

Des indicateurs de structure forestière, calculés à partir de données télédétectées MLS et TLS et capturées sur les sites de test (insitu), ont servi pour l'analyse de corrélation avec les mesures de séries temporelles satellitaires de Sentinel-1 et Sentinel-2, ainsi qu'avec les attributs modélisés de la structure forestière (hauteur du couvert forestier, l'étendue totale du couvert et la biomasse). Les observations MLS et TLS offrent des perspectives sous la canopée qui sont complémentaires des mesures au sommet de la canopée effectuées par les capteurs aéroportés (Sentinel 1, Sentinel 2, GEDI). Les analyses de corrélation ont été menées dans le contexte des traitements sylvicoles expérimentaux du projet BETA-FOR. Bien que les attributs de la structure forestière quantifiés par les indices spectraux issus des données satellitaires et les indicateurs issus des données télédétectées in situ (par exemple la complexité structurelle, couvert et ouverture) soient différents, de fortes corrélations bivariées ($|r| > 0{,}7$) ont été identifiées entre MLS box dimension, MLS canopy cover, le COI TLS, le VH Sentinel-1, le NMDI Sentinel-2 et l'étendue totale du couvert modélisée de l'IEDG . Les indices issus de données satellitaires aussi bien que les indicateurs issus des données in situ de la structure forestière distinguent avec précision les traitements de contrôle (structure forestière inchangée) et les traitements agrégés, mais ne sont pas systématiquement performant pour distinguer les traitements de contrôle et les traitements distribués. Par ailleurs, une sensibilité à la présence de bois mort sur pied dans les traitements agrégés a été constatée aussi bien pour les indices issus des données satellitaires que les indicateurs issus des données in situ.

Les relations entre la structure forestière et la biodiversité ont été quantifiées en intégrant des indicateurs d'hétérogénéité de la structure forestière basés sur les séries temporelles de Sentinel-1 et Sentinel-2, ainsi que des attributs modélisés de la structure forestière à partir des données GEDI. Les indicateurs de structure forestière identifient systématiquement la principale différence d'hétérogénéité de la structure forestière entre les traitements de contrôle et les traitements agrégés et, dans une moindre mesure, les différences structurelles entre les traitements de contrôle et les traitements distribués. Les données sur la diversité taxonomique des chauves-souris, des oiseaux, des gastéropodes, des syrphes, des insectes, des papillons de nuit, des araignées et des arbres servent de données de référence sur la biodiversité. Des corrélations ont été calculées entre les indicateurs d'hétérogénéité de la structure forestière et les mesures de la biodiversité, atteignant des valeurs supérieures à 0,4 pour plusieurs taxons : oiseaux, gastéropodes, syrphes, insectes et espèces d'arbres.

En résumé, les données multicapteurs satellitaires présentent un fort potentiel pour la caractérisation pluriannuelle de la dynamique de changement de la structure forestière à l'échelle nationale. Les séries chronologiques radar et multispectrales sont toutes deux adaptées au suivi de nouveaux traitements sylvicoles expérimentaux lorsqu'ils sont réalisés sous forme de coupes par trouées. Les analyses de corrélation entre les indicateurs issus de données satellitaires et de mesures téledetectées in situ de la structure forestière ont démontré l'alignement de plusieurs métriques, confirmant ainsi le potentiel des indicateurs issues des données satellitaires pour amplifier la couverture des observations insitu dans l'espace et dans le temps. Des relations entre la structure forestière et la biodiversité ont été identifiées sur la base de données multicapteurs satellitaires et de mesures de biodiversité in situ, suggérant l'opportunité que présente une intégration plus poussée de l'OT en écologie pour mieux éclairer la gestion forestière en vue de la préservation de la biodiversité.

Riassunto Italiano

Circa un terzo della superficie terrestre è coperto da foreste che forniscono habitat a numerosi animali e piante. Le foreste sono presenti in molti biomi diversi, come quello tropicale, subtropicale, temperato e boreale. Il sequestro del carbonio, il filtraggio dell'acqua e la creazione di habitat sono funzioni ecosistemiche esemplari delle foreste. La fornitura di queste funzioni ecosistemiche dipende dalle caratteristiche strutturali delle foreste, come le proprietà verticali e orizzontali, la frammentazione e la continuità temporale. Il tamponamento della temperatura, l'immagazzinamento dell'acqua e gli scopi ricreativi sono servizi ecosistemici selezionati per il benessere umano, risultanti dall'interazione delle funzioni ecosistemiche.

In Europa centrale, più di tre secoli di gestione forestale hanno alterato la struttura naturale delle foreste. In Germania, circa il 95 % delle foreste è gestito a fini forestali. In diverse regioni, la gestione selvicolturale ha portato a un'omogeneizzazione strutturale: poche specie arboree dominanti, strutture per classi di età e scarsità di legno morto sono caratteristiche tipiche. Inoltre, le foreste omogenee sono particolarmente sensibili ai disturbi naturali. Mancano informazioni continue sulla struttura forestale a scala nazionale per diversi attributi della struttura forestale e per diversi anni, per caratterizzare meglio le recenti dinamiche della struttura forestale in Germania durante i periodi di eventi di disturbo su larga scala. Inoltre, il monitoraggio di nuove tecniche di gestione forestale volte a migliorare la complessità strutturale delle foreste è di grande importanza per lo sviluppo di foreste più naturali, biodiverse e resilienti. Il tema di questa tesi affronta queste lacune conoscitive valutando i recenti cambiamenti della struttura forestale in Germania ad alta risoluzione spaziale per più anni nel contesto della biodiversità forestale.

Le osservazioni ad alto spazio-tempo derivate dai dati EO (Earth Observation) consentono di monitorare la dinamica della superficie terrestre. I dati EO comprendono informazioni derivate dallo spazio da diversi sensori, come radar (ad esempio Sentinel-1), multispettrali (ad esempio Sentinel-2) o Lidar (ad esempio GEDI), per quantificare la struttura e la biodiversità delle foreste. Una revisione sistematica della letteratura sul monitoraggio della biodiversità forestale con particolare attenzione ai dati EO, nell'ambito di questa tesi, ha mostrato che le ricerche precedenti integravano per lo più osservazioni a singolo sensore da satelliti multispettrali. Inoltre, gli studi erano spesso limitati a dati subnazionali sulle foreste. Inoltre, il potenziale dell'analisi multisensore delle foreste, così come l'integrazione di lunghe serie temporali, rimane poco studiato.

È stato sviluppato un nuovo flusso di apprendimento automatico che fa uso di dati EO multisensore per modellare l'altezza delle chiome delle foreste, la copertura totale delle chiome e la biomassa fuori terra dal 2017 al 2023 con una risoluzione spaziale di 10 m per la Germania. Più precisamente, le serie temporali satellitari di Sentinel-1 e Sentinel-2 servono come variabili predittive per i dati di campionamento sugli attributi della struttura forestale derivati da GEDI al fine di generare prodotti annuali. Sia a livello nazionale che regionale, sono state quantificate le dinamiche di cambiamento della struttura forestale. Per due punti caldi di perdita di copertura forestale in Germania, ovvero la foresta di Harz e quella di Turingia, è stata valutata una riduzione dell'altezza delle chiome superiore a 20 m, una copertura totale delle chiome superiore al 50 % e una densità di biomassa fuori terra fino a 200 Mg/ha.

Nell'ambito di un progetto di ricerca integrativo finanziato dalla DFG, BETA-FOR, sono stati attuati trattamenti selvicolturali sperimentali in foreste tedesche di latifoglie per valutare le relazioni tra struttura forestale e biodiversità. Per diversificare le condizioni di luce e gli habitat, sono state create diverse disposizioni di tagli (aggregati: abbattimento in gap, distribuiti: rimozione selettiva) in combinazione con varie strutture di legno morto. L'attuazione di queste patch di trattamento su piccola scala (50 m x 50 m) determina bruschi cambiamenti nella struttura della foresta. Per identificare i punti di cambiamento nelle serie temporali Sentinel-1 e Sentinel-2 è stato creato un nuovo quadro metodologico. Sulla base di un catalogo completo, sono stati calcolati vari indici spettrali e aggregati per patch e time-step come statistiche spaziali. Le metriche (combinazione di indici spettrali e statistiche spaziali) di Sentinel-1 (n = 98) e Sentinel-2 (n = 903) sono state valutate al fine di individuare le metriche che meglio valutano il cambiamento della struttura forestale (attuazione del trattamento selvicolturale sperimentale). In generale, i trattamenti aggregati sono stati valutati al meglio per entrambi i sensori utilizzando le statistiche di eterogeneità. È stato possibile identificare solo pochi trattamenti distribuiti, con vantaggi per le metriche del Sentinel-2. La polarizzazione VH di Sentinel-1 e l'NMDI di Sentinel-2 hanno determinato con precisione il maggior numero di trattamenti.

Integrando le informazioni sull'eterogeneità della struttura forestale basate su attributi modellati della struttura forestale e le metriche delle serie temporali satellitari di Sentinel-1 e Sentinel-2, sono state effettuate analisi di correlazione con gli indicatori della struttura forestale rilevati a distanza in situ. Le osservazioni MLS e TLS offrono una prospettiva sub-canopy che è complementare alle misure top-of-canopy dei sensori spaziali. Le analisi di correlazione sono state condotte nel contesto dei trattamenti selvicolturali sperimentali del progetto BETA-FOR. Sebbene gli indicatori spaziali e in situ quantifichino diversi attributi della struttura forestale, ossia la copertura e l'apertura delle chiome, l'eterogeneità strutturale e la complessità strutturale, sono state individuate forti correlazioni (> 0,7) tra la dimensione della scatola MLS, la copertura delle chiome MLS, il COI TLS, il VH Sentinel-1, l'NMDI Sentinel-2 e la copertura totale delle chiome GEDI modellata. Sia gli indicatori spaziali che quelli in situ della struttura forestale possono delineare con precisione tra i trattamenti di controllo (struttura forestale inalterata) e quelli aggregati, ma non in modo coerente tra i trattamenti di controllo e quelli distribuiti. Inoltre, è stata riscontrata una sensibilità alla presenza di legno morto in piedi nei trattamenti aggregati sia per gli indicatori spaziali che per quelli in situ.

Le relazioni struttura forestale-biodiversità sono state quantificate integrando indicatori di eterogeneità della struttura forestale basati sulle serie temporali Sentinel-1 e Sentinel-2, nonché attributi modellati della struttura forestale dai dati GEDI. Gli indicatori di struttura forestale caratterizzano in modo coerente la principale differenza di eterogeneità della struttura forestale tra i trattamenti di controllo e quelli aggregati e, in misura minore, le differenze strutturali tra i trattamenti di controllo e quelli distribuiti. I dati sulla diversità tassonomica di pipistrelli, uccelli, gasteropodi, sirfidi, insetti, falene, ragni e alberi servono come dati di riferimento per la biodiversità. Sono state calcolate correlazioni lineari tra gli indicatori di eterogeneità della struttura forestale e le misure di biodiversità, raggiungendo valori superiori a 0,4 per diversi taxa: uccelli, gasteropodi, sirfidi, insetti e specie arboree.

In sintesi, i dati multisensore rilevati dallo spazio presentano un grande potenziale per la caratterizzazione pluriennale delle dinamiche di cambiamento della struttura forestale a scala nazionale. Sia le serie temporali radar che quelle multispettrali sono adatte al monitoraggio di nuovi trattamenti selvicolturali sperimentali, quando condotti come tagli a raso. Le analisi di correlazione tra indicatori della struttura forestale rilevati dallo spazio e in situ hanno dimostrato l'allineamento di diverse metriche, confermando così il potenziale degli indicatori rilevati dallo spazio per migliorare la scala spaziale e temporale degli indicatori rilevati da remoto in situ. Diverse relazioni tra struttura forestale e biodiversità sono state identificate sulla base di dati multisensore rilevati dallo spazio e di misurazioni della biodiversità in situ, suggerendo una più profonda integrazione dell'osservazione della natura in ecologia per fornire informazioni migliori sulla gestione forestale ai fini della conservazione della biodiversità.

Streszczenie po Angielsku

Około jedna trzecia lądowej powierzchni Ziemi pokryta jest lasami, które stanowią siedliska dla licznych gatunków zwierząt i roślin. Lasy występują w różnych biomach, takich jak biom tropikalny, subtropikalny, umiarkowany i borealny. Sekwestracja węgla, filtracja wody oraz tworzenie siedlisk to przykładowe funkcje ekosystemowe lasów. Świadczenie tych funkcji ekosystemowych zależy od cech strukturalnych lasów, takich jak struktura pionowa i pozioma, stopień fragmentacji oraz ciągłość czasowa. Buforowanie temperatury, magazynowanie wody oraz funkcje rekreacyjne to wybrane usługi ekosystemowe mające znaczenie dla dobrostanu człowieka, wynikające ze współdziałania różnych funkcji ekosystemowych.

Ponad trzystuletnia historia gospodarowania lasami w Europie Środkowej doprowadziła do znaczącego przekształcenia ich naturalnej struktury. W Niemczech około 95 % lasów jest zarządzanych pod kątem gospodarki leśnej. W wielu regionach doprowadziło to do homogenizacji strukturalnej, cechującej się dominacją kilku wybranych gatunków drzew, podziałem na klasy wiekowe oraz niedoborem martwego drewna. Takie strukturalnie jednorodne lasy są szczególnie narażone na naturalne zaburzenia środowiska. Brakuje jednak ciągłych danych zbieranych na przestrzeni lat z całego kraju, które umożliwiłyby dokładną charakterystykę współczesnej dynamiki struktury lasów w Niemczech w obliczu rosnącej presji wielkoskalowych zaburzeń środowiska. Dodatkowo, monitoring działania nowoczesnych technik gospodarowania lasem, mających na celu zwiększenie złożoności strukturalnej lasów, jest kluczowy dla rozwoju bardziej naturalnych, bioróżnorodnych i odpornych ekosystemów leśnych. Tematyka niniejszej rozprawy doktorskiej uzupełnia wspomniane luki w wiedzy poprzez ocenę współczesnych zmian struktury lasów w Niemczech z wysoką rozdzielczością przestrzenną i czasową w kontekście ich bioróżnorodności.

Wysokiej rozdzielczości obserwacje czasowo-przestrzenne (dane EO, Earth Observation) umożliwiają monitorowanie dynamiki powierzchni Ziemi. Dane EO obejmują informacje pozyskiwane z różnych czujników satelitarnych, takich jak radar (np. Sentinel-1), czujniki wielospektralne (np. Sentinel-2), oraz lidar (np. GEDI), które umożliwiają ilościową ocenę struktury lasu i bioróżnorodności. Przeprowadzony w ramach niniejszej rozprawy doktorskiej systematyczny przegląd literatury dotyczący monitorowania bioróżnorodności lasów z wykorzystaniem danych EO ujawnił, że dotychczasowe badania opierały się głównie na danych z pojedynczych czujników satelitów wielospektralnych. Ponadto badania te często ograniczały się do szczebla regionalnego. Reasumując, potencjał analiz wieloczujnikowych oraz integracji długoterminowych szeregów czasowych wciąż nie został dostatecznie przebadany.

W ramach niniejszej rozprawy opracowano nowy schemat uczenia maszynowego wykorzystujący wieloczujnikowe dane EO do modelowania wysokości koron drzew, całkowitego zwarcia koron oraz biomasy nadziemnej z rozdzielczością przestrzenną 10 m na obszarze całych Niemiec w latach 2017–2023. Mówiąc szczegółowo, szeregi czasowe danych z Sentinel-1 i Sentinel-2 posłużyły jako zmienne objaśniające dla danych próbnych struktury lasu pochodzących z GEDI w celu generowania corocznych produktów (baz danych). Zmiany w strukturze lasów zostały ilościowo określone zarówno na poziomie krajowym, jak i regionalnym. Dla dwóch miejsc o szczególnym stopniu utraty pokrycia koron – Lasu Harzu i Lasu Turyńskiego – wykazano spadek wysokości koron drzew o ponad 20 m, spadek całkowitego zwarcia koron przekraczający 50 % oraz spadek gęstości biomasy nadziemnej do 200 Mg/ha.

W ramach integracyjnego projektu badawczego finansowanego przez DFG, BETA-FOR, w lasach liściastych Niemiec stworzono eksperymentalne powierzchnie badawcze w celu oceny relacji pomiędzy strukturą lasu a bioróżnorodnością. Te powierzchnie cechowały różne układy cięć (agregowane: zręby, rozproszone: selektywne usuwanie drzew), oraz zróżnicowana struktura martwego drewna, co poskutkowało dywersyfikacją warunków świetlnych i siedlisk. Wdrożenie wspomnianych zabiegów w małej skali (50 m x 50 m) spowodowało gwałtowne zmiany w strukturze lasu. W ramach rozprawy opracowano nowe ramy metodologiczne umożliwiające identyfikację punktów zmiany w szeregach czasowych Sentinel-1 i Sentinel-2. Na podstawie obszernego katalogu obliczono różne indeksy spektralne i agregowano je dla każdej działki i kroku czasowego jako statystyki przestrzenne. Oceniono łącznie 98 miar (kombinacji indeksów spektralnych i statystyk przestrzennych) z Sentinel-1 i 903 miary z Sentinel-2 pod kątem identyfikacji tych najlepiej obrazujących zmiany struktury lasu w obrębie eksperymentalnych powierzchni badawczych. Ogólnie, zabiegi agregowane były najlepiej wykrywane przez oba czujniki przy użyciu statystyk heterogeniczności. Jeśli chodzi o zabiegi rozproszone, jedynie nieliczne udało się w ogóle zidentyfikować, przy czym metryki Sentinel-2 wykazały większą skuteczność. Polaryzacja VH z Sentinel-1 oraz NMDI z Sentinel-2 najdokładniej identyfikowały wdrożone zabiegi na eksperymentalnych powierzchniach badawczych.

Poprzez integrację informacji o zróżnicowaniu struktury lasu na podstawie modelowanych atrybutów oraz miar satelitarnych serii czasowych z Sentinel-1 i Sentinel-2 przeprowadzono analizy korelacyjne ze wskaźnikami struktury lasu pozyskanymi metodami teledetekcji naziemnej. Obserwacje MLS i TLS dostarczają informacji spod warstwy koron, które uzupełniają dane z czujników satelitarnych określających strukturę jedynie z góry. Analizy korelacyjne przeprowadzono w kontekście eksperymentalnych zabiegów gospodarczych projektu BETA-FOR (opisanych powyżej). Pomimo że wskaźniki satelitarne i naziemne mierzą różne atrybuty struktury (np. zwarcie koron i otwartość, heterogeniczność strukturalna, złożoność strukturalna), zidentyfikowano silne korelacje ($|r| > 0{,}7$) między MLS box dimension, MLS canopy cover, TLS COI, Sentinel-1 VH, Sentinel-2 NMDI oraz modelowanym całkowitym zwarciem koron GEDI. Zarówno wskaźniki satelitarne, jak i naziemne dobrze rozróżniały kontrolne powierzchnie badawcze (niezmieniona struktura) od tych z agregowanymi cięciami, lecz nie zawsze skutecznie odróżniały powierzchnie kontrolne od tych z rozproszonymi cięciami. Ponadto zaobserwowano wrażliwość wskaźników, zarówno satelitarnych, jak i naziemnych, na obecność stojącego martwego drewna na powierzchniach z zabiegami agregowanymi.

Relacje między strukturą lasu a bioróżnorodnością zostały określone poprzez integrację wskaźników heterogeniczności struktury lasu z danych Sentinel-1 i Sentinel-2 oraz modelowanych atrybutów struktury z GEDI. Wskaźniki te dobrze odzwierciedlały główne różnice w heterogeniczności struktury między powierzchniami kontrolnymi a tymi z agregowanymi cięciami, a w mniejszym stopniu między kontrolnymi a tymi z cięciami rozproszonymi. Dane o różnorodności taksonomicznej nietoperzy, ptaków, ślimaków, bzygowatych, owadów, motyli, pająków i drzew posłużyły jako odniesienie dla bioróżnorodności. Współczynniki korelacji liniowej między wskaźnikami heterogeniczności struktury a miarami bioróżnorodności przekraczały wartość 0,4 dla kilku taksonów: ptaków, ślimaków, bzygowatych, owadów i drzew.

Podsumowując, dane satelitarne z wielu czujników mają duży potencjał do wieloletniej charakterystyki zmian struktury lasów na skalę krajową. Zarówno serie czasowe danych radarowych, jak i wielospektralnych są odpowiednie do monitorowania eksperymentalnych zabiegów gospodarczych, zwłaszcza zrębów. Analizy korelacyjne między wskaźnikami satelitarnymi i naziemnymi potwierdziły zgodność wielu miar, co wskazuje na potencjał wskaźników satelitarnych do skalowania wskaźników teledetekcyjnych w przestrzeni i czasie. Zidentyfikowano liczne relacje między strukturą lasu a bioróżnorodnością na podstawie danych z czujników satelitarnych i pomiarów naziemnych, co sugeruje potrzebę głębszej integracji danych EO w ekologii, aby lepiej wspierać zarządzanie lasami w kontekście ochrony bioróżnorodności.

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Abbreviations and Acronyms

agbd	above-ground biomass density
API	Application Programming Interface
ATBD	Algorithm Theoretical Basis Document
BEAST	Bayesian Estimator of Abrupt change, Seasonal change, and Trend
BFAST	Breaks for Additive Season and Trend
CCS	Crown Condition Survey
COI	Canopy Openness Index
COLD	COntinuous monitoring of Land Disturbance
cover	total canopy cover
cv	coefficient of variation
DBH	Diameter at Breast Height
DFD	German Remote Sensing Data Center
DFG	Deutsche Forschungsgemeinschaft
DI	Disturbance Index
DLM	Digital Landscape Model
DLR	German Aerospace Center
DRMAT	breakpoints-Detection algoRithm using MultivAriate Time series
DWD	Deutscher Wetterdienst
EDGE	Earth Dynamics Geodetic Explorer
EEA	European Environment Agency
EO	Earth Observation
EOC	Earth Observation Center
ESA	European Space Agency
EU	European Union
FHDI	Foliage-Height-Diversity-Index
GEDI	Global Ecosystem Dynamics Investigation
GEE	Google Earth Engine
GRD	Ground-Range-Detected
ha	hectare
HRL	High Resolution Layer
HVH	Height Variation Hypothesis
ICESat	Ice, Cloud, and land Elevation Satellite
ICESat-2	Ice, Cloud, and land Elevation Satellite-2
ISS	International Space Station
km	kilometer
km^2	square kilometer
Lidar	Light detection and ranging

LSWI	Land Surface Water Index
m	meter
Mg/ha	megagrams per hectare
MLS	Mobile Laser Scanning
MODIS	Moderate Resolution Imaging Spectroradiometer
MSI	Moisture Stress Index
NASA	National Aeronautics and Space Administration
NDREI	Normalized Difference Red Edge Index
NDVI	Normalized Difference Vegetation Index
NFI	National Forest Inventory
NFSI	National Forest Soil Inventory
nm	nanometer
NMDI	Normalized Multi-band Drought Index
PAI	Plant-Area-Index
PALSAR	Phased Array L-band Synthetic Aperture Radar
QGIS	Quantum Geographic Information System
R^2	Coefficient of determination
rh95	canopy height, 95th percentile
RMSE	Root Mean Square Error
SAR	Synthetic Aperture Radar
SDG	United Nations Sustainable Development Goal
SR	Simple Ratio
SSCI	Stand Structural Complexity Index
std	standard deviation
SVH	Spectral Variation Hypothesis
t/ha	tons per hectare
TCD	Tree cover density
TLS	Terrestrial Laser Scanning
UCI	Understory Complexity Index
USGS	United States Geological Survey
var	variance
VDDPI	Vertical Dual De-Polarization Index
VH	vertical transmit, horizontal receive
VHVVR	VH-VV Ratio
VV	vertical transmit, vertical receive
VVVHS	VV-VH Sum
WSCI	Waveform-Structural-Complexity-Index

Chapter 1

Introduction

1.1 Scientific Relevance and Research Motivation

1.1.1 Human Influence on Forests

Human activities have shaped the earth since centuries encompassing local to global scales, thus altering natural dynamics. Under the term "anthropocene" (Crutzen, 2006), the recent geological epoch is summarized which is dominantly characterized by human activities on the environment holding significant impacts on forest ecosystems (IPBES, 2019; IPCC, 2023). Deforestation, forest degradation, as well as fragmentation in the context of land use change affect the global carbon cycle by increasing atmospheric carbon dioxide contents and forcing global climate warming (Post et al., 1990; Hansen et al., 2013). As a consequence, forest habitats are changing in structure and declining in extent which is why increasing species extinction rates in forests (Stork, 2010; IPBES, 2019) contribute to the sixth global mass extinction in the context of global climate change in the anthropocene (Ceballos et al., 2015).

Forest ecosystems can provide numerous ecosystem functions (Forest Europe, 2020), such as carbon storage, habitat heterogeneity, and water filtration (Figure 1.1). The interplay of different ecosystem functions generates ecosystem services to humans which are essential to their well-being. In general, ecosystem services are classified into four categories: supporting, provisioning, regulating, and cultural ecosystem services (Millennium ecosystem assessment, MEA, 2005). Exemplary supporting ecosystem services of forests are nutrient cycling, soil formation, as well as primary production, which maintain the three other ecosystem services. Provisioning ecosystems comprise for example food, fresh water, fuel, and wood. Regulating ecosystem services have a controlling effect on climatic conditions, flooding events, disease distribution, or water purification. Educational aspects, and recreational purposes are summarized as cultural ecosystem services (Millennium ecosystem assessment, MEA, 2005; Brockerhoff et al., 2017).

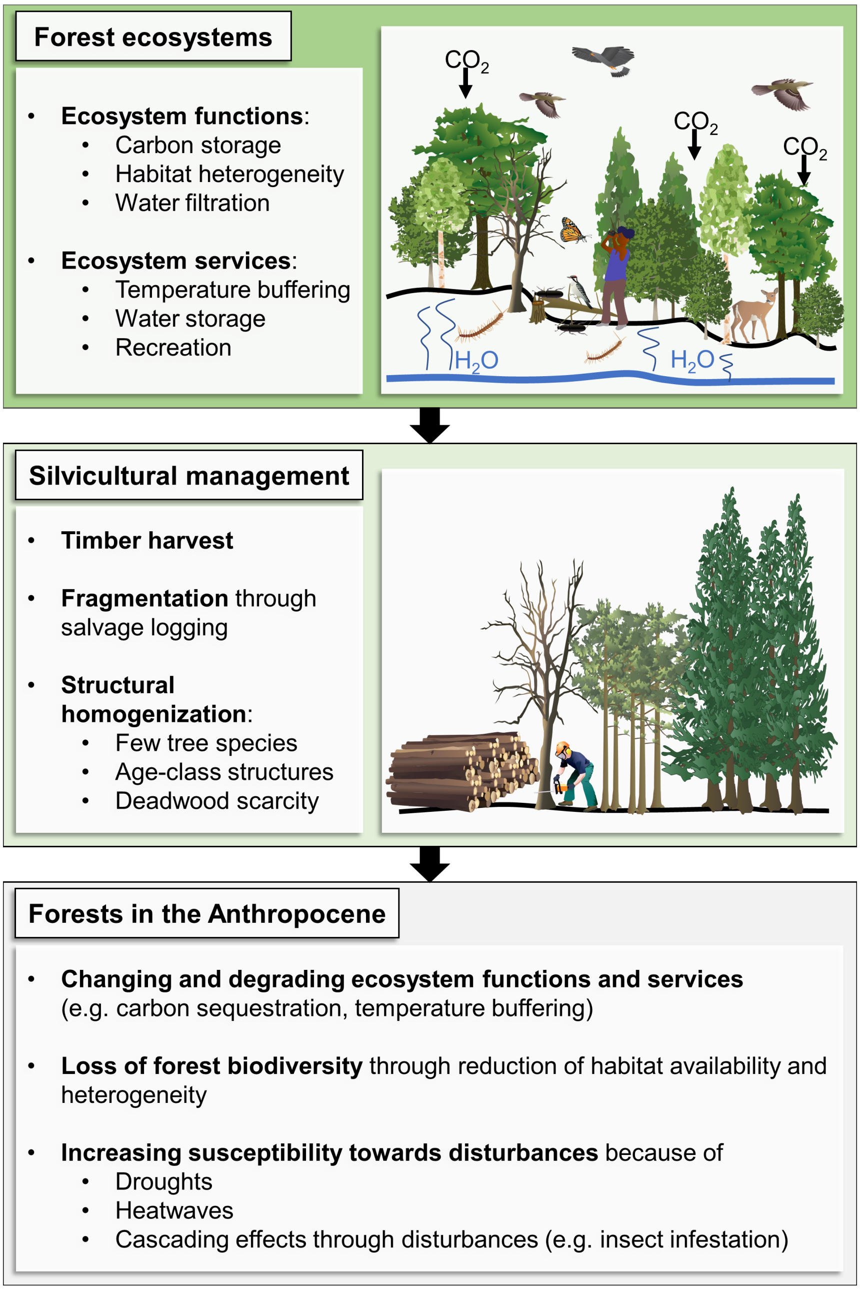

Figure 1.1: Schematic figure of forests in the Anthropocene. Graphics are extracted from the University of Maryland (https://ian.umces.edu/media-library/, accessed on 24 December 2024).

Forest ecosystems and their provision of ecosystem services are dependent on the forest management type. Traditional silvicultural management focuses on the extraction of timber and has led to fragmented forests through salvage logging practices (Müller et al., 2018; Messier et al., 2021). With the establishment of wide-spread plantation forestry, forests were transformed towards homogeneous structures characterized by few tree species, age-class structures, and low amount and diversity of deadwood (Chaudhary et al., 2016; Seliger et al., 2023). Overall, many ecosystem services, such as carbon sequestration and temperature buffering, are further degrading as a consequence of climate change conditions, accompanied by forest biodiversity loss. Furthermore, an increasing susceptibility of forests towards disturbances, such as droughts and heatwaves, is expected (Müller et al., 2018; Senf et al., 2020a; Rakovec et al., 2022).

The relationship of drought conditions in Central Europe to excess forest mortality has been confirmed by Senf et al. (2020a) resulting in about 500.000 ha with forest canopy mortality from 1987 to 2016. In addition, multiple consecutive droughts years since 2018 in Central Europe have further reduced the vitality of forests (Schuldt et al., 2020; Buras et al., 2021; Holtmann et al., 2024). In Germany, forest canopy cover loss amounts to about 920,000 ha from 2017 to 2024 (German Aerospace Center (DLR), 2025). Hotspots of forest canopy cover loss are located in Central Germany which are further characterized by declining forest structure: loss of canopy height (> 20 m), reduction in total canopy cover (> 60 %), and decline in above-ground biomass density (> 150 Mg/ha) (Kacic et al., 2023).

Forest structure-biodiversity relationships have been identified by multiple studies (Bohn and Huth, 2017; Heidrich et al., 2020) linking vertical and horizontal structural properties to diversity of taxa, as well as ecosystem functions. At the European level, about 75 % of the forests are even-aged, thus resulting in homogeneous forest structures, such as canopy height and canopy cover. In addition, only 17 % of European forests are mixed forests, i.e. consisting of both coniferous and broadleaved trees. Furthermore, one third of Europe's forests are dominated by a single tree species (Forest Europe, 2020). Forests with homogeneous forest structures are more susceptible to disturbances (Holtmann et al., 2024) and provide fewer ecosystem services (Figure 1.2, adapted from Messier et al. (2021)) which is why there is a need to diversify forest structures. Heterogeneous forest structures characterized by high tree species diversity, uneven-aged trees, and increasing amount and diversity of deadwood supports future resilience and multifunctionality of forests (Müller et al., 2018; Messier et al., 2021).

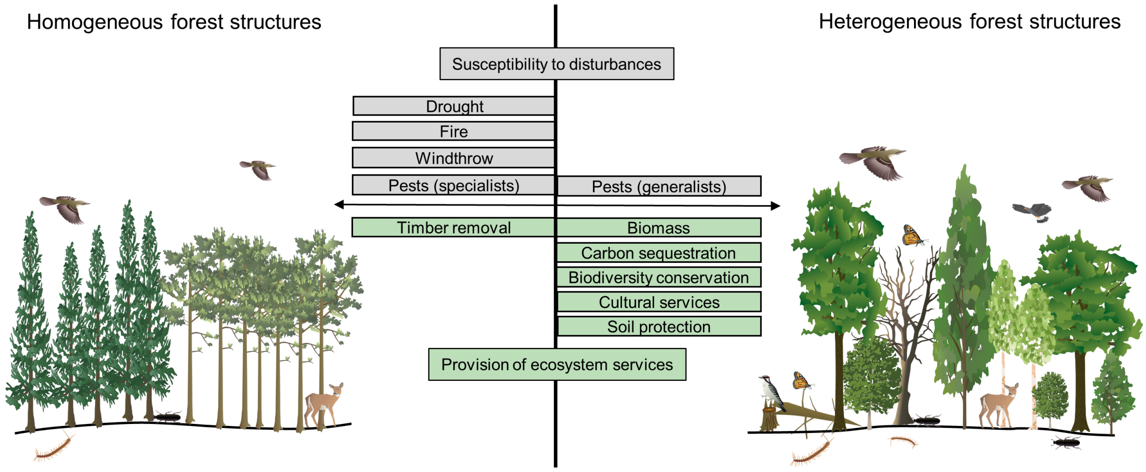

Figure 1.2: Schematic figure of forest structure-biodiversity relationships in the context of susceptibility to disturbances and provision of ecosystem services (adapted from Messier et al. (2021)). Graphics are extracted from the University of Maryland (https://ian.umces.edu/media-library/, accessed on 24 December 2024).

1.1.2 The Role of Forest and its Management in Germany

Forests cover about one third of the German land surface (about 11.4 million ha) and consist of both broadleaved and coniferous trees. The composition and distribution of tree species in German forests has been shaped by centuries of forest management (Federal Ministry of Food and Agriculture (BMEL)). About 95 % of Germany's forested area is managed for forestry purposes (Bolte and Rock, 2021). There are four different types of forest ownership in Germany: private forests (43 % of German forest cover), land forests (32 %), corporate forests (22 %), and federal forests (3 %). In total, there are about 1.8 million private owners of forests. Most of the private forests are small parcels with an average forest area of about 2.5 ha (Federal Ministry of Food and Agriculture (BMEL)).

Since 2018, a strong increase of logged timber was reported reaching more than 60 million m³ in 2020 and 2021 for spruce, fir, douglas fir, and other coniferous trees (excluding pine and larch). In comparison, from 2013 to 2017 the rate of logged timber for aforementioned tree species never exceeded 30 million m³. The increase in timber logging was a result of salvage logging, i.e. large-scale removal of damaged trees through disturbance events (e.g. windthrow and subsequent insect infestation in consecutive drought years since 2018) (Thorn et al., 2018). From 2017 to 2020, timber logging of damaged trees continuously increased with a peak of 60.1 million m³ of damaged timber in 2020 (about 75 % of total tree removal). In the following years, the amount of removed timber declined continuously, but still held three times higher rates in 2023 (38.7 million m³) compared to 2017 (12.3 million m³) (Statistisches Bundesamt (Destatis), d). The analysis of die-off rates since 1990 shows that spruce trees are most heavily affected amounting to more than 4 % in 2020 and 2022. From 1990 to 2019, all years hold values lower than 1 % for die-off of spruce trees (Johann Heinrich von Thünen Institute (Federal Research Institute for Rural Areas, Forestry and Fisheries) - Institute of Forest Ecosystems, 2023).

Spruce trees cover about 25 % of the German forests, thus being the most dominant tree species in Germany (Federal Ministry of Food and Agriculture (BMEL)). In most locations spruce trees are growing outside their natural habitat which explains their susceptibility to increased die-off rates under drought conditions (Obladen et al., 2021). Pine trees are the second most abundant tree species in Germany covering about 23 % of forest area. In total, about 55 % of German forest are dominated by coniferous trees. The naturally dominant tree species in Germany is beech which only contributes with a share of about 16 % to the recent tree species distribution. The fourth dominant tree species in Germany is oak amounting to 10 % in forest cover (Federal Ministry of Food and Agriculture (BMEL)). Overall, about 24 % of the German forests are monocultures. In comparison, mixed forests (composed of more than a single tree species) hold a cover of about 76 % (Federal Ministry of Food and Agriculture (BMEL)).

Different forest management regulations are targeting a transformation of homogeneous forest structures to heterogeneous forest structures (Figure 1.2). At the European level, the Nature Restoration Law of the Biodiversity Strategy of the European Union (EU) aims for an "increasing trend for standing and lying deadwood, uneven aged forests, forest connectivity, abundance of common forest birds and stock of organic carbon" in order to develop heterogeneous forest structures holding higher habitat heterogeneity, resilience to disturbances, and multifunctionality (European Commission, 2020a, 2023). The EU Forestry Strategy is connected to the EU Biodiversity Strategy and targets declining greenhouse gas emissions, thus supporting climate neutrality (European Commission, 2020b). At the national level, Germany is pursuing the Forest Strategy ("Waldstrategie") 2050 (BMEL, 2021) aiming to establish close-to-nature forestry which should strengthen the multifunctionality of forests in the context of the United Nations Sustainable Development Goal (SDG) 15 (Sayer et al., 2019).

1.1.3 Monitoring Forest Structure and Biodiversity in Germany

Forests in Germany are undergoing severe changes through disturbances, specifically since the repeated drought years starting 2018 (Johann Heinrich von Thünen Institute (Federal Research Institute for Rural Areas, Forestry and Fisheries) - Institute of Forest Ecosystems, 2023; Holtmann et al., 2024). Assessing the change dynamics of forests quantitatively is of high interest for foresters and policy makers in order to maintain ecosystem functions and associated services, as well as supporting future forest resilience under global climate change conditions (Wellbrock and Bolte, 2019; Gschwantner et al., 2022). Monitoring forest structure is of specific relevance due to forest structure-biodiversity relationships, i.e. the linkage of structural habitat characteristics to the biological diversity of taxa, functions, and phylogeny (Bohn and Huth, 2017; Heidrich et al., 2020).

The assessment of forest condition in Germany is traditionally conducted in the context of sampling campaigns at annual to decadal intervals. In Germany, the well-established forest monitoring practices rely on plot measurements organized in regular grids covering Germany at varying spatial resolutions: National Forest Inventory (NFI) ("Bundeswaldinventur"), National Forest Soil Inventory (NFSI) ("Bodenzustandserhebung"), Crown Condition Survey (CCS) ("Waldzustandserhebung") (Wellbrock and Bolte, 2019; Holzwarth et al., 2020).

Although different forest monitoring projects assessed forest conditions based on EO data for Germany, there is not yet an operational forest monitoring system based on EO data (Copernicus Netzwerkbüro Wald, 2025). The potential of high spatio-temporal observations derived from spaceborne sensors to characterize forest vitality, structure, and biodiversity has been demonstrated by numerous studies (DeFries, 2013; Achard and Hansen, 2016; Camarretta et al., 2020; Lechner et al., 2020). Therefore, the integration of area-wide, consistent and open-source EO time-series data can supplement sampling campaigns. Satellite radar data from Sentinel-1, as well as multispectral data from Sentinel-2, hold a great potential to characterize forest structural characteristics (Silveira et al., 2023) that can be linked to forest biodiversity measurements (Bae et al., 2019; Hoffmann et al., 2022).

Monitoring forest structure and forest biodiversity requires an inter-disciplinary approach to combine remote sensing expertise for the characterization of forest structure and ecological knowledge to assess biodiversity (Cavender-Bares et al., 2022). The present thesis is embedded in the BETA-FOR project which aims to enhance the structural complexity between patches for improving multidiversity and multifunctionality of German broadleaved production forests (Mueller et al., 2022a,b). Therefore, the project addresses the need to monitor forest structure and biodiversity through research on experimental silvicultural treatments altering forest structure (spatial arrangement of trees and deadwood structures) and its influence on forest biodiversity.

1.2 Research Objectives

As outlined in section 1.1, the provision of forest ecosystem services and susceptibility of forests to disturbances (Figure 1.1) is highly dependent on silvicultural management practices since they influence the structural characteristics of forests (Figure 1.2). Spatially continuous and multi-annual data on forest structure in Germany is lacking which is essential for foresters and policy makers to plan the transformation of homogeneous forest structures to heterogeneous forest structures. In addition, the potential of spaceborne data to characterize the enhancement of forest structural complexity through experimental silvicultural treatments is understudied. The integration of spaceborne data for forest structure monitoring can provide additional information on vertical and horizontal structural properties at high spatio-temporal resolutions supporting in-situ observations of NFI campaigns.

The present thesis aims to provide novel insights on EO techniques for forest structure analyses and multi-scale characterization of forests. More precisely, spaceborne Lidar data (GEDI) is combined with satellite radar (Sentinel-1) and multispectral data (Sentinel-2) to model forest canopy height, total canopy cover, and above-ground biomass density as annual products from 2017 to 2023 for entire Germany. Therefore, the first consistent spaceborne-based data set is generated to study recent forest structure change dynamics in Germany. In addition, satellite time-series of Sentinel-1 and Sentinel-2 are analyzed to assess to potential to characterize different experimental silvicultural treatments enhancing the structural complexity. Furthermore, comparative analysis are carried out to identify correlations of modeled forest structure attributes, Sentinel-1 and Sentinel-2 indicators of forest structural complexity to in-situ observations on forest structure based on MLS and TLS. Lastly, relationships among spaceborne indicators of forest structure and in-situ biodiversity samples are investigated to asses to which extent spaceborne data on forest structure can be used as surrogate of biodiversity measurements. In the following, the research objectives of this thesis are listed:

- **Objective 1**: A systematic literature review on the integration of remote sensing data for forest biodiversity monitoring is conducted. Articles with a focus on spectral diversity methods are reviewed to assess spatio-temporal foci of the investigated study areas, integrated sensor types and applied methods. Therefore, recent developments in the field of remotely sensed forest biodiversity monitoring are characterized, and research gaps identified.

- **Objective 2**: A key objective of the thesis is the development of a multi-annual forest structure modeling workflow combining GEDI, Sentinel-1, and Sentinel-2 data in order to generate the first spaceborne-based products of canopy height, total canopy cover, and above-ground biomass density for Germany from 2017 to 2023 at 10 m spatial resolution. The novel products facilitate the analyses of recent forest structure change dynamics at national and regional level in the context of repeated drought years since 2018.

- **Objective 3**: Based on a new methodological framework to assess enhanced forest structural complexity, Sentinel-1 and Sentinel-2 time-series metrics are tested to assess the change in forest structure through novel experimental silvicultural treatments. By making use of a Bayesian time-series decomposition modeling approach, Sentinel-1 and Sentinel-2 indices and spatial statistics are identified that are recommended for monitoring the enhancement of forest structural complexity.

- **Objective 4**: The potential of spaceborne data to characterize different levels of forest structural complexity is assessed. Modeled attributes of forest structure based on GEDI, Sentinel-1, and Sentinel-2 data (objective 2), as well as Sentinel-1 and Sentinel-2 time-series metrics characterizing the enhancement of forest structural complexity (objective 3), are compared to in-situ forest structure data derived from MLS and TLS.

- **Objective 5**: Forest structure-biodiversity relationships are investigated in order to explore the linkage of spaceborne indicators on forest structure and in-situ measurements of forest biodiversity (taxonomic diversity of e.g. spiders, hoverflies, birds). Therefore, spaceborne indicators are identified that are best suited for monitoring forest biodiversity.

The research objectives are linked to research questions which need to be answered to assess the potential of spaceborne data for forest structure and biodiversity analyses. Based on a systematic literature review on forest biodiversity monitoring integrating EO data, the first group of questions addresses the current research focus and aims to identify gaps for further research:

Research Questions 1:

1. How extensively has forest biodiversity monitoring based on remotely sensed spectral diversity been researched, and what are recent thematic and spatial foci?
2. What are typical data characteristics (sensors, temporal resolutions, spectral indices), methodological concepts, and biodiversity aspects (scales, environmental foci)?
3. Which research limitations and gaps are identified, and how can they potentially be investigated using spaceborne remote sensing data?

The second group of research questions focuses on the development of a novel workflow to derive multi-annual products of forest structure attributes for Germany:

Research Questions 2:

1. What is the potential of forest structure modeling using spaceborne data, and what are challenges to combine GEDI, Sentinel-1, and Sentinel-2 data?
2. How can a multi-annual modeling workflow be implemented to derive products on forest canopy height, total canopy cover, and above-ground biomass density?
3. What are spatio-temporal dynamics of forest structure in Germany, and how accurately are forest structure change dynamics assessed based on the multi-annual products?

The third group of research questions refers to the generation of a new methodological framework to assess enhanced forest structural complexity based on satellite time-series:

Research Questions 3:

1. Can the change in forest structure through small-scale experimental silvicultural treatments be characterized by satellite data using Bayesian time-series decomposition models?
2. To which extent can the implementation events of two groups of experimental silvicultural treatments, namely aggregated (gap felling) and distributed (selective thinning), be detected from Sentinel-1 and Sentinel-2 time-series data?
3. What are the best time-series characteristics (indices, spatial statistics, change point types) of Sentinel-1 and Sentinel-2 to assess the treatment implementation events?

The fourth group of research questions is related to comparative analyses of spaceborne and in-situ remote sensing indicators of forest structural complexity:

Research Questions 4:

1. Which spaceborne forest structure indicators hold highest correlations to in-situ remotely sensed indicators (MLS, TLS) characterizing forest structure conditions of experimental silvicultural treatments?
2. What is the potential of spaceborne and in-situ indicators to delineate aggregated, distributed and control treatments holding different conditions in forest structural complexity?
3. Can experimental silvicultural treatments with a presence of standing deadwood structures be differentiated from treatments with an absence of standing deadwood structures, and is there a different potential of only spaceborne indicators to combined spaceborne and in-situ indicators?

The last group of research questions is about the investigation of forest structure-biodiversity relationships linking spaceborne indicators of forest structure to in-situ biodiversity measurements:

Research Questions 5:

1. Can spaceborne forest structure indicators characterize the structural differences among experimental silvicultural treatments (control district vs. enhanced districts, i.e. aggregated and distributed treatments) of six regions?
2. Are in-situ biodiversity measurements sensitive to the enhancement of forest structural complexity (enhanced districts), thus showing high correlations to spaceborne forest structure indicators?

1.3 Thesis Outline

Chapter 1 introduces the scientific relevance and research motivation for forest structure and forest biodiversity monitoring. In addition, five research objectives and associated research questions are defined.

Chapter 2 provides a background on forest characteristics, biodiversity scales, as well as biodiversity monitoring categories. In the following, the results of a systematic literature review on forest biodiversity based on remote sensing data are presented.

Chapter 3 presents the study area of this dissertation, namely the forests in Germany. After an introduction to the physical geography of Germany, the distribution and usage, as well as the status and disturbance history of German forests follows. Lastly, a patch-network of experimental silvicultural treatments enhancing the forest structural complexity is explained.

Chapter 4 focuses on the development of a novel workflow to derive multi-annual products of forest structure attributes. By combining data derived from spaceborne Lidar (GEDI), satellite radar (Sentinel-1), and satellite multispectral (Sentinel-2), forest canopy height, total canopy cover, and above-ground biomass density are modeled using a machine-learning algorithm. The analysis of the derived annual products from 2017 to 2023 characterizes recent forest structure changes since the drought conditions starting in 2018.

Chapter 5 introduces a new methodological framework to assess enhanced forest structural complexity based on satellite time-series. By calculating numerous spectral indices and spatial statistics for Sentinel-1 and Sentinel-2 time-series, change points are assessed that indicate the change in forest structure through the implementation of experimental silvicultural treatments using Bayesian probabilistic models. Therefore, the potential of Sentinel-1 and Sentinel-2 data is analyzed to characterize forest structural changes through different management practices.

Chapter 6 presents a comparative analysis of spaceborne and in-situ remote sensing indicators of forest structural complexity. Correlations among indicators derived from MLS and TLS, as well as modeled attributes of forest structure (chapter 4) and satellite time-series indicators of forest structural complexity (chapter 5) are quantified to provide insights to which extent spaceborne remote sensing can upscale in-situ indicators of forest structure.

Chapter 7 focuses on the assessment of relationships of spaceborne forest structure indicators and in-situ biodiversity measurements. Multi-sensor spaceborne indicators (chapter 6) are related to diversity measurements of different taxonomic groups in order to understand the strength of forest structure-biodiversity relationships.

Chapter 8 summarizes the main findings of this dissertation and answers the research questions defined in chapter 1. Furthermore, an outlook for future research directions is given.

Chapter 2

A Review on Remote Sensing of Forest Biodiversity*

In order to understand the developments of methods and remote sensing data for forest biodiversity monitoring, a systematic literature review was carried out. This chapter provides an overview on remotely sensed forest biodiversity monitoring based on 109 studies that were published between 2002 and 2022. In the first section the relevance of different forest structural characteristics promoting biodiversity is explained (section 2.1). In addition, the general assessment of forest structure-biodiversity relationships from a remote sensing perspective is considered. In the following, various biodiversity scales and categories of biodiversity are the focus (section 2.2). The results of the literature review (section 2.3) are sub-divided into properties of the reviewed studies (section 2.3.1) and remotely sensed forest biodiversity monitoring (section 2.3.2). Properties of the reviewed studies are on the one hand the temporal and spatial distribution, and on the other hand an overview on the different remote sensing sensors integrated for monitoring. Methods and thematic foci are assessed in the following to provide an overview on current research best-practices, but also identifying research gaps. The chapter closes with a discussion on the methodological validity of reviewed studies (section 2.4) and an overall summary (section 2.5).

2.1 Background on Forest Characteristics

Forests are among other ecosystems a key ecosystem to ensure biodiversity and ecosystem functioning (Butchart et al., 2010; Gaston, 2000). Tropical forests are considered to be hotspots of biodiversity since they hold enhanced species richness and multifunctionality (Reid, 1998; Wilson et al., 1988). Furthermore, healthy forests, i.e. rich in biodiversity, provide a great variety of ecosystem services being essential for the well-being of species

*Parts of this chapter have been published in Kacic and Kuenzer (2022).

living in the forest (Maclaurin and Sterelny, 2008). The ecosystem services of forests can be grouped into provisioning (e.g. fresh water, carbon sequestration), regulating (e.g. buffering of drought conditions through water reservoirs in the soil and vegetation) and cultural services (e.g. recreational purposes for humans) (Brockerhoff et al., 2017).

The resilience of forests, and thus the continuous functioning of ecosystem services, is dependent on the taxonomic, functional, and structural diversity of species in forests (Wilson et al., 1988). Since the different aspects of diversity make up the overall biodiversity of forests, monitoring of the different aspects is an essential task during times of global climate change. Research on global warming in combination with more frequent extreme events (e.g. drought) has confirmed concerns on the future preservation of forests harboring high biodiversity (Betts et al., 2017; Dirzo et al., 2014). Within the framework of planetary boundaries different categories fostering the earth's functioning for human well-being are assessed. By investigating potential limits (boundaries) of the earth's crucial functions, forests have been identified as key ecosystem due to its comprehensive ecosystem functions so that humanity can cope with global climate change conditions (Steffen et al., 2015).

Global biodiversity loss as response to global climate change is the main characteristic of the Anthropocene, i.e. the geological time period predominantly shaped by humans (Dirzo et al., 2014). Unprecedented dynamics of biodiversity decline at global levels are interpreted by multiple research groups as the beginning of the earth's sixth mass extinction event (Barnosky et al., 2011; Ceballos et al., 2017; Mittermeier et al., 2011). The most significant dynamics leading to global biodiversity loss are reduced forest area cover, reduction of protected areas (only about 20 % of the forest hotspots of biodiversity are protected), and negative dynamics for the Red List Index (about 30 % of all inventoried species are prone to extinction) (Almond et al., 2020; IUCN, 2022; Keenan et al., 2015).

Overall, forests are under pressure globally due to climate change conditions that reduce forest vitality and potential future resilience. Continuous monitoring of forest conditions based on spaceborne data is an essential task to track and quantify forest loss, changes in forest structure, and forest biodiversity.

2.2 Scales and Categories of Biodiversity Monitoring

Monitoring of forest biodiversity can be conducted at different scales in order to focus on complementary spatial characteristics of diversity. The concept of biodiversity scales originates from traditional in-situ measurements during forest inventories which are detailed as small-scale assessments of floristic and faunistic properties but restricted in their spatial extents and temporal resolution (Palmer, 1995; Palmer et al., 2002). In addition, such inventories are time-consuming and cost-intensive which is why the concept of biodiversity scales was translated to remotely sensed data (e.g. airborne and spaceborne sensors) (Hakkenberg et al., 2023; Rocchini et al., 2021).

The schematic Figure 2.1 presents the different biodiversity scales, namely α-diversity, β-diversity, and γ-diversity, assessed through in-situ, airborne and spaceborne measurements. The concept of biodiversity scales is a hierarchical concept: at local scale (α-diversity), the within community diversity is assessed e.g. through species richness, Shannon-Wiener index or Simpson index (Colwell et al., 2009; Shannon and Weaver, 1948; Simpson, 1949). The turn-over in species composition (β-diversity), i.e. the between community diversity among local communities (α-diversity), constitutes a link between local and regional scales. Different dissimilarity measurements from traditional in-situ sampling, such as Jaccard index or Bray-Curtis dissimilarity, are commonly used for the analyses of β-diversity (Sørensen, 1948; Clarke et al., 2006). Landscape diversity (γ-diversity) is the largest spatial scale (highest hierarchical level) since it can be subdivided into α-diversity and β-diversity through additive or multiplicative approaches (Tuomisto, 2010a,b). The total species richness at landscape-level is one typical measurement of γ-diversity (Hill, 1973).

For the assessment of forest biodiversity at different scales, global data at high spatio-temporal scales is indispensable since traditional in-situ forest inventory are limited to small-scale sample areas at selected time steps (Palmer, 1995; Palmer et al., 2002; Nagendra, 2001). Spaceborne remote sensing offers repeated measurements of different sensor systems being sensitive to specific characteristics of various aspects of the earth's surface dynamics (Gillespie et al., 2008). Open data policies of different global mapping missions (e.g. Landsat by NASA, the Sentinels by ESA) have strongly benefited the continuous monitoring in space and time of various vegetation characteristics (Kuenzer et al., 2014, 2015). The availability of multi-dimensional spaceborne remote sensing data cubes in combination with increased access and knowledge in planetary computing have unlocked tracking dynamics of vegetation properties at previously unknown levels (Gorelick et al., 2017). For example, the characterization of forest structure from spaceborne Lidar systems (e.g. GEDI) enables measuring the vertical and horizontal properties of forests. Previous studies have identified close relationships of forest structure and forest biodiversity since multivariate properties (canopy cover, canopy height, above-ground biomass density, structural complexity) of habitat structures are assessed (Gao et al., 2014; Lelli et al., 2019; Storch et al., 2018).

From a remote sensing perspective, the analysis of forest biodiversity can be sub-divided into four categories (Wang and Gamon, 2019). The categories differ in characteristics of

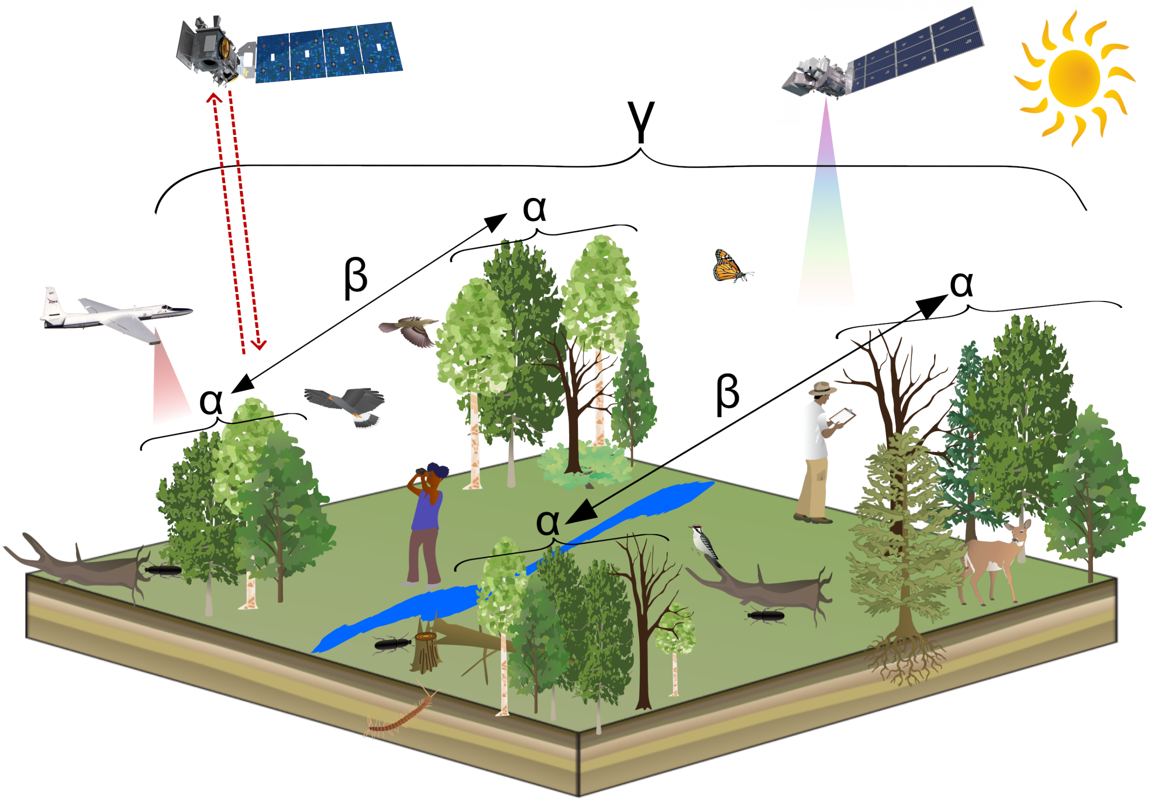

Figure 2.1: Schematic figure of biodiversity scales and sensors. α-diversity describes local community diversity, β-diversity assesses the turn-over in diversity among local communities, and γ-diversity characterizes landscape diversity. Since the focus of the review is on forest biodiversity based on airborne and spaceborne sensors, exemplary graphics are shown for an airborne system (e.g. Lidar), active satellite sensor (e.g. radar; left), and passive satellite sensor (e.g. multispectral; right). Graphics are extracted from the University of Maryland (https://ian.umces.edu/media-library/, accessed on 24 December 2024), and NASA Science (https://science.nasa.gov/get-involved/toolkits/spacecraft-icons, accessed on 1 September 2022).

forest biodiversity that are the focus, e.g. habitat structures, species distribution, functional traits, and spectral variation. The category "habitat mapping" summarizes concepts for species area curve estimation and habitat heterogeneity assessment (Kerr et al., 2001; Jennings, 2000; Stoms and Estes, 1993). Characterizing the distribution of different species (both faunistic and floristic species) is the targeted characteristic of forest biodiversity analysis of the category "species mapping" (Roberts et al., 1998; Ustin et al., 2004). Those first two categories already show one typical difference in ecosystem characterization: on the one hand the primary goal to measure habitat structures (indirect mapping of mobile species based on sessile species), and on the other hand the direct mapping of specific indicator species for forest biodiversity estimation. The third category "functional diversity" is mainly targeting the analyses of plant functional traits of dominant species being present in the canopy (Cavender-Bares et al., 2017; Ustin and Gamon, 2010). Another category of forest biodiversity monitoring is "spectral diversity" which assesses forest biodiversity based on the spectral variation hypothesis (SVH) (Torresani et al., 2024). For spectral diversity there are three established concepts, namely vegetation indices, spectral information content, and spectral species. The presentation of the different spectral diversity concepts follows in the section 2.3.2. The SVH hypothesizes a link of the heterogeneity or complexity measured from a remotely sensed sensor as pixel variation to the varying structural properties of habitat characteristics. Therefore, it is assumed that different properties of habitat characteristics have the potential to provide various ecological niches harboring a greater diversity of species. Overall the SVH aims to provide a theoretical foundation for a positive relationship among spectral diversity and biodiversity. The results of the following literature review are solely based on forest biodiversity analyses through spectral diversity in order to provide a detailed understanding of the potential for monitoring forest biodiversity based on the SVH. Due to its generalized hypothesis in the context of remote sensing data, the validity of the SVH has been questioned by different studies (Fassnacht et al., 2022; Schmidtlein and Fassnacht, 2017). To provide further details on the discussion of the validity of the SVH, a separate section (section 2.4) follows after the presentation of the literature review results (section 2.3).

2.3 Results of the Literature Review

The literature review focuses on the analyses of forest biodiversity based on remotely sensed spectral diversity from airborne and spaceborne sensors. A systematic literature search was conducted in Web of Science and Google Scholar in order to find publications that fulfill the following criteria. The different criteria were concatenated using "AND" statements in order to only query articles that address all defined criteria (Table 2.1):

- Thematic focus on the spectral diversity category for forest biodiversity assessment.
- Integration of airborne or spaceborne remote sensing sensors as primary data source.
- Published scientific articles.
- Language of the article should be English.

Of the total number of articles (n = 552) found after the systematic literature search (conducted on 26 August 2022) using the search string, an additional filtering by reading the titles and abstracts reduced the number of articles (n = 134). After a full text read of previously filtered articles, 109 articles were considered for this review. For those articles metadata of the article and specific information on methods and data were extracted and systematically stored in a data base. The analyses can be sub-divided into two parts, that will

Table 2.1: Search string for systematic literature review on forest biodiversity monitoring based on remotely sensed spectral diversity. The four criteria (spectral diversity, remote sensing, document type, language) need to be fulfilled so that an article was considered. Abbreviations of keys: TS = thematic search, DT = document type, LA = language.

Criteria	Key	Value
Spectral diversity	TS	"spectral variation hypothesis" OR "spectral variability hypothesis" OR "spectral heterogeneity" OR "spectral diversity" OR "optical diversity" OR "alpha diversity" OR "beta diversity" OR "gamma diversity" OR "spectral species"
Remote sensing	TS	"remote sensing" OR "earth observation" OR satellite OR IKONOS OR Quickbird OR WorldView OR Pleiades OR Rapideye OR GeoEye OR Planet OR Skysat OR SPOT OR Landsat OR Sentinel OR AVHRR OR MODIS OR Envisat OR Aster OR ALOS OR TanDEM-X OR TerraSAR-X OR DESIS OR PRISMA OR EnMAP OR Hyperion OR GEDI OR "optical imagery" OR "optical satellite" OR "Synthetic Aperture Radar" OR Radar OR RadarSat OR COSMO OR SRTM OR "microwave satellite" OR "multispectral satellite" OR "hyperspectral satellite" OR "imaging spectroscopy" OR "thermal satellite" OR "airborne laser scanning"
Document type	DT	Article
Language	LA	English

be presented in the next sections: general properties of the reviewed studies and remotely sensed analyses of forest biodiversity.

2.3.1 Properties of the reviewed Studies

The articles on forest biodiversity monitoring based on spectral diversity were published between 2002 and 2022. In general, the total number of articles per year increases from 2002 to 2022. Before 2009, the total number of articles published per year amounts to a maximum number of four. Since 2009 only four years show a total number of published articles per year below four (2010, 2011, 2013, 2015). Within a three year period, most articles were published between 2019 and 2021 (n = 37).

For an initial analysis of the focus research discipline, a categorization based on the Web of Science categories was conducted. The Web of Science categories were regrouped into four broader categories: ecology, environmental sciences (env. sciences), env. sciences / remote sensing, remote sensing. The temporal distribution of reviewed articles sub-divided into the four categories is shown in Figure 2.2.

Overall, most studies are categorized as env. sciences (41.3 %) which were published since 2002 with a total maximum number of articles per year in 2019 (n = 10). Also in the following year 2020, five articles were published with a focus on env. sciences. The inter-disciplinary group env. sciences / remote sensing amounts to 32.1 % of all reviewed studies. The first study of this category was published in 2007. The year 2021 shows the highest number of articles (n = 8) published per year for the category env. sciences / remote sensing. Articles on ecology (14.7 %) and remote sensing (11.9 %) were published less frequently, but are present since 2002.

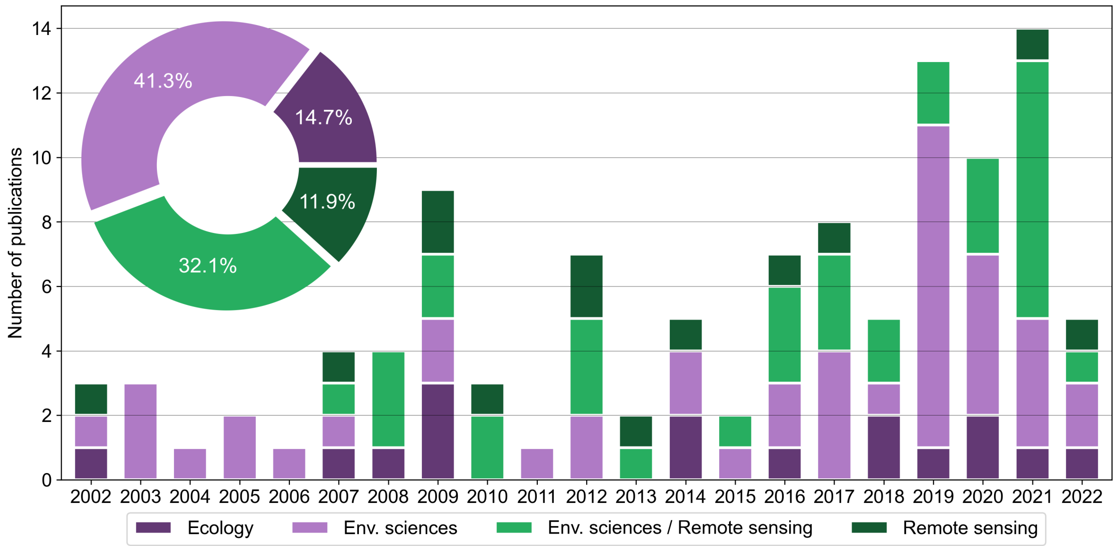

Figure 2.2: Temporal distribution of reviewed articles subdivided into reclassified Web of Science categories. Please find the reclassification scheme of Web of Science categories in the supplementary material of Kacic and Kuenzer (2022).

From all reviewed articles (n = 109), only four articles are at the continental scale (Europe: n = 3, North America: n = 1) and none at the global scale. The remaining 105 articles analyzed forest biodiversity at the sub-continental level. The map of study areas of reviewed articles at the country-level presents a maximum of 15 articles that analyzed study areas in the United States (Figure 2.3a). Second most articles per country assessed study areas in India. The analysis of study areas for forest biodiversity monitoring at the country-level is limited to few countries with more than five articles: United States, India, Germany, Italy, China, South Africa, Peru.

At the continental level, the study areas of reviewed articles are unevenly distributed (Figure 2.3b). Most articles explored forest biodiversity in European countries (n = 34) with a clear focus of central and southern European countries (Germany: n = 7, Italy: n = 9). Study areas on the Asian continent amount to 25 articles. The analysis of forest biodiversity in Asian countries is focused as well on few countries (India: n = 12, China: n = 5). Also

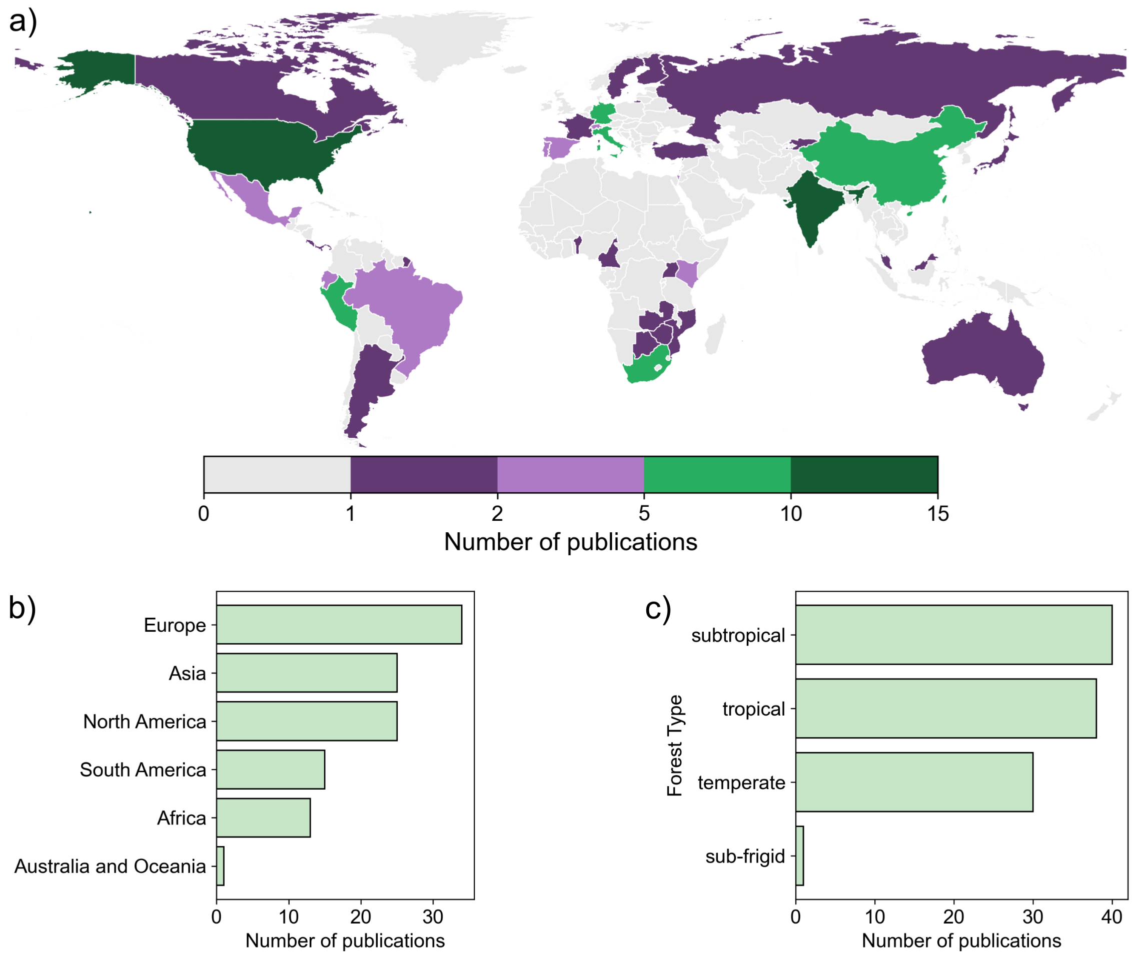

Figure 2.3: Map of the spatial distribution of study areas of reviewed articles at country level (a), continental statistics (b), and statistics of reviewed articles by forest type (c) according to Xu et al. (2022).

for North American study areas there are 25 articles with a clear focus on the United States (n = 15). Fewest study areas of reviewed articles were located in South America (n = 15), Africa (n = 12), and Australia and Oceania (n = 1).

The analysis of study areas categorized into forest types (Xu et al., 2022) presents relatively similar numbers of published articles for subtropical (n = 40), tropical (n = 38), and temperate forests (n = 30). The analysis of forest biodiversity on sub-frigid forests is limited to a single article.

For the analysis of forest biodiversity based on spectral diversity a wide range of sensors and sensor types were integrated in the reviewed articles (Figure 2.4). From all reviewed articles, 69.7 % of all integrated sensors are multispectral systems that measure vegetation properties in the visible, near infrared, and short-wave infrared wavelengths. The measurement of spectral diversity of multispectral (optical sensors) is therefore an optical diversity, i.e. variability of pixels characterizing vitality and photosynthetic activity of vegetation. About 20 % of all reviewed studies assess forest biodiversity based on hyperspectral (10.3 %) and Lidar sensors (9.7 %). Those two sensor types assess different properties of vegetation since hyperspectral sensors are optical systems with many bands limited to narrow wavelength ranges. Data from Lidar sensors is capable to assess vertical and horizontal structural vegetation properties based on an active sensor technology emitting photons to measure distance. Topo radar (n = 5.5%), multisensor platforms (n = 3.4%), and synthetic aperture radar (SAR) data (n = 1.4%) are only used in few studies.

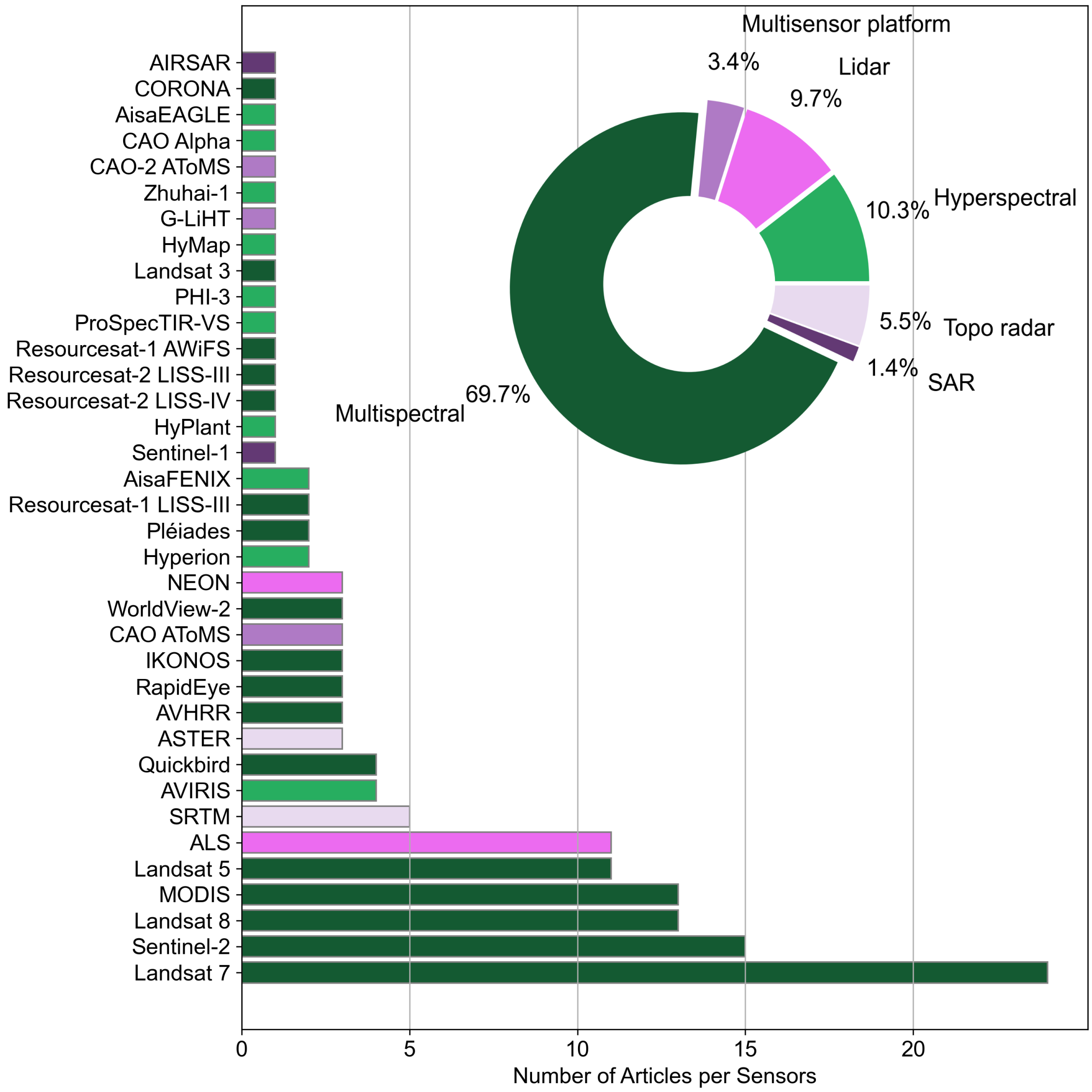

Figure 2.4: Overview of the different remote sensing sensors used in the reviewed articles.

The most popular sensors for assessing forest biodiversity based on spectral diversity are from the Landsat mission (Landsat 7: n = 24, Landsat 8: n = 13, Landsat 5: n = 11), Sentinel-2 (n = 15), and Moderate Resolution Imaging Spectroradiometer (MODIS) (n = 13). Key differences among those sensors are the spatial and temporal resolution. Sentinel-2 has a highest spatial resolution of 10 m, which is rather similar to the sensors from the Landsat mission holding a highest spatial resolution of 30 m. MODIS data comes at a highest spatial resolution of 250 m, but about daily temporal resolution. Since the pairwise Sentinel-2 constellation, there is a highest temporal resolution of the data of about five days. The temporal resolution of Landsat imagery of a single sensor amounts to 16 days. The combination of different Landsat sensors (or other multispectral sensors, e.g. Sentinel-2) can significantly reduce the temporal resolution.

The distribution of the temporal periods of remotely sensed data from the reviewed studies delineates the different sensor types and temporal resolutions (Figure 2.5). The most common sensor type, namely multispectral sensors, was mostly integrated as time-series information, i.e. integrating at least 12 time steps. The longest time-series of multispectral data covers about 16 years. The overall longest time-series was analyzed for forest biodiversity monitoring based on multiple sensors spanning the time period from 1987 to 2011. One general finding on time-series analysis is that in recent years (2016-2022) more studies (n = 13) were conducted than in the previous 14 years (2002-2015). The integration of single multispectral observations capturing a static picture of forest biodiversity are present for reviewed studies across the complete time period assessed (2002-2022). Since 2016, eleven articles integrated as data source only a mono-temporal observation from a multispectral sensor. In the period from 2002-2015 21 articles assessed forest biodiversity based on a mono-temporal multispectral observation.

Hyperspectral data was predominantly processed for spectral diversity related forest biodiversity monitoring as mono-temporal observations in reviewed articles published from 2006 to 2020. Only a single article from 2007 made use of multi-temporal hyperspectral observations.

Data from Lidar sensors was only integrated as mono-temporal observations. Several articles combined Lidar data from single observations aggregated as one data set without temporal delineation of the time stamps of single observations. Reviewed articles using Lidar data for spectral diversity based forest biodiversity analysis were first published in 2019 in the context of the Height Variation Hypothesis (HVH) (Torresani et al., 2020) being based on similar principles as the SVH. Overall, multi-temporal analyses (two to eleven time-steps) are less frequently conducted as time-series analyses. The longest multi-temporal analysis ranges from 1990 to 2014 based on multiple sensors.

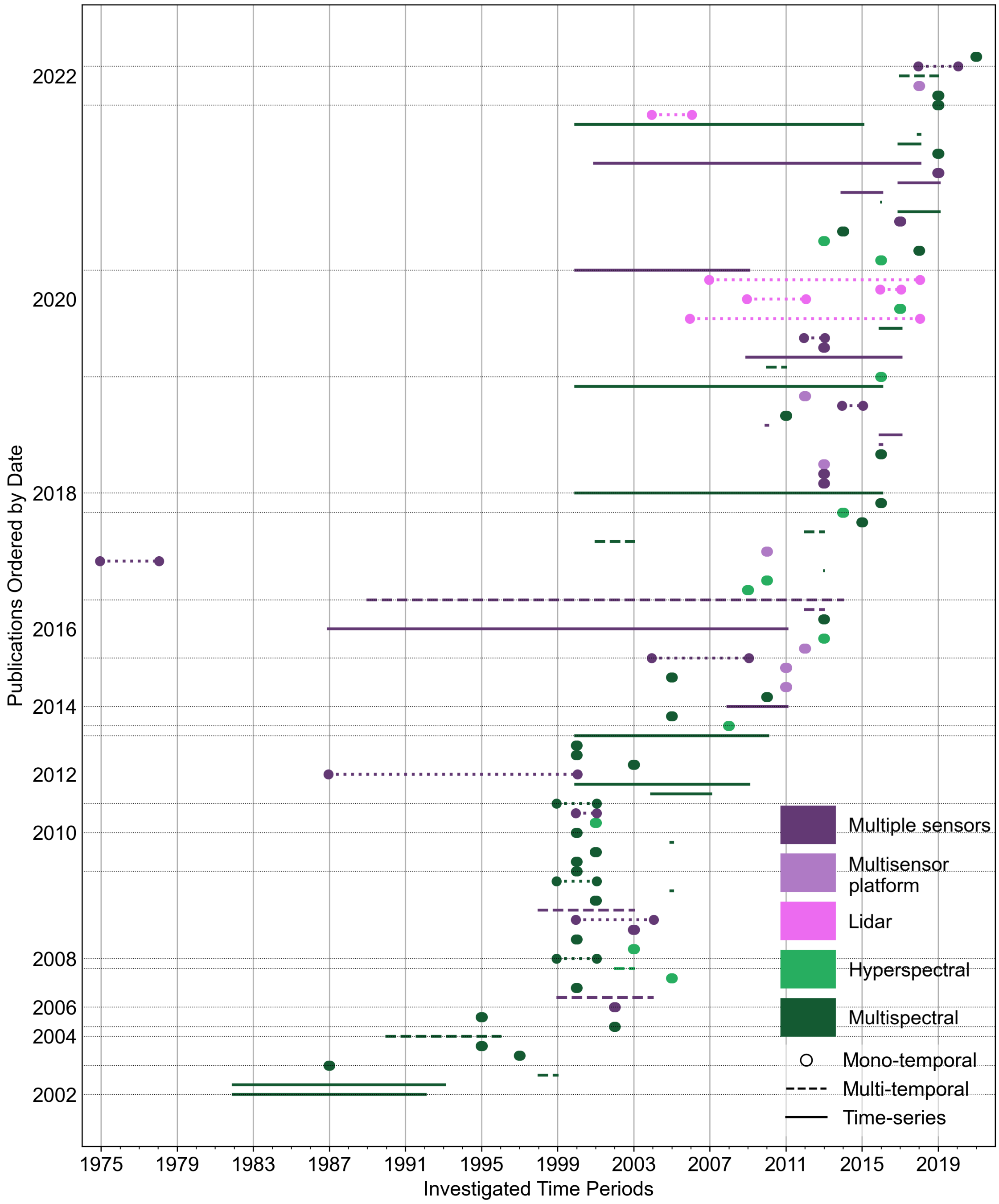

Figure 2.5: Analysis on the investigation periods of remote sensing data in comparison to the publication year of all reviewed studies.

2.3.2 Remote Sensing of Forest Biodiversity

In the previous section 2.2, the categories of biodiversity monitoring (Wang and Gamon, 2019), e.g. spectral diversity, were introduced. In the following, the different concepts of spectral diversity (vegetation indices, spectral information content, spectral species) will be explained more in detail and the temporal distribution of articles applying the concepts are under study (Figure 2.6).

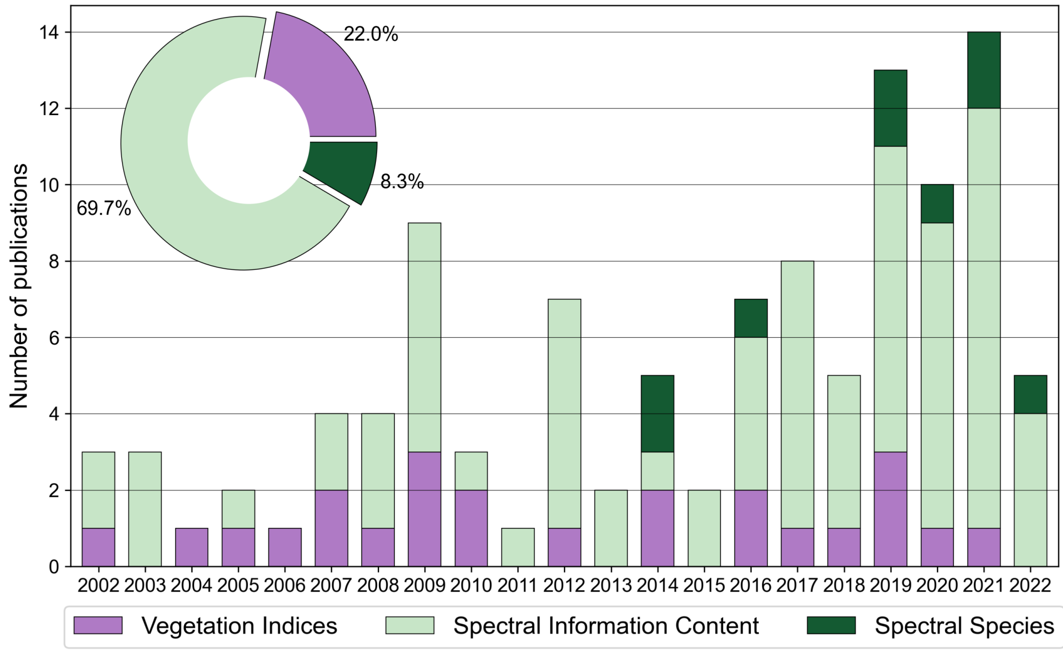

Figure 2.6: Temporal distribution of the reviewed articles grouped by the spectral diversity concepts.

The category of vegetation indices integrates spectral indices derived from multispectral and hyperspectral sensors in order to assess the variation among pixels in space and time (Lausch et al., 2016; Rocchini et al., 2018; Zeng et al., 2022). In following analysis steps, the variation measured in the remotely sensed image is extracted for locations of in-situ measurements with the goal to correlate the two measurements. In-situ measurements are often characterizing the diversity of plant species (e.g. tree species diversity), thus linking the spectral diversity with a single proxy of forest biodiversity (Wang and Gamon, 2019). Many articles are relying on the concept of vegetation indices. About 22 % of all reviewed studies are inferring forest biodiversity through remotely sensed measurements of vegetation indices. The earliest studies on forest biodiversity published in 2002 based on spectral diversity (Oindo, 2002; Oindo and Skidmore, 2002) investigate the variation for the most commonly used vegetation index, namely the Normalized Difference Vegetation Index (NDVI). For all years in the reviewed period (2002-2022) there are only few years (n = 5) without a published article on vegetation indices for studying forest biodiversity based on remotely sensed spectral diversity. The maximum number of published articles on spectral diversity measured as vegetation indices amounts to three and occurred two times for the time period under study (2009, 2019).

The second concept of spectral diversity, spectral information content, is the mostly commonly applied concept of the reviewed articles. More than 69 % of all reviewed studies rely on spectral information content which characterizes forest biodiversity based on principles of information theory (Wang and Gamon, 2019): a multidimensional variable space for remotely sensed metrics is calculated based on e.g. the coefficient of variation or ordination techniques. Multiple articles on spectral information content integrate multi-variate data (e.g. multiple spectral indices or spectral bands) to avoid relying on a single spectral index or spectral band being correlated to in-situ measurements of forest biodiversity. The analysis of reviewed articles integrating spectral information content presents an increasing popularity since the year 2016. In the period from 2016 to 2022 at least four articles were published per year on forest biodiversity characterized through concepts of spectral information. In previous years (2002-2015) a minimum of four published articles on spectral information content exist for the years 2009 and 2012. In recent years most articles on spectral diversity were published in general, as well as most studies on spectral information content (2019: n = 8, 2020: n = 8, 2021: n = 11).

Spectral species is the third concept of spectral diversity for forest biodiversity monitoring. Compared to the other two concepts, namely vegetation indices and spectral information content, the spectral species concept was developed and published more recently. The first publications (Féret and Asner, 2014a,b) from 2014 introduced the spectral species concept. In comparison to the other two concepts of spectral diversity, the spectral species concepts is based on an unsupervised clustering algorithm to derive remotely sensed spectral clusters (species) that represent homogeneous structures of specific forest structural characteristics. The initial study (Féret and Asner, 2014a) of the spectral species concept maps α-diversity (Shannon diversity) and β-diversity (Bray-Curtis dissimilarity) using an ordination method (principal component analysis, non-metric multidimensional scaling) and unsupervised clustering (k-means). After its initial publication based on airborne hyperspectral data, following articles translated the spectral species concept to spaceborne data, such as Sentinel-2 (Chraibi et al., 2021; Gastauer et al., 2022) and MODIS (Rocchini et al., 2021). The spectral species concept was applied in about 8 % of all reviewed articles and is in comparison to the two more established concepts (vegetation indices and spectral information content) understudied so far.

In order to understand the focus on biodiversity scales (α-diversity, β-diversity, γ-diversity), as well as on floristic and faunistic environmental foci, in the following those two aspects will be further investigated. After assigning the specific model responses (biodiversity scales) for each reviewed article, the distribution of number of publications grouped by biodiversity scales (Figure 2.7a) shows that most articles focus on the local scale of diversity (α-diversity, n = 93). There are 50 articles that assess the turnover in species composition (β-diversity). About one third of all reviewed articles (n = 34) addresses α-diversity, as well as β-diversity. The analysis of γ-diversity (landscape diversity) remains understudied since only two studies characterize the largest spatial scales of the three biodiversity scales (Senf et al., 2020b; Wang et al., 2022).

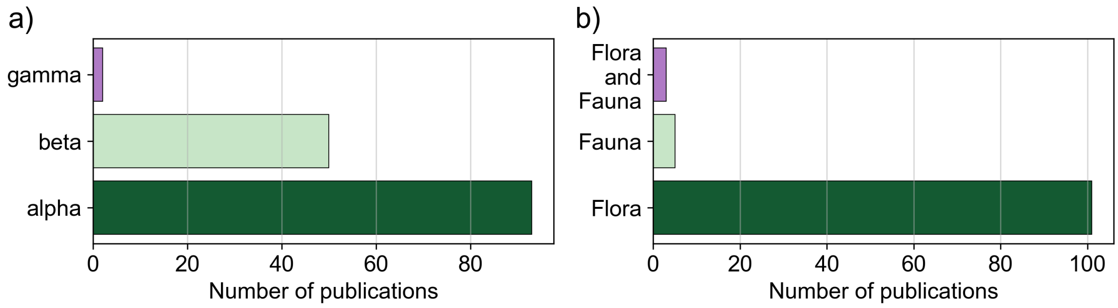

Figure 2.7: Analysis of the different biodiversity scales (a) and environmental foci (b). α-diversity describes local community diversity, β-diversity assesses the turn-over in diversity among local communities, and γ-diversity characterizes landscape diversity.

The distribution of reviewed articles grouped by the environmental focus (flora, fauna, flora and fauna) reveals that the analysis of forest biodiversity based on remotely sensed spectral diversity has a clear focus on the assessment of floristic diversity (Figure 2.7b). About 93 % of all reviewed articles assess floristic characteristics of diversity. Tree species diversity is the most commonly used surrogate of floristic diversity (Gillespie et al., 2008; Schäfer et al., 2016). The analysis of faunistic diversity (4.6 % of all reviewed articles) or combined analysis of floristic and faunistic diversity (2.7 % of all reviewed articles) is only conducted in few of the reviewed articles (about 7 %).

Previous results have shown that the analysis of spectral diversity for the analysis of forest biodiversity is primarily focused on optical remote sensing sensors (e.g. multispectral and hyperspectral sensors, Figure 2.4). The calculation of spectral indices being specifically sensitive towards different aspects of vegetation characteristics is a well-established practice for all categories of biodiversity monitoring. From all reviewed articles (n = 109), the majority (n = 103) is based on optical remote sensing data from which 75 articles calculated spectral indices. The analysis of the number of specific spectral indices being integrated in reviewed articles shows that there is a great imbalance in the variety of calculated spectral indices (Figure 2.8). The well-established spectral index NDVI was integrated in most articles (56.7 %). Overall, most spectral indices that were at least considered in two reviewed articles are based on the spectral wavelength category "Red-NIR" (red to near-infrared).

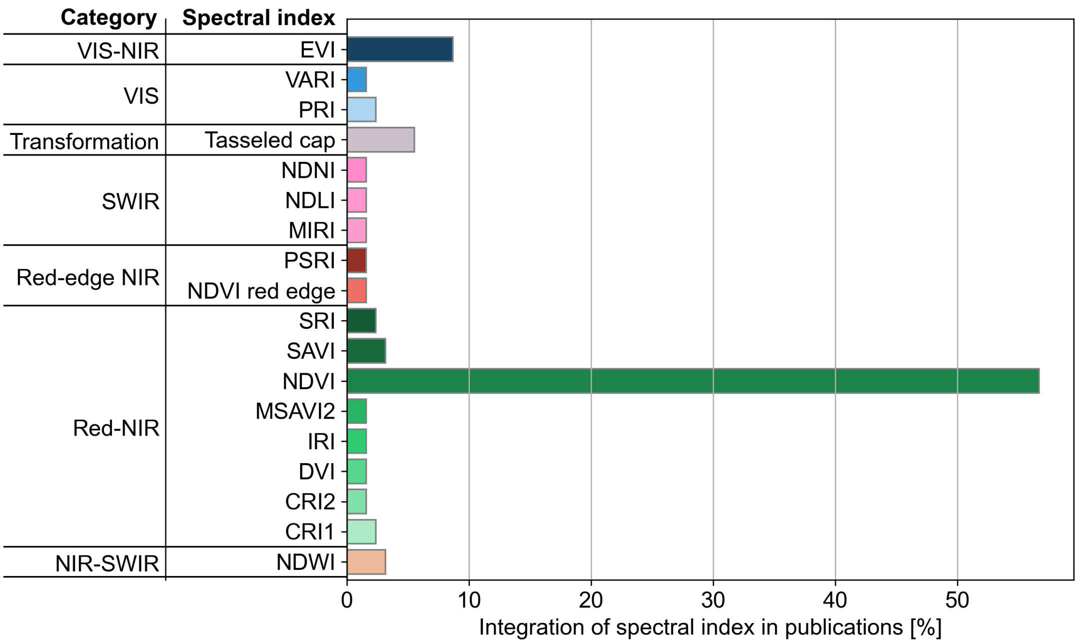

Figure 2.8: Statistics about calculated spectral indices which were integrated in 75 reviewed articles. Only spectral indices are shown that are used at least in two reviewed articles. Abbreviations: CRI1 = Carotenoid Reflectance Index 1, CRI2 = Carotenoid Reflectance Index 2, DVI = Difference Vegetation Index, EVI = Enhanced Vegetation Index, IRI = Infrared Index, MIRI = Mid-Infrared Index, MSAVI2 = Modified Soil Adjusted Vegetation Index 2, NDLI = Normalized Difference Lignin Index, NDNI = Normalized Difference Nitrogen Index, NDVI = Normalized Difference Vegetation Index, NDWI = Normalized Difference Water Index, NIR = near-infrared, PRI = Photochemical Reflectance Index, PSRI = Plant Senescence Reflectance Index, SAVI = Soil Adjusted Vegetation Index, SRI = Simple Ratio Index, SWIR = short-wave infrared, VARI = Visible Atmospherically Resistant Index, VIS = visible bands.

2.4 Discussion on the Spectral Variation Hypothesis

The SVH is based on the generalized hypothesis that the spectral variation assessed through remote sensing data characterizes a heterogeneity of habitat characteristics or specific species. Both the indirect link of remotely sensed habitat characteristics, as well as the direct mapping of the variation of specific species are considered to be representative relationships for the assessment of forest biodiversity (Torresani et al., 2024). The major points of discussion on the validity of the SVH are addressing potential scale mismatches of remotely sensed and in-situ data, remote sensing sensor limitations, and inconsistent relationships among the spectral diversity measurements from remote sensing and the selected in-situ measurement predicting forest biodiversity due to spatio-temporal dynamics of floristic and faunistic characteristics Fassnacht et al. (2022). Several of the raised concerns about the validity of the SVH come up for different analyses on the earth's surface dynamics based on remote sensing data. Specific concerns in the context of the SVH for forest ecosystems are that forest biodiversity is shaped through three-dimensional characteristics of vegetation structures, a great variety of ecological niches, or multifaceted direct (e.g. deforestation, fragmentation, silvicultural management practices) and indirect anthropogenic influences (e.g. altered disturbance regimes due to global climate change). Therefore, the stability of identified relationships of forest biodiversity based on remote sensing data require the monitoring over time in order to track dynamics of forest biodiversity under changing conditions (Fassnacht et al., 2022; Schmidtlein and Fassnacht, 2017; Wang and Gamon, 2019).

The discussion on potential scale mismatches arises from the fact there is not a single spatial scale that best characterizes forest biodiversity from a remote sensing perspective (e.g. pixel size, spatial data availability) and in-situ measurements (e.g. plot size, spatial sampling coverage). Therefore, different spatial resolutions of remote sensing sensors are needed, as well as varying experimental designs of in-situ measurements comprising a range of sampling efforts at different spatial scale (e.g. plot area). The different biodiversity scales of α-diversity, β-diversity, and γ-diversity which were explained in earlier sections (e.g. Figure 2.1) need to be assessed from both remote sensing and in-situ data. The results of the systematic literature review show that there is a clear focus on multispectral remote sensing sensors (Figure 2.4) targeting floristic characteristics (Figure 2.7b) at the local community level (α-diversity, Figure 2.7a).

Another point that has significant influence on the investigated relationships among remotely sensed spectral diversity and in-situ measurements of biodiversity is a temporal mismatch. For larger-scale coverage of in-situ biodiversity, those measurements are often aggregated and treated as if the observations were taken at the same time (Wang and Gamon, 2019; Bawa et al., 2002; Fairbanks and McGwire, 2004). When being related to mono-temporal remotely sensed data, potential temporal mismatches can result in misleading and invalid relationships, suggesting an inaccurate link to forest biodiversity. Therefore, the integration of time-series remote sensing data (e.g. from Sentinel-2) has the potential to provide information on vegetation structure of several time steps which might be more robust predictors for forest biodiversity than mono-temporal observations (Torresani et al., 2019, 2021).

Furthermore, the integration of a single type of remote sensing sensor limits the characterization of vegetation properties to specific characteristics, such as photosynthetic activity and water content (multispectral sensors, e.g. Sentinel-2), surface roughness and moisture content (radar sensors, e.g. Sentinel-1), or vertical and horizontal structure (Lidar sensors). Therefore, the integration of multiple sensors (Figure 2.4, 2.5) should be best-practice for a multi-variate characterization holding the potential to assess the multi-faceted characteristics of habitat structure serving as potential predictor for forest biodiversity.

Most reviewed articles assess floristic diversity as forest biodiversity proxy (Figure 2.7b), in most cases for selected taxonomic levels (Ferreira et al., 2016; Fricker et al., 2015). Those specific taxonomic levels might be indicator species for overall forest biodiversity. Nevertheless, for an improved understanding of multidiversity (aggregation of e.g. taxonomic, phylogenetic, and functional diversity), multi-variate in-situ sampling campaigns hold great potential to identify further indicator species and understand spatio-temporal benefits and limitations of remotely sensed spectral diversity as proxy for forest biodiversity (Mueller et al., 2022a).

2.5 Summary

After the formulation of the SVH about twenty years ago, there is an increasing interest in the analysis of forest biodiversity based on remotely sensed spectral diversity. In recent years, forest biodiversity is not only assessed from purely ecological or remote sensing perspectives, but increasingly from interdisciplinary perspectives, i.e. environmental sciences in combination with remote sensing. The spatial focus of the reviewed articles mostly targets forest biodiversity in Europe, followed by Asia and North America. Forest biodiversity in study areas of hotspots of biodiversity (e.g. tropical forests) in South America and Africa are understudied.

The systematic literature review on remotely sensed spectral diversity for the assessment of forest biodiversity showed that the concept of spectral diversity is mostly explored for multispectral sensors. Overall, there is a great majority of articles investigating forest biodiversity based on single sensor data, thus limiting the analysis of forest biodiversity to specific characteristics. Furthermore, the integration of multi-sensor data for cross-validation and investigation of complementary vegetation characteristics remains limited.

The characterization of forest biodiversity is mostly conducted based on mono-temporal remote sensing observations. Therefore, only data on selected time steps is integrated which might not necessarily cover the temporal dynamics of vegetation characteristics shaping forest biodiversity. So far, only few studies make use of long time-series (e.g. from Landsat) or dense multi-annual time-series (e.g. Sentinel-1 and Sentinel-2) in order to investigate inter- and intra-annual dynamics of vegetation for the assessment of forest biodiversity.

Overall, there is the need for forest biodiversity assessments that move beyond the local community level (α-diversity) which is studied by most reviewed articles. Investigating the turn-over in community diversity (β-diversity) and larger-scale diversity (γ-diversity) is needed to better understand relationships of the different biodiversity scales in order to improve monitoring and conservation of high biodiversity areas. In addition, the in-situ measurement of forest biodiversity linked to remotely sensed spectral diversity is mostly measuring floristic diversity. The analysis of faunistic diversity or combined analysis of floristic and faunistic diversity are limited to few articles.

To sum up, the field of forest biodiversity monitoring based on remotely sensed spectral diversity currently has a focus on mono-temporal observations of multispectral spaceborne sensors. Furthermore, the vegetation structures measured are related in most cases to floristic diversity measurements at the α-diversity scale. There is great potential for future studies to investigate long and dense time-series of multi-sensor data to characterize forest biodiversity as α-diversity, as well as β-diversity and γ-diversity.

Chapter 3

Study Area: Forests in Germany

The forest structure and forest biodiversity is analyzed for German forests. In order to characterize the study area, the physical geography and climatic conditions are explained (section 3.1). In the following, the forests of Germany are introduced by providing information on the distribution and usage (section 3.2.1), as well as the status and disturbance history (section 3.2.2). Lastly, a patch-network of experimental silvicultural treatments enhancing the forest structural complexity is presented which serves as study area for regional analysis (section 3.3).

3.1 Physical Geography of Germany

Germany is located in Central Europe sharing borders with Denmark, Poland, the Czech Republic, Austria, Switzerland, France, Belgium, Luxembourg, and the Netherlands (Figure 3.1a). In the north, Germany holds coastlines to the North Sea (north-west) and Baltic Sea (north-east). Germany is sub-divided into 16 federal states covering together an area of about 357.000 square kilometer (km²). The elevation is ranging from sea level to 2.962 m in Germany with an increase from north to south (Figure 3.1b). The most prominent mountain regions are the Harz and Thuringian forests in Central Germany, the Bavarian forest in the south-east, the Palatinate forest in the south-west, the Black forest in the south-west, and the northern Alps in the south. The highest peak in Germany, namely the Zugspitze (2.962 m), is located in the Alps. The classification of silvicultural landscapes is based on climatic and forest-ecological criteria (Johann Heinrich von Thünen Institute (Federal Research Institute for Rural Areas, Forestry and Fisheries) - Institute of Forest Ecosystems, 2022). There are seven silvicultural landscapes in Germany (Figure 3.1c): northern lowlands, loess hills, western low mountain ranges, eastern low mountain ranges, mesozoic escarpment, pre-alpine, and alpine (from north to south).

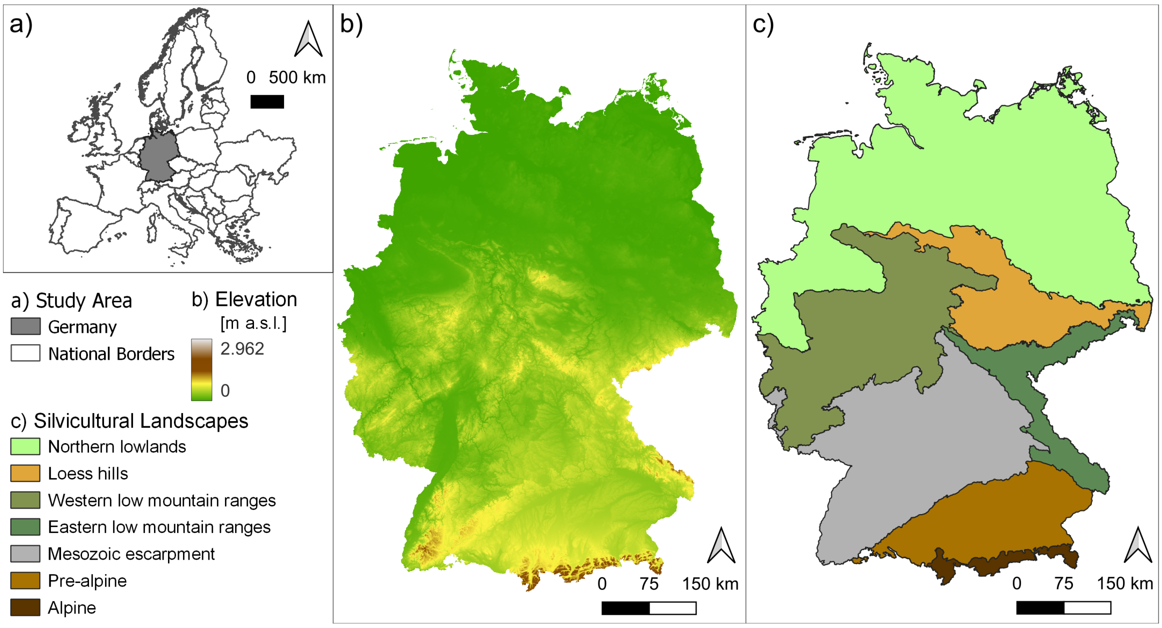

Figure 3.1: Maps of the study area (a), elevation (b) and silvicultural landscapes (c) of Germany. Vector data of national boundaries is based on GADM (2022). Elevation data was provided by NASA JPL. Silvicultural landscapes were derived from Johann Heinrich von Thünen Institute (Federal Research Institute for Rural Areas, Forestry and Fisheries) - Institute of Forest Ecosystems (2022).

Germany is characterized by a humid temperate climate with warm summers (Peel et al., 2007). Figure 3.2 shows mean air temperature and mean precipitation from 1991 to 2020 for Germany.

The year 2024 was the warmest year (annual mean temperature of 10.9 C°) since the Deutscher Wetterdienst (DWD) recordings since 1881. The mean annual temperature for Germany is 9.3 C° (1991-2020). There is a positive linear trend from 1881 to 2024 in annual mean temperature amounting to 1.9 Kelvin. The precipitation rates are relatively stable over the year with a mean annual sum of 789 l/m² (DWD, 2022, 2025). Since 2018 there is a strong increase in temperature highlighted by multiple years (2018, 2019, 2020, 2022, 2023, 2024) holding a annual mean temperature of more than 10 C° (Kaspar et al., 2023; DWD, 2025). In addition to rising temperatures in recent years, multiple consecutive drought years have been reported since 2018 (Boeing et al., 2022).

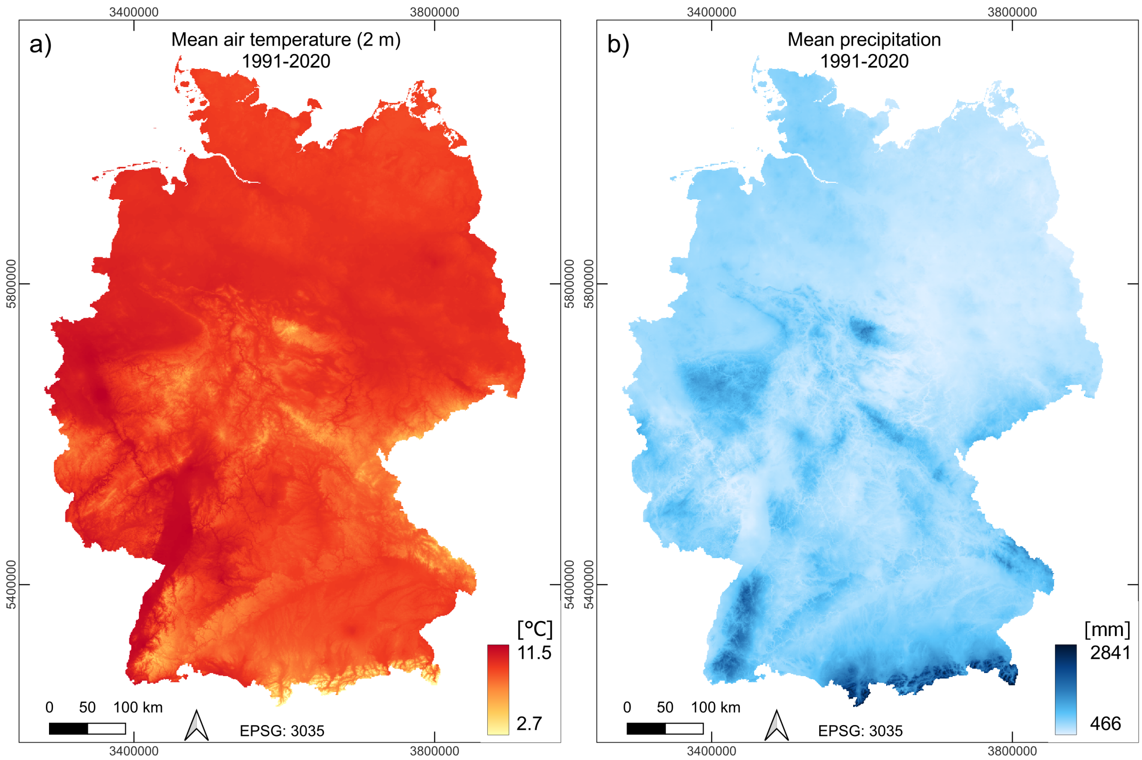

Figure 3.2: Maps of mean air temperature (DWD, 2021a) and mean precipitation (DWD, 2021b) (1991-2020) for Germany.

3.2 Forests in Germany

In the following two sections, the distribution and usage (section 3.2.1), as well as the status and disturbance history (section 3.2.2) of German forests are elaborated.

3.2.1 Distribution and Usage

Forests are a dominant land cover in Germany holding a share of about 32 %. Coniferous forests represent about 55 % of the forest cover. In comparison, deciduous forests make up about 45 % (Figure 3.3). Deciduous forests are dominating in western Germany and low-land regions in central and southern Germany. Coniferous forests cover north-eastern low-land regions, as well as mountainous regions in central and southern Germany. The most dominant tree species is spruce (25 %) which is found in most cases outside its natural habitat due to plantation forestry. The second most dominant tree species is pine (23 %) which is specifically prevalent in north-eastern and south-western Germany. Similar to spruce, pine stands developed through silvicultural planting, and are therefore overrepresented in comparison to natural growth conditions. The most dominant broad-leaved tree species are beech (16 %) and oak (10 %) which constitute the two naturally dominating tree species for Central European lowland forests (Federal Ministry of Food and Agriculture (BMEL)).

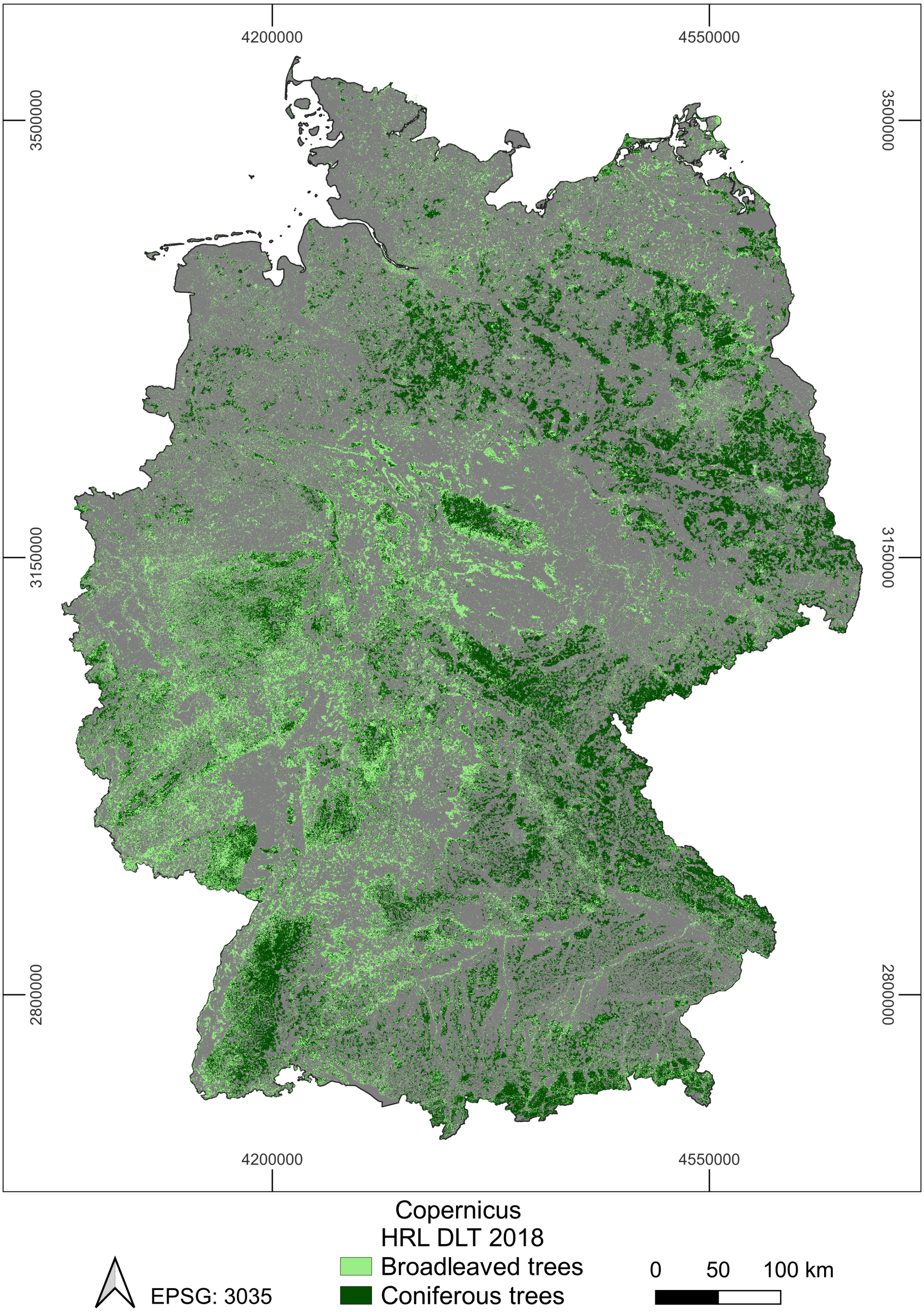

Figure 3.3: Distribution of forest in Germany based on Copernicus High Resolution Layer (HRL) Dominant Leaf Type (DLT) 2018 (Copernicus HRL DLT, 2018).

Silvicultural management is present in most German forests in different types: forest ownership can be classified into four types, namely private forest, land forest, corporate forest, and federal forest. Private forests are dominating by cover in Germany (43 %), followed by land forests (32 %), and corporate forests (22 %). Federal forests only comprise about 3 % of all forest area in Germany (Statistisches Bundesamt (Destatis), b). Centuries of silvilcultural management in Germany have led to a dominance of age-class plantation characterized by monocultures, similar structural conditions, and low deadwood amount (Müller et al., 2018; Mueller et al., 2022a).

3.2.2 Status and Disturbance History

Multiple consecutive drought years in combination with heatwaves have challenged the vitality of German forests since 2018 (Buras et al., 2020, 2021; Rakovec et al., 2022). Different disturbance structures have developed in the context of recent extreme environmental conditions in Central Europe (Statistisches Bundesamt (Destatis), a). Insect infestations are a dominant cascading effect of disturbances, e.g. bark beetle outbrakes in spruce plantations. Therefore, an increased share of timber harvest as salvage logging comes from disturbance agents, such as bark beetle and windthrow. Salvage logging, i.e. the economic focus on timber harvest due to susceptibility of large-scale tree damage, amounts to 75 % in 2020 and 81.4 % in the year after (Statistisches Bundesamt (Destatis), c). A significant increase in die-off was reported for spruce trees amounting to more than 4 % in 2020 and 2022. Also for the other three dominant tree species in Germany, namely pine, beech and oak, increasing die-off rates are present since 2020. In addition to unprecedented die-off rates, strong increases in average crown thinning for all four dominant tree species since 2018 are an indicator of reduced vitality (Johann Heinrich von Thünen Institute (Federal Research Institute for Rural Areas, Forestry and Fisheries) - Institute of Forest Ecosystems, 2023).

The analysis of forest canopy cover loss based on Landsat and Sentinel-2 time-series has demonstrated the large-scale losses of canopy cover in German forests since 2018 (Thonfeld et al., 2022). Based on an updated time-series of forest canopy cover loss (German Aerospace Center (DLR), 2025) spanning the period from 2017 to 2024 (about 923,000 hectare (ha)), annual forest canopy cover loss is quantified (Figure 3.4). The year 2017 shows the forest canopy cover conditions before the first recent drought year (2018). Only few areas in eastern Germany are characterized by forest canopy cover loss. Since 2018, there are large-scale areas of forest canopy cover loss reaching more than 10 % per hexagon cell (edge distance of 10 kilometer (km)). The disturbance dynamics are more wide-spread from 2018 to 2020 focusing on Central and eastern Germany. In 2021 and 2022 four hotspots of forest canopy cover loss are apparent (from west to east): the region around Siegen-Wittgenstein, Harz forest, Thuringian forest, and Saxon Switzerland (Saxony). In 2023, continuous forest canopy cover loss of more than 10 % are present for the Thuringian forest. In 2024, the forest canopy cover loss dynamics are still dominating in the Thuringian forest, but further regions in Central and southern Germany develop. From 2017 to 2024, forest canopy cover loss of more than 50 % characterizes continuous regions in the Harz and Thurinigian forests. Those two hotspots of forest canopy cover loss in Germany will be the regional focus for forest structure change analysis (section 4.3.2).

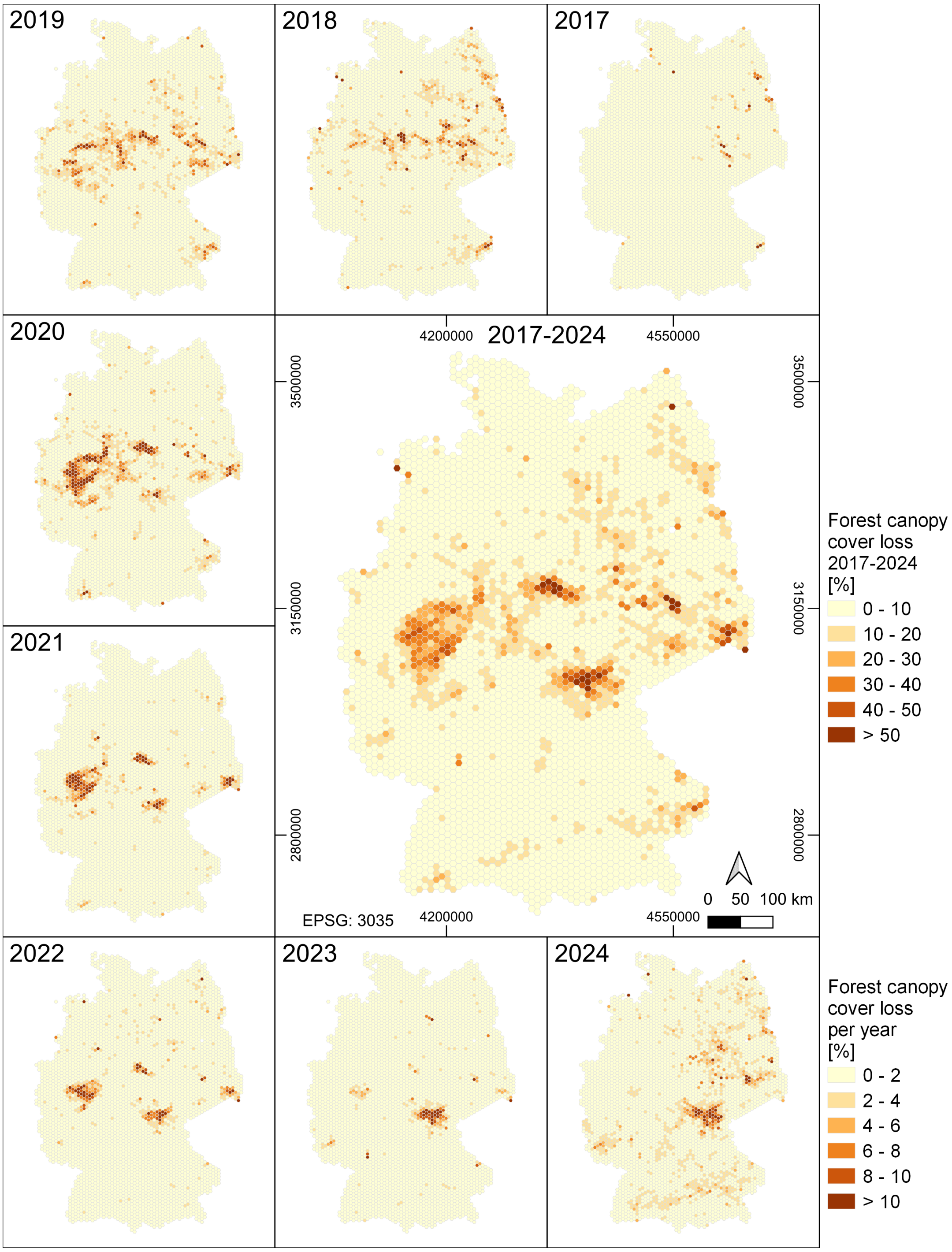

Figure 3.4: Forest canopy cover loss from 2017-2024 in Germany according to German Aerospace Center (DLR) (2025).

3.3 Patch-Network of experimental silvicultural Treatments enhancing Forest structural complexity

Within the context of the inter-disciplinary BETA-FOR project (Mueller et al., 2022a,b), a patch-network of experimental silvicultural treatments enhancing forest structural complexity was established. The patch-network focuses on broad-leafed forests in six regions of Germany: "University forest" (focus region), "Bavarian forest", "Passau", "Saarland", "Hunsrück", and "Lübeck" (Figure 3.5). The enhancement of forest structural complexity aims to improve forest biodiversity and multifunctionality through diversity of habitat structures (Mueller et al., 2022a). The proposal of novel silvicultural practices focusing on "management for complexity" (Müller et al., 2018; Messier et al., 2021) has gained in relevance since excess dynamics of tree mortality in recent years in Central Europe (Senf et al., 2020a).

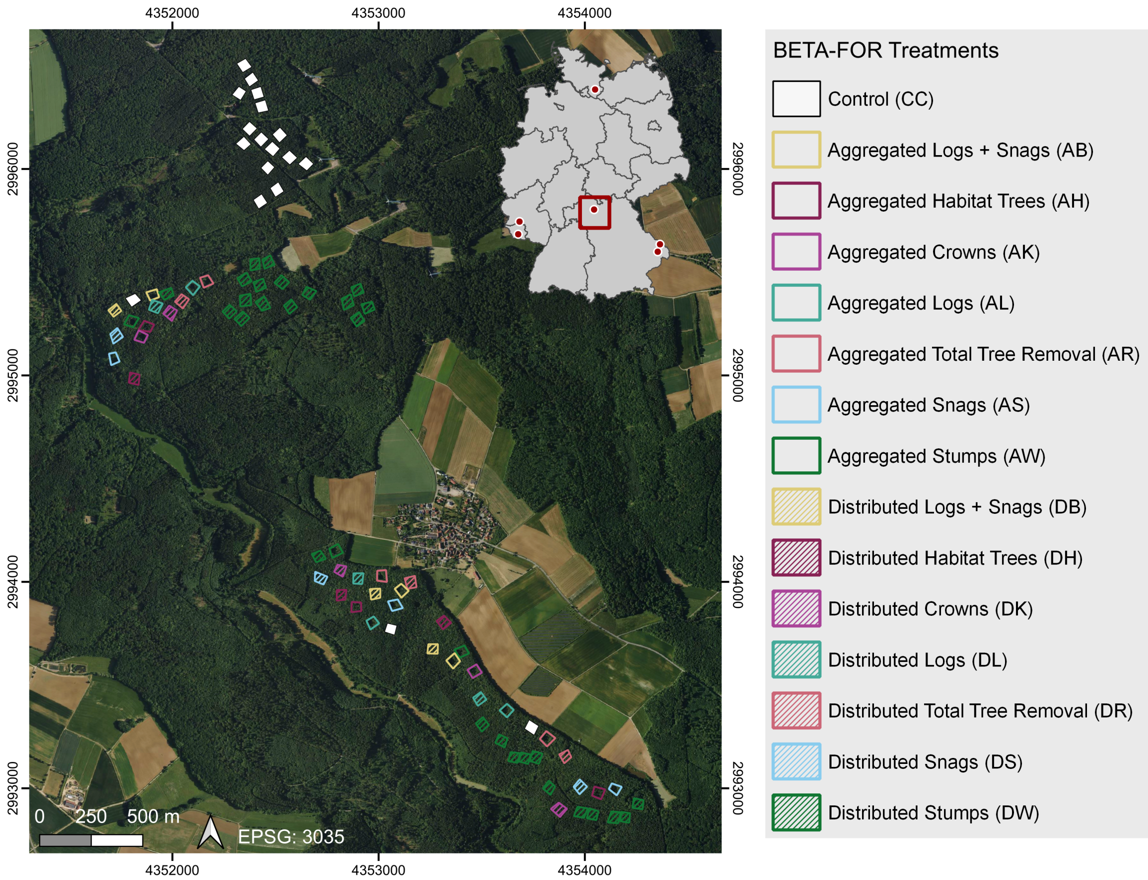

Figure 3.5: Overview of BETA-FOR project (Mueller et al., 2022a,b) study regions and patches in the focus region "University forest".

Various experimental silvicultural treatments were implemented as aggregated and distributed treatments (Figure 3.6).

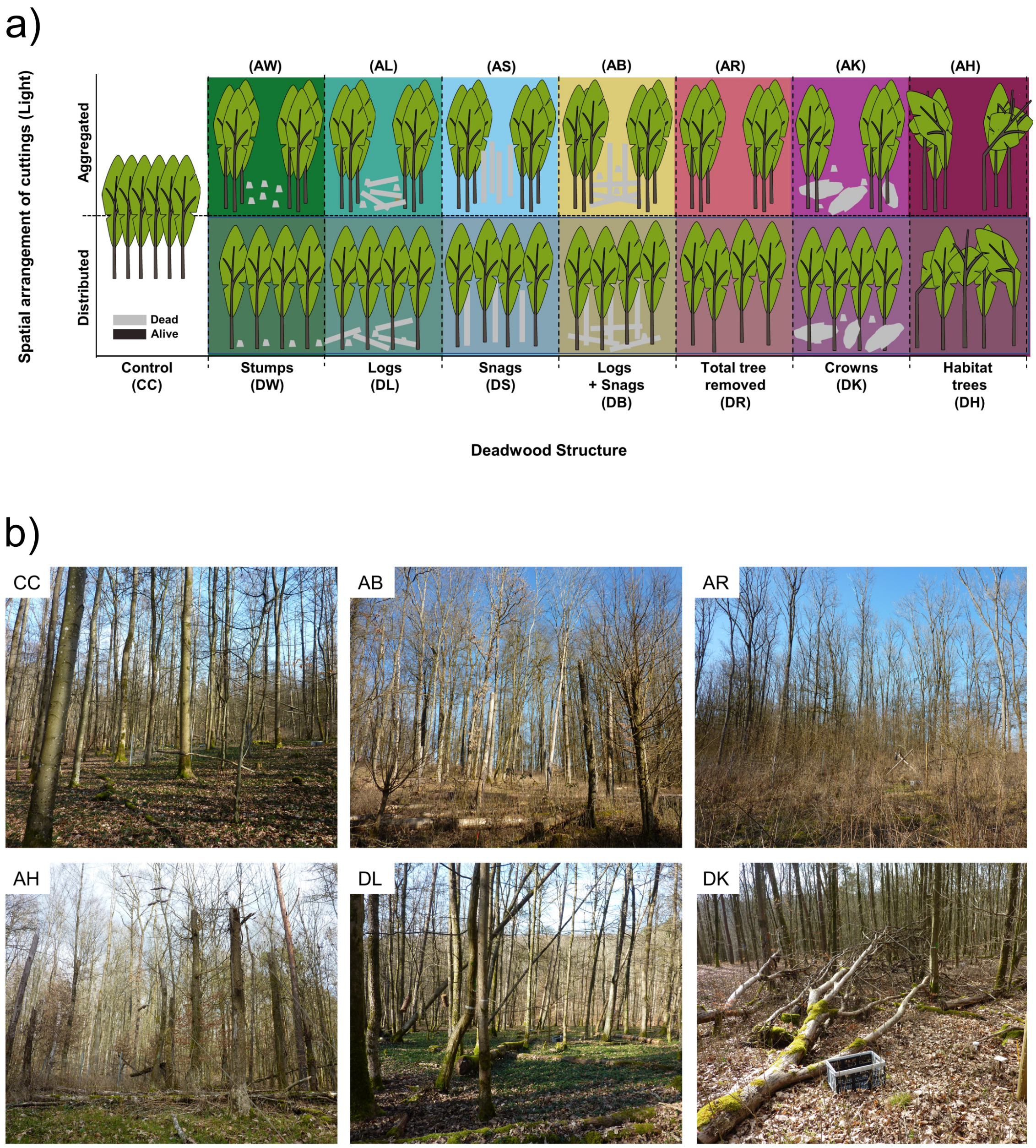

Figure 3.6: Overview of experimental silvicultural treatments enhancing the forest structural complexity. Schematic figure (a) of spatial arrangement of cuttings and deadwood structures of experimental silvicultural treatments which were implemented in the context of the BETA-FOR project (Mueller et al., 2022a,b). Photos of selected experimental silvicultural treatments at the focus region "University forest" in spring 2023 of the BETA-FOR project (b). Please see Figure 3.5 for the location of the University forest.

Aggregated treatments are characterized by a centered gap in the patch (50 m x 50 m) were all trees were removed. In comparison, selective thinning (randomized tree removal in the complete patch area) was conducted as distributed treatments. For both aggregated and distributed the same amount of tree biomass (about 30 % per patch) was removed. The spatial arrangement of cuttings has different implications on the light conditions of the patch. Aggregated treatments hold a cleared area with direct sunlight in contrast to distributed treatments with small-scale canopy openings at the locations of removed tree crowns. In addition to tree removal, different deadwood structures were created ranging from an absence of deadwood to a combination of downed and standing deadwood structures. Furthermore, habitat trees (tilting of trees, bark removal, creation of caveats) were established. Aggregated and distributed treatments with total tree removal, crowns remaining, and habitat trees were only implemented in the focus region "University forest". Therefore, regional analysis (chapter 5, chapter 6) on forest structure based on remote sensing data are focusing on the "University forest" due to a greater variety of experimental silvicultural treatments.

Control treatments were established in all regions as reference of unchanged forest structure conditions. The implementation periods of experimental silvicultural treatments vary among regions: "University forest" (November and December 2018), "Bavarian forest" (winter 2015/2016), "Passau" (winter 2015/2016), "Saarland" (winter 2015/2016), "Hunsrück" (winter 2016/2017), and "Lübeck" (winter 2016/2017). Each region is subdivided into region sites which are pairs of control and experimental districts (aggregated and distributed treatments). The "University Forest" consists of three region sites ("U01", "U02", "U03"), each holding 30 patches (15 control and 15 experimental treatments), i.e. 90 patches in total. The "Bavarian Forest" is sub-divided into four region sites ("B04", "B05", "B06", "B07") with 72 patches in total (36 control and 36 experimental treatments). The other regions are called satellite sites since each of them only consists of one pair of control and experimental treatment districts (18 patches in total: 9 control and 9 experimental treatments): "Passau" ("P08"), "Hunsrück" ("H09"), "Saarland" ("S10"), and "Lübeck" ("L11").

Chapter 4

A novel Workflow for multi-annual Products of Forest Structure Attributes*

The analysis of forest structure enables the characterization of forest structure attributes that measure vertical and horizontal properties of vegetation. Based on a novel workflow, multi-annual products of forest structure attributes are derived for Germany. In comparison, the NFI data for Germany only provides sample estimates of forest structure conditions from local plot measurements (Johann Heinrich von Thünen Institute (Federal Research Institute for Rural Areas, Forestry and Fisheries) - Institute of Forest Ecosystems, 2023; Storch et al., 2018). By combining data from different spaceborne sensors, the first products on various forest structure attributes at continuous scale for Germany (10 m spatial resolution) are generated. The modeled forest structure attributes, namely canopy height, total canopy cover, above-ground biomass density, are freely available as annual products spanning the period from 2017 to 2023.

In the first section, the spaceborne data of Sentinel-1 radar, Sentinel-2 multispectral, and GEDI Lidar is explained (section 4.1). In the following, the methodological approach comprising the pre-processing of spaceborne data and the modeling workflow in order to derive continuous products of forest structure attributes is introduced (section 4.2). The results section (section 4.3) is sub-divided into a forest structure characterization for Germany and a regional assessment of forest structure dynamics in the context of recent disturbances for the Harz and Thuringian forests. In the discussion section (section 4.4), the multi-annual forest structure dynamics in Germany are discussed and potentials, as well as drawbacks of spaceborne forest structure modeling are elaborated. The summary section (section 4.5) provides an overview on the forest structure modeling workflow and summarizes main findings.

*Parts of this chapter have been published in Kacic et al. (2023).

4.1 Spaceborne Data

The forest structure products for Germany from 2017 to 2023 are based on data from the spaceborne sensors Sentinel-1, Sentinel-2, and GEDI. In order to derive continuous maps for Germany on canopy height, total canopy cover, and above-ground biomass density as multi-annual products, yearly spaceborne data sets are calculated for the individual forest structure attributes per year. In the following, general data characteristics of spaceborne radar, multispectral, and Lidar are provided.

4.1.1 Radar Data

Satellite radar data of the Sentinel-1 sensors was integrated to characterize forest structure conditions. The mapping mission Sentinel-1 from the European Space Agency (ESA) consists of a pairwise constellation of polar-orbiting satellite sensors. Both satellites hold a SAR sensor which continuously measures land and ocean surface dynamics. The sensors are equipped with a C-band radar sensor (5.405 GHz) being sensitive to forest structure characteristics based on indirect surface roughness and moisture measurements (Berger et al., 2012; Malenovsky et al., 2012; Kacic et al., 2024).

For modeled forest structure attributes, the Sentinel-1 Ground-Range-Detected (GRD) product was used. The Sentinel-1 GRD product has a spatial resolution of 10 m and comes in a temporal resolution of up to six days for Germany during times of a pairwise satellite constellation. In December 2021, the instrument electronics power supply of Sentinel-1B experienced an anomaly which could not be solved. Therefore, with the launch of Sentinel-1A in April 2014 (data available since October 2014) and the launch of Sentinel-1B in April 2016 (data available since October 2016), there is a pairwise coverage for about five years. As a replacement of Sentinel-1B which mission has ended officially in August 2022, Sentinel-1C was launched in December 2024 and is expected to deliver first data in summer 2025.

4.1.2 Multispectral Data

Multispectral satellite data from ESA's Sentinel-2 mapping mission was obtained to characterize forest structure conditions based on data in spectral wavelengths covering the visible to short-wave infrared light. The Sentinel-2 mission is a mapping mission of pair-wise polar-orbiting satellites (Sentinel-2A and Sentinel-2B). The multispectral sensors are characterizing 12 spectral bands at 10 m to 60 m spatial resolution. For the assessment of vegetation properties, the ten spectral bands in 10 m and 20 m are typically used: blue (wavelength of Sentinel-2A and Sentinel-2B: 443.9 nanometer (nm), 442.3 nm), green

(496.6 nm, 492.1 nm), red (560 nm, 559 nm), red edge 1 (664.5 nm, 665 nm), red edge 2 (740.2 nm, 739.1 nm), red edge 3 (782.5 nm, 779.7 nm), near-infrared (835.1 nm, 833 nm), red edge 4 (864.8 nm, 864 nm), short-wave infrared 1 (1613.7 nm, 1610.4 nm), short-wave infrared 2 (2202.4 nm, 2185.7 nm) (Berger et al., 2012; Malenovsky et al., 2012; Gorelick et al., 2017).

With the launch of Sentinel-2A in June 2015 (data available since July 2015) and the launch of Sentinel-2B in March 2017 (data available since April 2017), a theoretical temporal resolution of up to five days can be reached in Germany during the time of a pair-wise constellation. In September 2024 a third Sentinel-2 satellite (Sentinel-2C) was launched as a replacement for Sentinel-2A which is nearing its mission end.

4.1.3 Lidar Data

Spaceborne Lidar data from GEDI (National Aeronautics and Space Administration (NASA)) characterizes forest structure characteristics near-globally. The sensor is mounted on the International Space Station (ISS) and was operational from April 2019 to March 2023. The sampling mission follows the orbit of the ISS (about 52 ° north to 52 ° south) and conducts measurements at footprint-level (about 25 m) of vertical and horizontal structural attributes. The Lidar sensor was specifically designed for the assessment of vegetation characteristics as it operates in the near-infrared (1064 nm). The full-waveform Lidar sensor samples vegetation structure along eight ground-tracks. The along-track sampling distance amounts to about 60 m. The spacing across-track samples is about 600 m. Therefore, within the ISS orbit all temperate and tropical forests are characterized by various forest structural attributes which are sub-divided into different data sets (Dubayah et al., 2020).

Higher-level data sets derived from the full-waveform data (L1A, L1B), available as sampling data, are L2A, L2B, L4A, and L4C. At the time of developing the forest structure modeling workflow, the L4C data set (Footprint Level Waveform Structural Complexity Index, de Conto et al. (2024) was not yet available which is why it is not further elaborated and integrated in the next sections. The following GEDI data sets of sampling points characterizing different forest structural attributes are considered for the continuous modeling of forest structure conditions in Germany. The considered forest structure attributes and the official abbreviation are given in brackets:

- L2A: Elevation and Height Metrics (canopy height, 95th percentile (rh95), [m])
- L2B. Canopy Cover and Vertical Profile Metrics (total canopy cover (cover), [%] of ground covered by vegetation from a top-of-canopy perspective)

- L4A: Footprint Above Ground Biomass (above-ground biomass density (agbd), [Mg/ha] = [tons per hectare (t/ha)])

4.2 Methodological Approach

The combination of satellite data from the mapping missions Sentinel-1 and Sentinel-2 with spaceborne data from the sampling mission GEDI enables the derivation of wall-to-wall products of forest structure for Germany at high spatial resolution (10 m). In the following, information are given about the pre-processing steps of Sentinel-1, Sentinel-2, and GEDI data. The pre-processing steps comprise spatial filtering, temporal aggregation, as well as quality filtering in order to remove artifacts (section 4.2.1). In a next step, the analysis-ready spaceborne data is integrated in the multi-annual forest structure attribute modeling workflow (section 4.2.2) consisting of three data processing steps: the preparation of response and predictor variables, running the machine-learning regression models, and validating the models.

All Sentinel-1 and Sentinel-2 data pre-processing and calculation of temporal-spectral metrics was conducted in Google Earth Engine (GEE) (Python application programming interface (API), modules: ee (Gorelick et al., 2017), eemont (Montero et al., 2023), geemap (Wu, 2020)). GEE is a cloud computing platform which offers planetary scale computation capacity and cloud storage of spaceborne data (Gorelick et al., 2017). The GEDI data was downloaded and pre-processed on a virtual machine using Python 3.12.4 (van Rossum, 1995). The most important Python modules used for downloading and processing of GEDI data are requests (Chandra and Varanasi, 2015), h5py (Collette et al., 2023), numpy (Oliphant et al., 2006), pandas (McKinney, 2012), geopandas (Rajamani and Iyer, 2023), and shapely (Gillies, 2013). The modeling of GEDI-derived attributes of forest structure based on Sentinel-1 and Sentinel-2 temporal-spectral metrics, as well as the model validation (calculation of efficiency criteria) was implemented in GEE. The final steps of model validation (comparative statistics to other products) were conducted in Python using a virtual machine processing the forest structure products (exported from GEE). Maps were generated using Quantum Geographic Information System (QGIS) version 3.28.10 (QGIS Development Team, 2021).

4.2.1 Pre-processing

In the following, the pre-processing steps of the satellite (Sentinel-1, Sentinel-2) and spaceborne data (GEDI) are explained more in detail.

4.2.1.1 Sentinel-1

Sentinel-1 GRD data for Germany was obtained for the years 2017 to including 2023 in GEE. Only data during the vegetation period from April to including September was considered. Based on a workflow to prepare analysis-ready Sentinel-1 GRD data (Mullissa et al., 2021), speckle filtering, radio-metric terrain normalization, and border-noise removal was conducted. In the following, the vertical transmit, vertical receive (VV) and VH bands holding a 10 m spatial resolution were selected.

As annual products for 2017 to including 2023, temporal-spectral metrics were calculated that enable the aggregation of time-series data using different statistics in order to characterize different vegetation conditions over time (Hansen et al., 2014; Potapov et al., 2021). The time-series data for each band was aggregated temporally as percentiles (25th, 50th, 75th, standard deviation), thus characterizing average, as well as extreme vegetation structure conditions.

4.2.1.2 Sentinel-2

Sentinel-2 level-2A data (surface reflectance, processed using sen2cor, Main-Knorn et al. (2017)) was integrated for the analysis of forest structure in Germany. Similar to the Sentinel-1 data, only scenes during the vegetation period (April to including September) were integrated for the years 2017 to including 2023. The harmonized collection of Sentinel-2 level-2A data was accessed using GEE.

Since Sentinel-2 sensors are optical sensors, i.e. sensitive to atmospheric artifacts (e.g. clouds, cloud shadows, haze), the masking (removal) of such data is a critical step in order to only consider data that truly characterizes the earth's surface properties. Based on ESA's Sentinel-2 cloud probability data, clouds (and other artifacts) were masked. To reduce the data volume and focus on spectral characteristics that best measure vegetation conditions, the following 10 m and 20 m bands were selected: blue, green, red, red edge 1, red edge 2, red edge 3, near-infrared, red edge 4, short-wave infrared 1, short-wave infrared 2. The bands with higher spatial resolution (10 m) are blue, green, red, and near-infrared. In GEE data cubes of mixed spatial resolutions are resampled to the higher spatial resolution.

The calculation of temporal-spectral metrics was considered in a similar manner, as conducted for Sentinel-1 data. For each year (2017 to including 2023), the following percentiles were calculated band-wise: 10th, 25th, 50th, 75th, 90th. Therefore, not only average conditions of vegetation are assessed, but also extreme conditions (e.g. leaf-on and leaf-off characteristics in spring and autumn).

4.2.1.3 Global Ecosystem Dynamics Investigation (GEDI)

All available GEDI version 2 (L2A, L2B) and 2.1 (L4A) data for Germany spanning the peak vegetation period (June to including August 2019, 2020, 2021, 2022) was obtained through the LP DAAC platform by NASA and United States Geological Survey (USGS) (L2A: https://lpdaac.usgs.gov/products/gedi02_av002/, L2B: https://lpdaac.usgs.gov/products/gedi02_bv002/) and the ORNL DAAC platform by USGS (L4A:https://daac.ornl.gov/cgi-bin/dsviewer.pl?ds_id=2056).

As an initial step, the GEDI data was quality filtered in order to remove Lidar degraded shots or shots with a low sensitivity. Based on the Algorithm Theoretical Basis Document (ATBD) documents (Tang and Armston, 2020) provided by the GEDI Science Team, quality filtering was applied:

- Removal of low-quality shots: value = 0 for "quality_flag" (L2A), "l2a_quality_flag" (L2B), "l2b_quality_flag" (L2B), "l2_quality_flag" (L4A), "l4_quality_flag" (L4A)
- Removal of degraded shots: value > 0 for "degrade_flag" (L2A, L2B, L4A)
- Removal of low-sensitivity shots: value < 0.95 for "sensitivity" (L2A, L2B, L4A)

Based on annual filtering for 2019 to including 2022, yearly subsets per GEDI data set were prepared for modeling. To generate yearly subsets for the modeling of forest structure attributes in 2017 and 2018, the GEDI data from 2019 was filtered to shots that did not experience canopy cover loss. Similarly, the data for 2022 was prepared as reference of forest structure conditions for 2023 by removing shots in canopy cover loss areas. The data on canopy cover loss stems from the Forest Canopy Cover Loss product (German Aerospace Center (DLR), 2025) which was initially published by Thonfeld et al. (2022).

All remaining GEDI data was filtered to the land cover classes "tree cover", "grassland", and "cropland" based on the Worldcover data for 2020 at 10 m spatial resolution by ESA. Therefore, the GEDI data do not only represent forest characteristics but also structural characteristics of low vegetation and bare ground which are underrepresented if a filtering is only applied to forested areas. In addition, the structural characteristics of low vegetation and bare ground mimic post-disturbance structures.

For each year and attribute of forest structure (canopy height, total canopy cover, aboveground biomass density), the GEDI samples were randomly sampled to 10,000 shots and subsequently split into training (70 %) and testing (30 %). Therefore, the assessment of model validation can be conducted independently from the data used for training the model.

4.2.2 Multi-annual Forest Structure Modeling Workflow

The modeling part of the workflow in order to derive annual products for 2017 to including 2023 of three forest structure attributes is based on a machine learning regression model. Figure 4.1 illustrates the combination of Sentinel-1 GRD, Sentinel-2 L2A and GEDI data (L2A, L2B, L4A) in random forest regression models. In the following sections, the response and predictor metrics are explained in detail, as well as the model parametrization, followed by the model validation assessment.

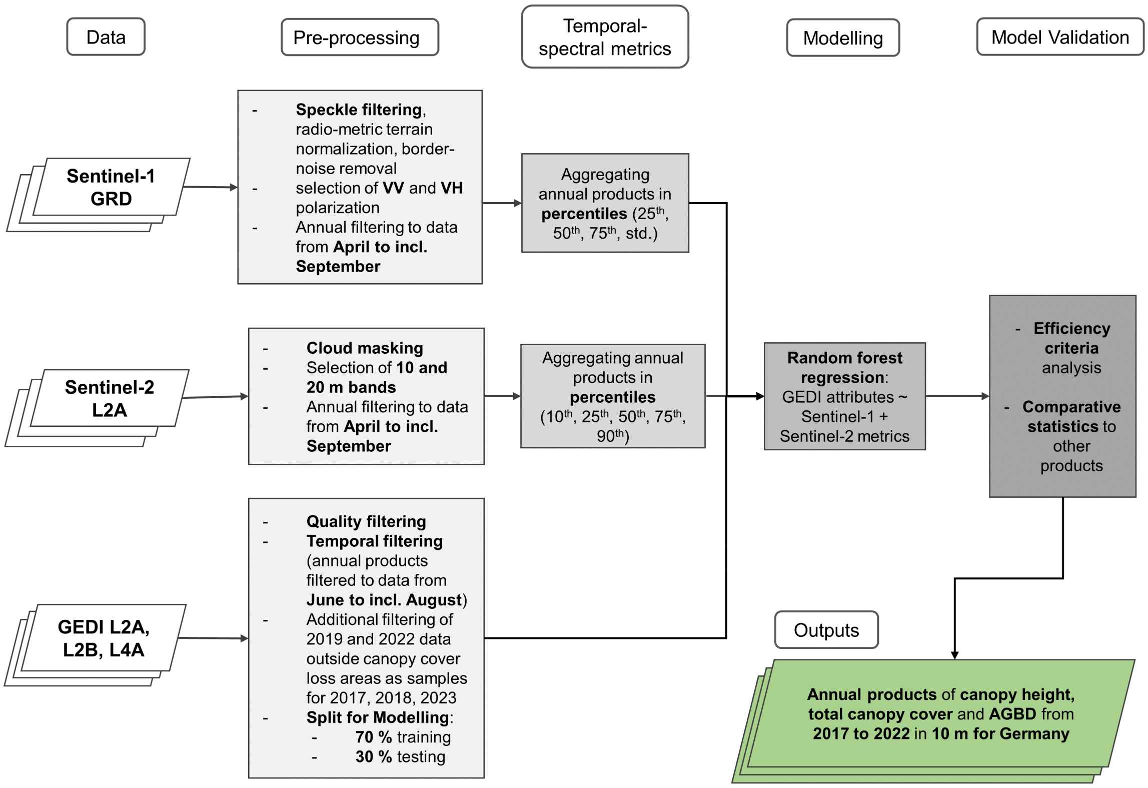

Figure 4.1: Schematic workflow chart of forest structure modeling.

4.2.2.1 Response and Predictor Metrics

After pre-processing the spaceborne data, there are annual data sets prepared for modeling: Sentinel-1 and Sentinel-2 derived temporal spectral metrics at continuous coverage for Germany and analysis-ready GEDI samples on canopy height (L2A), total canopy cover (L2B), and above-ground biomass density (L4A).

For each year from 2017 to including 2023 and each attribute of forest structure, a random forest regression model is trained. The response metrics are the training samples from GEDI modeled by the predictor metrics of Sentinel-1 and Sentinel-2, i.e. the temporal-spectral metrics. Therefore, for the years were GEDI data is available for the summer months (June to including August for 2019, 2020, 2021, 2022) there is a temporal match to the yearly derived temporal-spectral metrics of Sentinel-1 and Sentinel-2. To model the years 2017 and 2018, GEDI data from 2019 is used with canopy cover loss areas being removed for the respective years (section 4.2.1.3). For 2023, GEDI samples from 2022 are integrated which did not experience a disturbance (canopy cover loss) since 2022. The training of the 2017, 2018, and 2023 models is based on temporally matching temporal-spectral metrics of Sentinel-1 and Sentinel-2. The prediction of the forest structure attributes for 2017, 2018, and 2023 is applied to the temporal-spectral metrics of 2017, 2018, 2023. The derived products of the three forest structure attributes for 2017, 2018, and 2023, thus represent the structural conditions of the specific years, only the model training was based on temporally matching data (2019, 2022). A similar workflow to model forest structure conditions for years without GEDI data available was adapted by other studies (e.g. Turubanova et al. (2023)).

4.2.2.2 Machine-learning Regression Modeling

For all years and forest structure attributes, random forest regression models were used. Random forest models are based on multiple decision-trees in order to assess relationships among predictor and response metrics. Through model averaging of the individual decision-tree based models, the predictive accuracy is enhanced, as well as a reduced model overfitting (Breiman, 1996, 2001). Multiple studies have demonstrated the high performance of random forest regression models for the prediction of quantitative response metrics (e.g. forest structure attributes, Potapov et al. (2021); Lang et al. (2023)).

For the training of the random forest regression models the default parameter settings were used in order to allow maximum flexibility for the generation decision-trees (e.g. number of minimum leaf population, metrics per split). Based on 200 decision trees per attribute and year the random forest regression models are trained with 7,000 GEDI samples. Previous studies have shown that 200 decision trees are sufficient (Kacic and Da Ponte, 2021), as well as 7,000 samples for the size of the study area (Potapov et al., 2021).

The 21 modeling products (seven years, three attributes of forest structure) are derived at 10 m spatial resolution. Since the temporal period of GEDI samples covers the peak vegetation period (June to including August), the multi-annual forest structure products for Germany represent summer conditions per year.

Based on a vector vegetation layer of the Digital Landscape Model (DLM) at the scale of 1:250,000 for Germany (Bundesamt für Kartographie und Geodäsie, 2020) and the Copernicus High Resolution Layer (HRL) Forest Type 2015 (European Environment Agency,

2017) a mask of stocked forest area was generated. The mask was applied to all products of forest structure for Germany, so that forest structure characteristics can be assessed accurately.

4.2.2.3 Model Validation

Each model is validated against the respective testing GEDI samples which are independent from model training. Therefore, for each year and attribute, the model accuracy was assessed based at the shot locations of GEDI testing samples. By extracting the predicted values, the following model efficiency criteria were calculated: Coefficient of determination (R^2) and Root Mean Square Error (RMSE).

In addition, the predicted products of forest structure for canopy height (2019 and 2020) and total canopy cover (2018) were validated against existing products. For a temporal matching of the predicted models and the existing products, only selected years of modeled forest structure for Germany were used. The canopy height model for 2019 was compared to the global canopy height map (30 m spatial resolution) by Potapov et al. (2021) which is based on GEDI and Landsat data. For a comparative analysis of the canopy height model from 2020 for Germany, the global canopy height model (10 m spatial resolution) for 2020 by Lang et al. (2023) was derived. The global product by Lang et al. (2023) is based on GEDI and Sentinel-2 data. Predicted total canopy cover for 2018 was validated against data from Copernicus HRL tree cover density 2018 (10 m spatial resolution, Copernicus HRL TCD (2018)) by the European Environment Agency (EEA).

4.3 Results

In the following sections, the results of the multi-annual forest structure modeling workflow for Germany will be presented. Starting with a national perspective (section 4.3.1), the forest structure for Germany will be characterized based on seven years of data products comprising three forest structure attributes (canopy height, total canopy cover, aboveground biomass density). The second section of the results section shows regional assessments of forest structure dynamics in the context of recent disturbances (section 4.3.2). Two hotspots of canopy cover loss since 2018 are analyzed based on the multi-annual forest structure data, as well as difference statistics identifying areas of major changes from 2017 to 2023. The results section closes with the model accuracy assessment which is subdivided into a statistical analysis of model efficiency criteria and comparative assessments of multi-annual forest structure attributes for Germany against existing products.

4.3.1 Forest Structure Characterization for Germany

Canopy height is a key attribute of forest structure focusing on vertical vegetation properties of forests. The maps of forest canopy height for Germany present large-scale characteristics, such as spatial differences and temporal dynamics (Figure 4.2). Based on the multi-annual data on canopy height from 2017 to including 2023 hotspots of changes in canopy height can be identified, as well as areas of rather unaltered canopy height structures. Major changes in canopy height are apparent when comparing the years 2017 and 2023: elevated values of canopy height (greater than 25 m) which characterized many forested areas of Central Germany in 2017 experienced strong declines towards low canopy height values (values lower than 10 m). Specifically since 2021 declining canopy height values are presented for some forests of Central Germany. Areas of stable conditions of canopy height (values greater than 20 m) are specifically present in south-western and south-eastern regions of Germany.

Total canopy cover is another important attribute of forest structure which is based on vertical and horizontal properties. Based on the sum of vertical vegetation cover, total canopy cover is derived, thus considering canopy cover material, as well as vegetation cover of the mid and low vertical strata.The multi-annual maps of total canopy cover for Germany (Figure 4.3) present relatively closed forest canopy cover for the forests of Germany with values up to 80 %. Central, south-western and south-eastern regions are characterized by specifically dense forest canopy covers. In comparison, some forested areas in eastern and southern regions of Germany present a greater mix of total canopy cover, i.e. open and closed forest canopy covers.

Recent total canopy cover conditions of forests in Germany for the year 2023 present strong changes since 2017. Similar to the dynamics of forest canopy height, large-scale areas of forests in Central Germany are characterized by low total canopy cover values (lower than 20 %). Those areas of forest canopy cover opening are occurring at larger-scale since 2021. Forests with densest canopy cover in Germany are located in the south-west.

Above-ground biomass density characterizes the vegetation mass per area above ground level. Modeled above-ground biomass density for Germany from 2017 to including 2023 shows drastic changes for the forested areas (Figure 4.4). In 2017, highest values for above-ground biomass density are shown for forests with large-scale continuous cover in Central Germany, north-eastern, south-western, as well as south-eastern forests. With values higher than 250 Mg/ha, those forest areas are specifically high in biomass volume compared to other areas and therefore particularly relevant for carbon storage processes, but also silvicultural management.

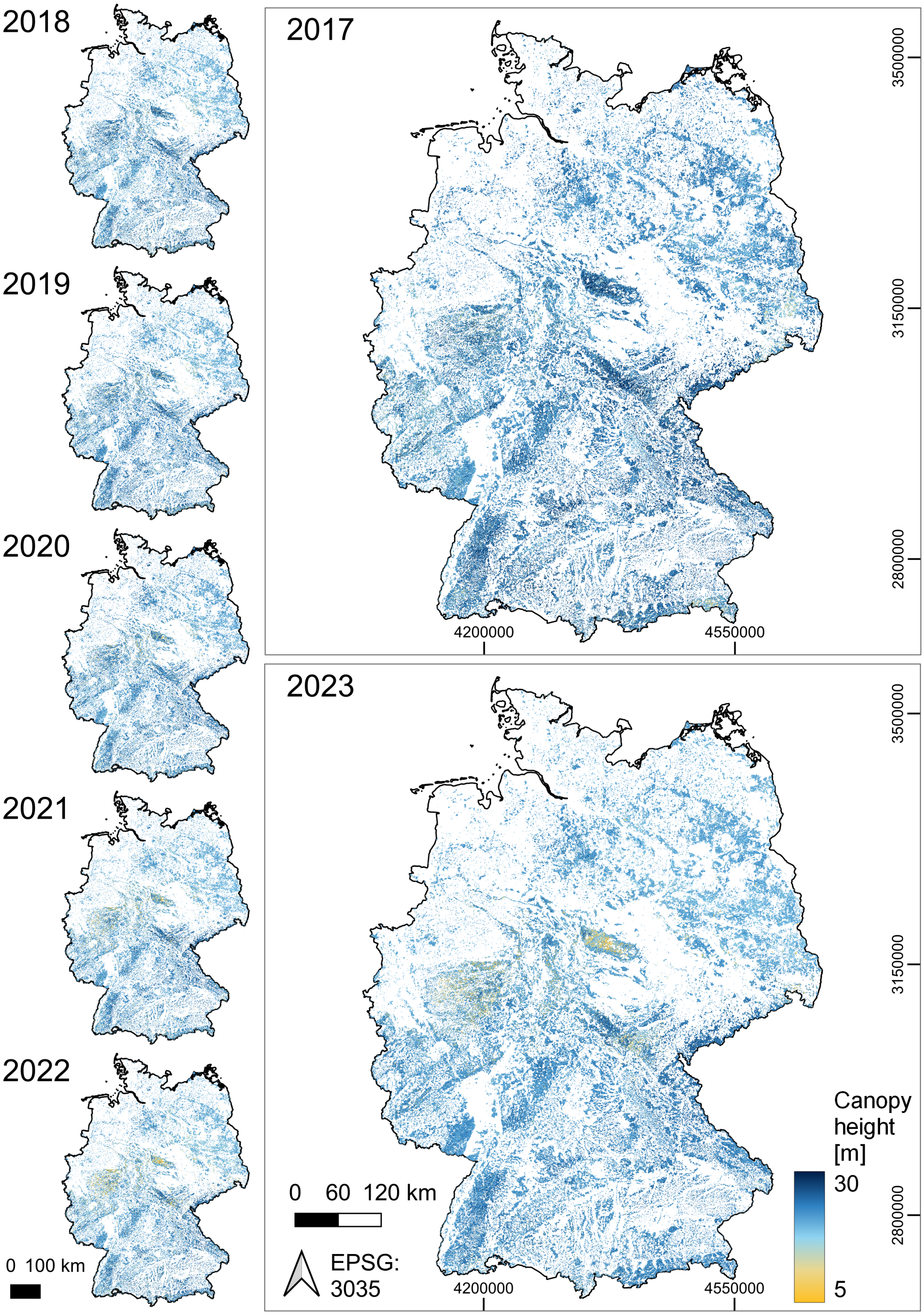

Figure 4.2: Maps of canopy height in Germany (2017 to 2023).

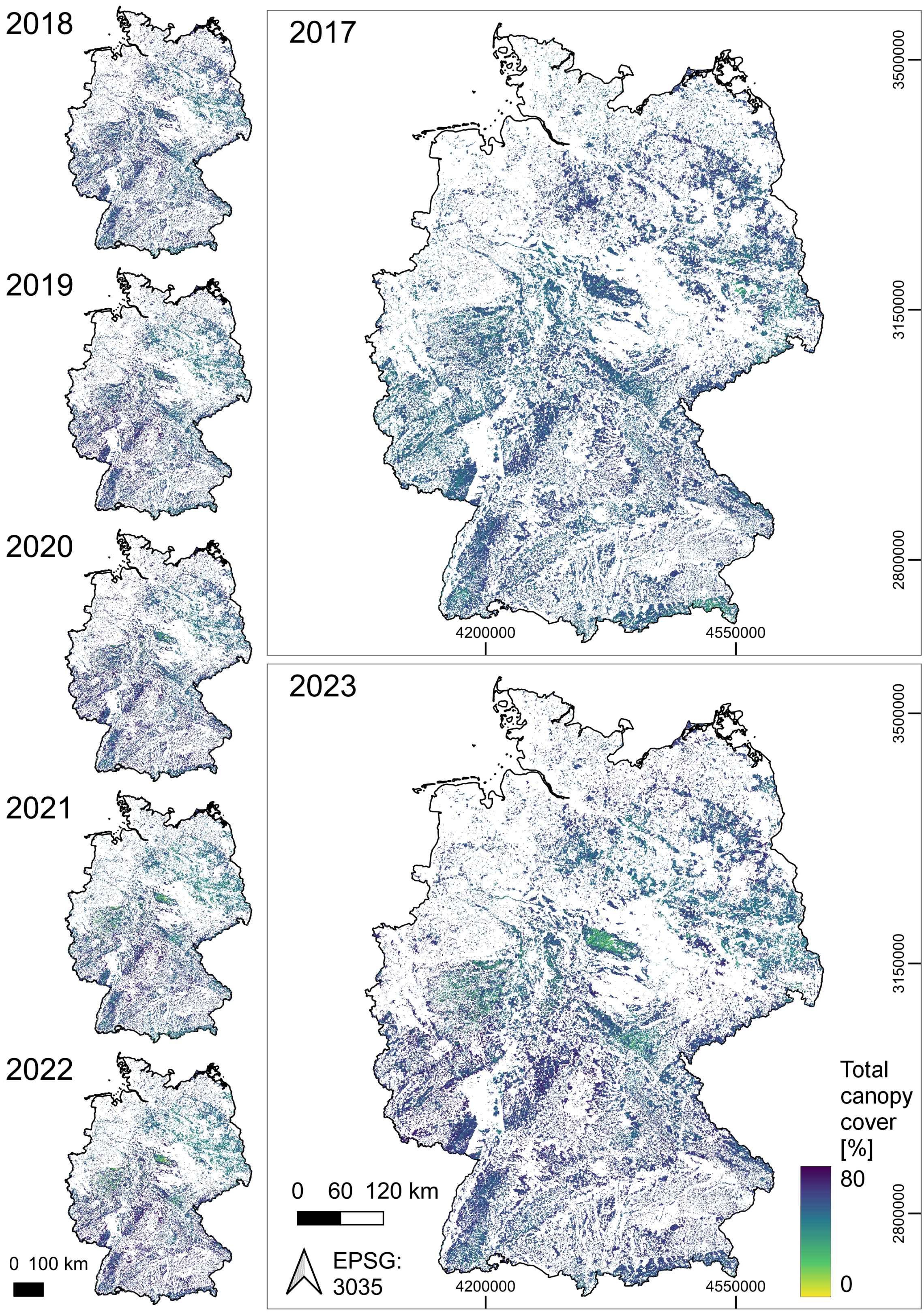

Figure 4.3: Maps of total canopy cover in Germany (2017 to 2023).

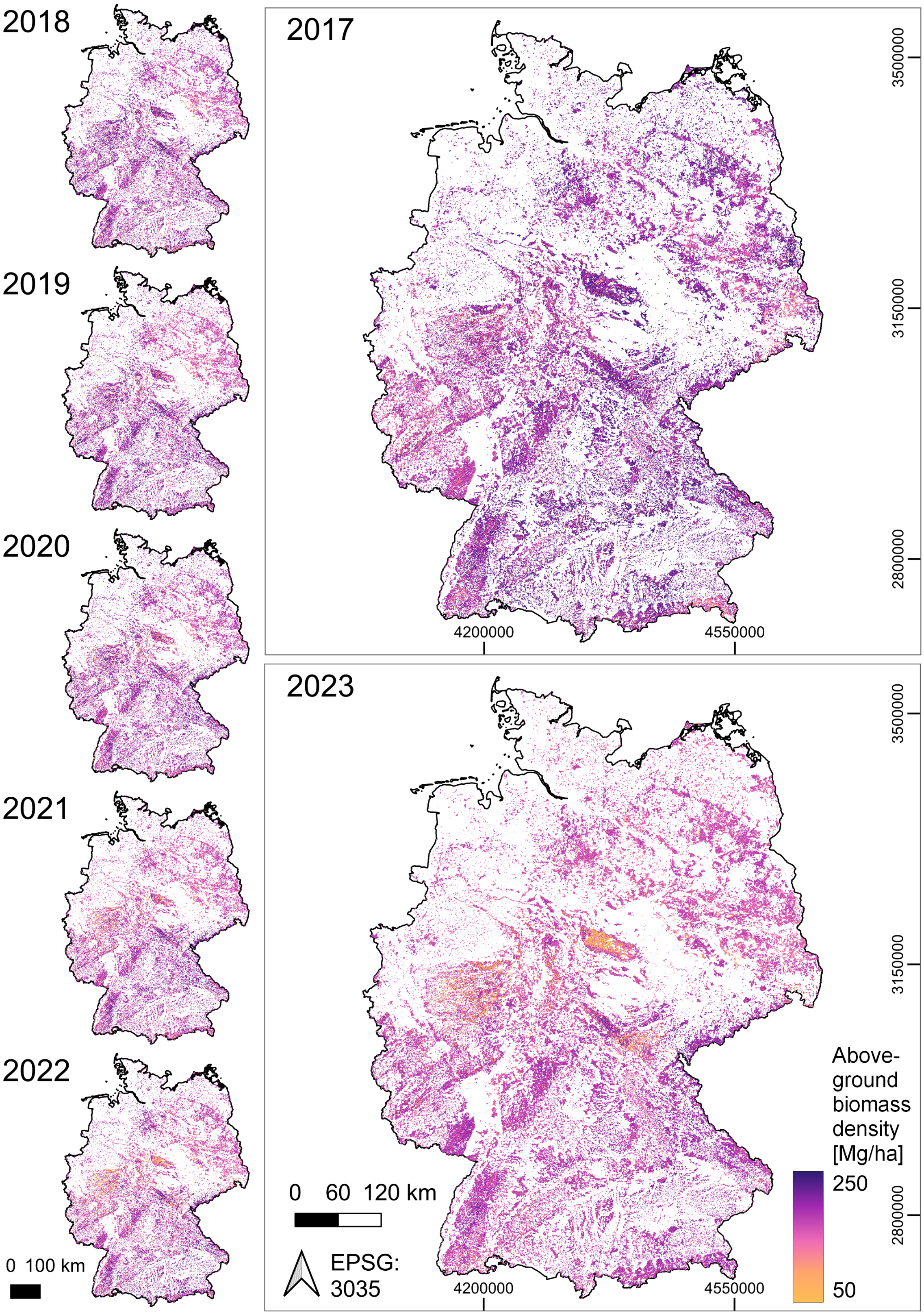

Figure 4.4: Maps of above-ground biomass density in Germany (2017 to 2023).

Since 2017, the maps of above-ground biomass density for Germany present declining trends for biomass volume in many forested areas. In 2023, previous hotspots of above-ground biomass density in Central Germany have changed to low biomass volume with values lower than 80 Mg/ha. In addition, areas of enhanced above-ground biomass density in north-eastern Germany in 2017 present declining values for 2023 (about 150-200 Mg/ha).

Overall, the findings based on multi-annual data of above-ground biomass density are aligned with the spatio-temporal dynamics found for canopy height and total canopy cover. Large-scale areas with high canopy heights, dense canopy covers and maximum above-ground biomass density of Central Germany are characterized by declining canopy height, rather sparse canopy covers and comparably low biomass volume.

4.3.2 Regional Assessment of Forest Structure Dynamics

For a more detailed analysis of forest structure dynamics at the regional level, the following two sections assess the changes in different forest structure attributes for the Harz forest (section 4.3.2.1) and the Thuringian forest (section 4.3.2.2). The two regions were identified in the previous section 4.3.1 as hotspots of forest structure change in the context of recent disturbances.

4.3.2.1 Harz Forest

The Harz forest is located in Central Germany and constitutes the most northern low mountain range in Germany (Figure 3.1b,c). Forests at higher altitudes are coniferous stands surrounded by broadleaved forest of lower elevations (Figure 3.3).

In 2017, the modeled products of forest structure present high forests with canopy heights up to 30 m (Figure 4.5). In addition, the forests of the Harz are characterized by mostly dense, connected and continuous forest canopy covers. Furthermore, the forests harbor high above-ground biomass in 2017 with most areas holding values higher than 200 Mg/ha. An area which is different in 2017 to aforementioned high, dense, and biomass-rich forests, is situated around the Harz Nationalpark which is located in the north-western area of the Harz forest (center coordinates: x = 4,360,000; y = 3,190,000). Forests in the Harz Nationalpark are at highest elevations of the low mountain range (Figure 3.1b) and are comparably low in canopy height (about 10-15 m), at a lower level of total canopy cover (50-60 %), and not as high in above-ground biomass (below 150 Mg/ha) in 2017 as the surrounding forests.

In the following years, there are large-scale dynamics of forest structure changes. From 2018 to 2019, starting around the north-western areas of the Harz forests, there is an increase in forest areas which are declining in all attributes of forest structure: canopy heights lower than 10 m, total canopy cover declining to 0-20 %, and reduced above-ground

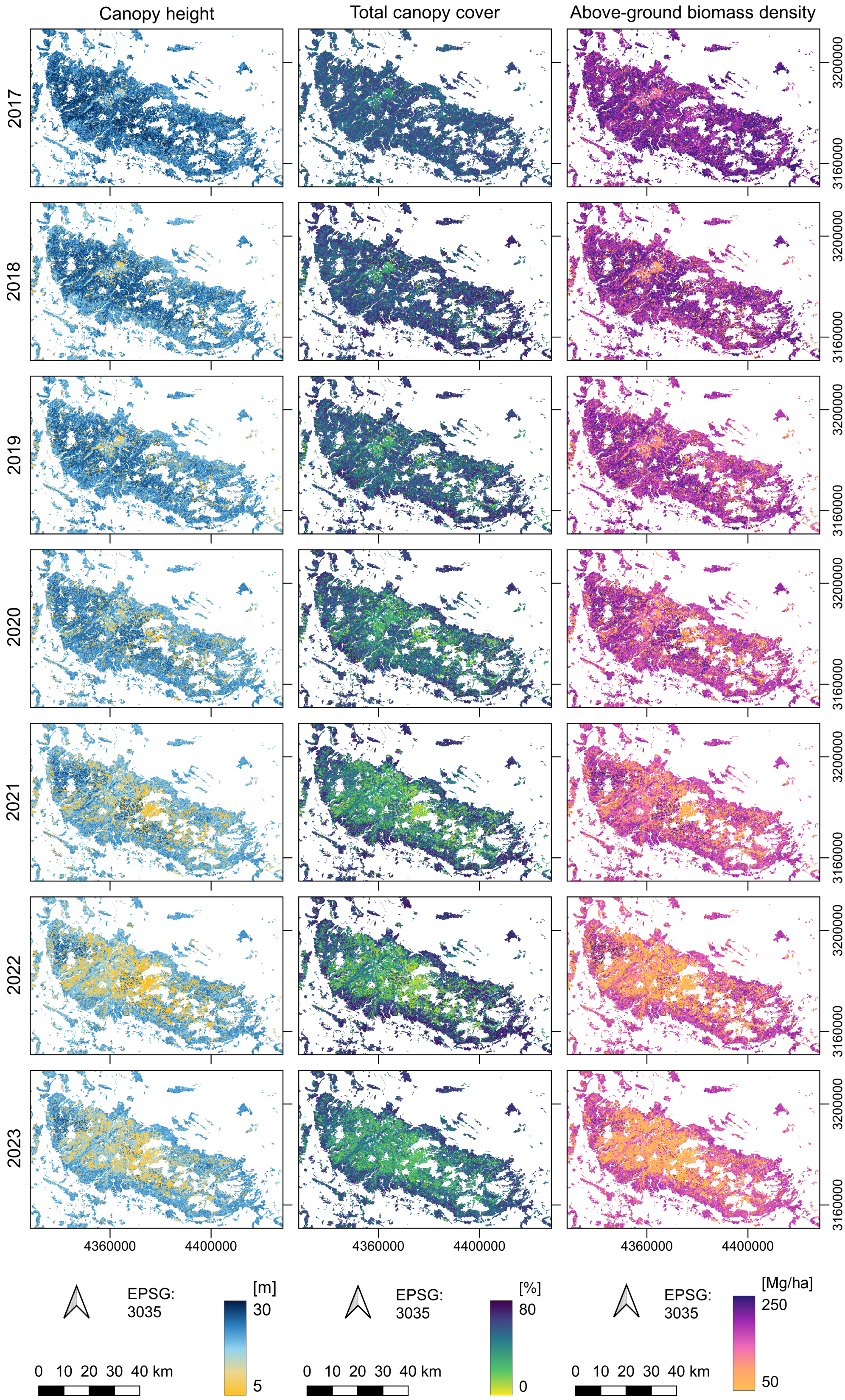

Figure 4.5: Maps of forest structure attributes in the Harz forest from 2017 to 2023.

biomass density amounting to values lower than 100 Mg/ha. From 2020 to 2022, most coniferous forests are affected by continuous decline in forest structure. The forests which were characterized in 2017 by high values for all attributes of forest structure, are not only holding low canopy heights (values lower 10 m) in 2022, but also open canopy covers (total canopy cover lower than 20 %), as well as low above-ground biomass density (values lower than 100 Mg/ha). The year 2023 shows a similar condition for the forest in the Harz region based on the three attributes of forest structure as for 2022: the large-scale dynamics of forest structure decline since 2018 are only present for the coniferous stands, leaving the broad-leaved forest at the outer-bound of the Harz forest in similar condition over time.

Based on a difference analysis for canopy height, total canopy cover, and above-ground biomass density from 2023 to 2017, the changes during the seven years become more clear (Figure 4.6). By calculating the difference from the 2023 to the 2017 data per forest structure attribute, increasing values are positive and declining values are negative.

The difference maps of the three forest structure attributes indicate negative dynamics for canopy height, total canopy cover, and above-ground biomass density at large-scale for most of the Harz forests. Overall, the negative dynamics are limited to the area of coniferous stands (Figure 3.3). There is a strong decline in canopy height for coniferous stands up to -30 m from 2017 to 2023 (Figure 4.6a). The same areas are characterized by a loss in canopy cover for most areas in range of -70 % to -50 % (Figure 4.6b). The decline in canopy height and total canopy cover goes along with reduced above-ground biomass density for coniferous stands amounting to losses of up to -200 Mg/ha (Figure 4.6c). There are few positive dynamics in terms of forest structure development from 2017 to 2023: The most significant dynamic is the increasing total canopy cover for broad-leaved forests in the Harz (Figure 3.3) characterized by a gain of up to 20 % in total canopy cover (Figure 4.6b).

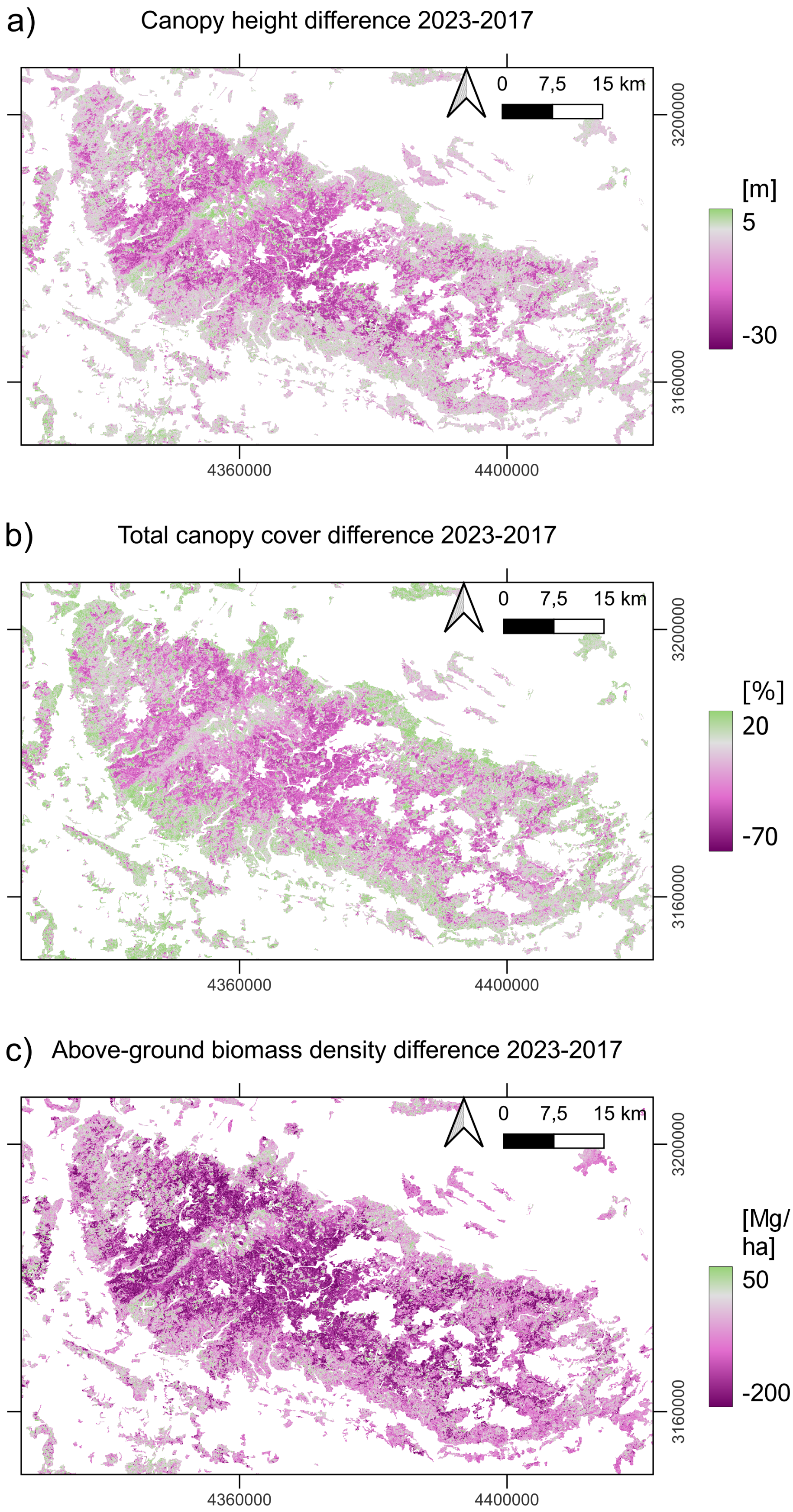

Figure 4.6: Difference maps of forest structure attributes in the Harz forest (2023-2017).

4.3.2.2 Thuringian Forest

The Thuringian forest is located in central-eastern Germany and is dominated by coniferous trees as the Harz forest. In comparison to the Harz forest, the Thuringian forest is part of the eastern low mountain ranges (Figure 3.1c) but at a similar elevation level (Figure 3.1b).

The first four years (2017-2020) of the multi-annual forest structure data indicate relatively stable conditions, i.e. no significant changes in canopy height, total canopy cover, or above-ground biomass density at a regional scale (Figure 4.7).

From 2017 to including 2020, the Thuringian forest is characterized by elevated values for canopy height (many areas with a canopy height greater than 20 m), total canopy cover (dense canopy covers are predominantly located in the north-eastern parts with values exceeding 70 %), and above-ground biomass density (up to 250 Mg/ha and few areas with values lower than 150 Mg/ha).

In the year 2021, the Thuringian forests are experiencing first changes in forest structure in the central areas. The decline in canopy height (values lower than 10 m) is accompanied by an increasing area of open canopy covers (values lower than 10 %), as well as reduced above-ground biomass density (values lower than 80 Mg/ha). In 2022 the areas of low canopy height, sparse canopy covers and low above-ground biomass density reach a maximum extent: a fragmented landscape is the result characterized by a mosaic of unaltered forest structure and reduced forest structure properties in terms of canopy height, total canopy cover, and above-ground biomass density. In comparison to the Harz region, the changes in forest structure are not as connected and continuous.

The maps of bi-annual difference (2023-2017) assessed for the three attributes of forest structure highlight significant areas of forest structure change dynamics (Figure 4.8). For canopy height, total canopy cover, as well as above-ground biomass density, there is a dominance of negative values indicating losses in forest structure. The losses are most clear for canopy height and above-ground biomass density: a reduction in vertical structure is exceeding values of 25 m in canopy height (Figure 4.8a). In addition, the declines in above-ground biomass density amount to more than 150 Mg/ha in many areas (Figure 4.8c). The difference maps for total canopy cover present bi-directional dynamics: on the one hand there are some areas with slight increases in total canopy cover (up to 20 %), and on the other there are many areas characterized by declining total canopy cover in a range of -70 % to -50 % (Figure 4.8b).

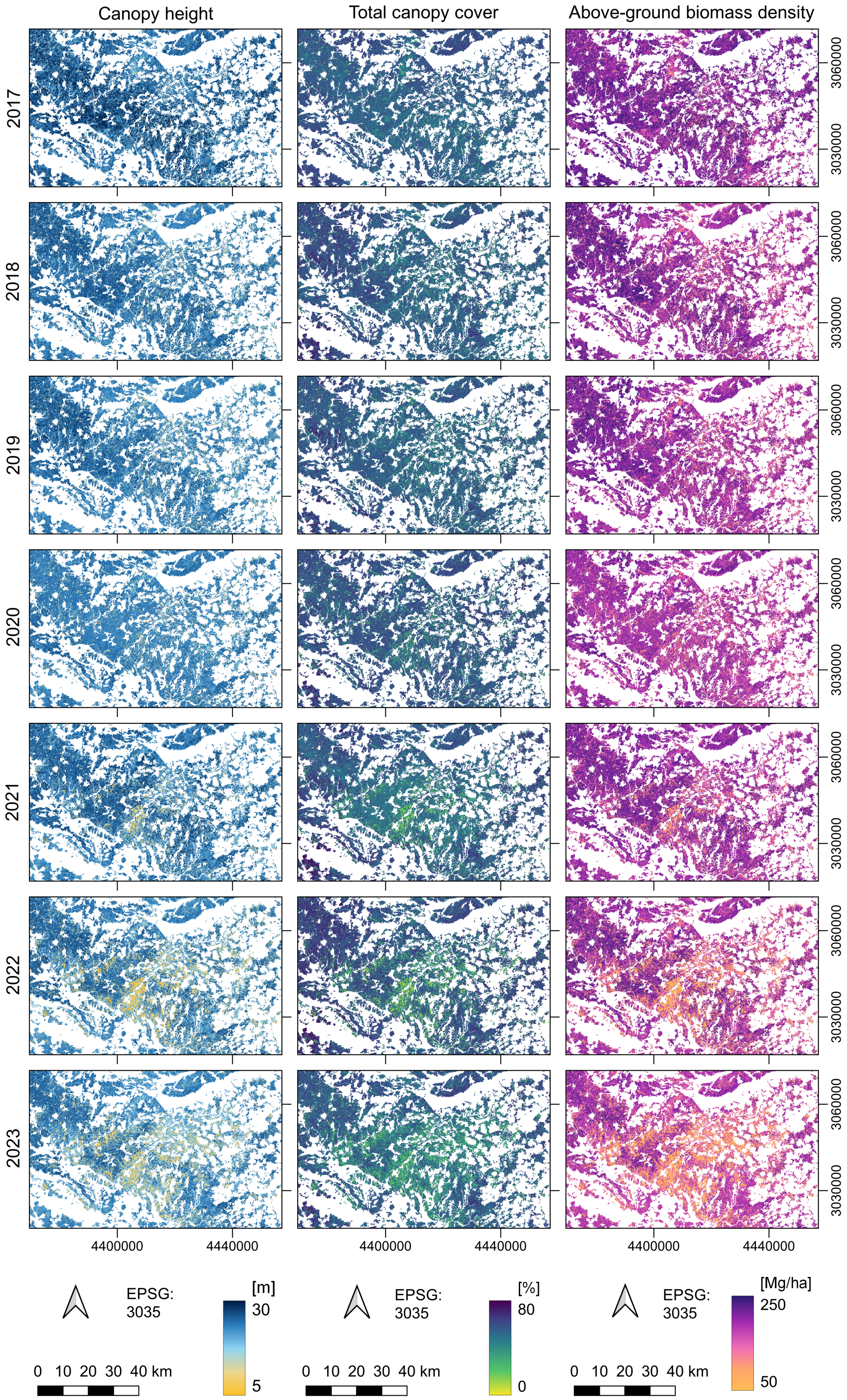

Figure 4.7: Maps of forest structure attributes in the Thuringian forest from 2017 to 2023.

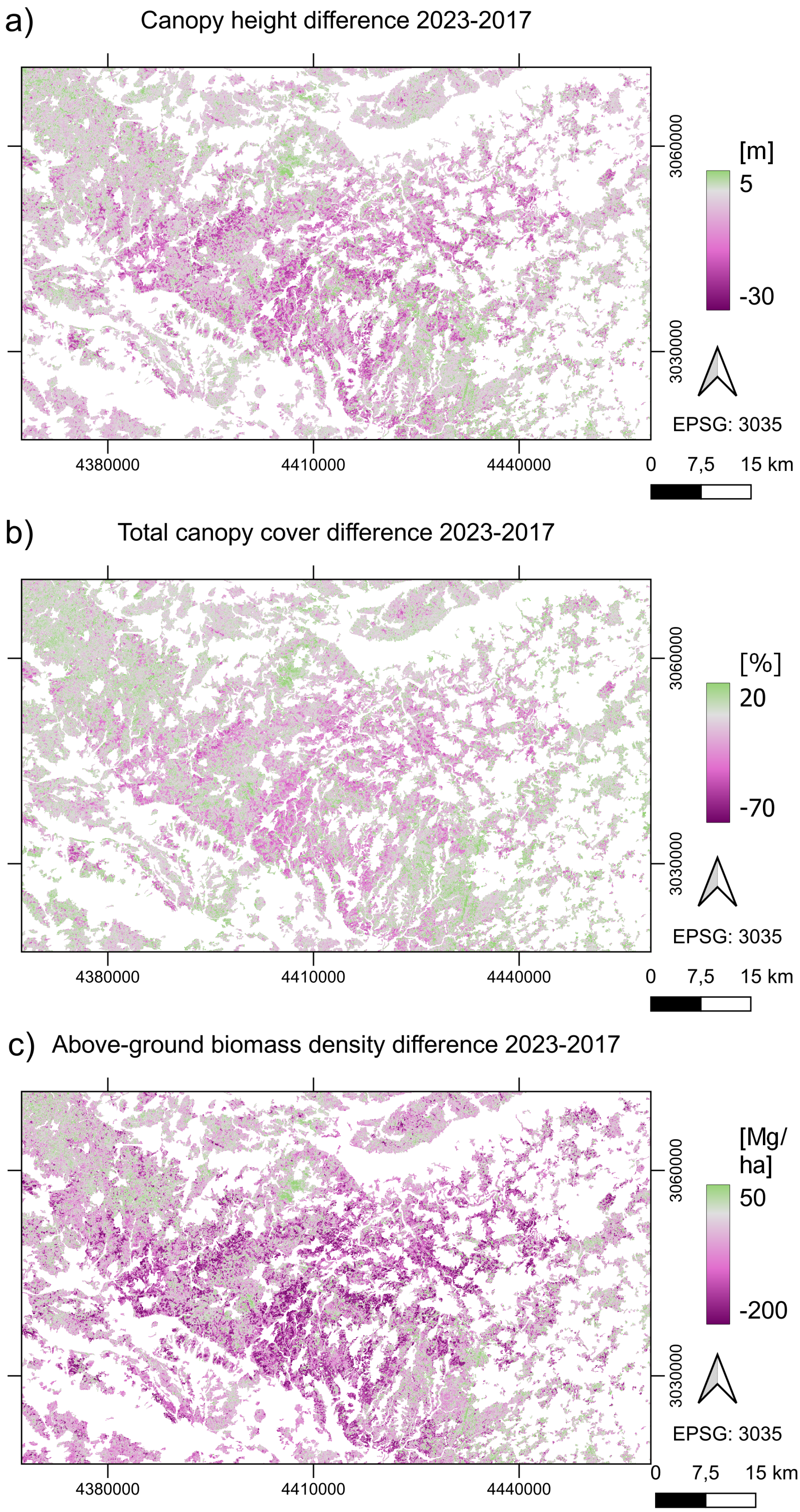

Figure 4.8: Difference maps of forest structure attributes in the Thuringian forest (2023-2017).

4.3.3 Accuracy Assessment

The model accuracy assessment was on the one hand conducted based on efficiency criteria describing the model performance. On the other hand, selected generated products of multi-annual forest structure for Germany were compared to existing products.

In Figure 4.9, the model accuracy based on the efficiency criteria R^2 and RMSE are depicted for the three attributes of forest structure, sub-divided into single years and mean across all years. Based on mean values for 2017 to 2023 according to the R^2, the models for total canopy cover present highest accuracy (mean R^2 = 66.0 %). The mean R^2 for the canopy height models amounts to 63.8 %, followed by the above-ground biomass density models (R^2 = 57.4 %). For the canopy height models (R^2 = 69.7 %) and the above-ground biomass models (R^2 = 62.8 %), the highest R^2 was reached in 2018. In contrast, the model with highest R^2 in total canopy cover (R^2 = 68.4 %) was reached in 2017. For the best models of canopy height, total canopy cover, above-ground biomass density the RMSE amounts to 6.2 m (2018), 18.3 % (2017), and 61.3 Mg/ha (2018), respectively. Across all attributes of forest structure, the years 2021 and 2023 hold lowest model accuracy according to both R^2 and RMSE.

In order to assess the accuracy of the generated products of forest structure for Germany, the products of canopy height (2019 and 2020), as well as total canopy cover (2018) were validated to existing products. The canopy height product for Germany from 2019 was compared to the global product on canopy height by Potapov et al. (2021). There is a general agreement of the models amounting to a RMSE of 4.6 m and a Pearson's correlation coefficient r of 0.52. The two products show best agreement for modeled canopy height in the range of 20 m to 27 m. In the range of 5 m to 15 m, there is an overestimation of canopy height based on the product for Germany. The comparison of modeled canopy height for 2020 presents generally higher values for the global canopy height product of Lang et al. (2023). The overestimation of canopy height of Lang et al. (2023) in comparison to the product for Germany is quantified as RMSE of 6.4 m. The Pearson's correlation coefficient of 0.47 indicates a systematic overestimation of Lang et al. (2023) compared to the product for Germany. The comparison of modeled total canopy cover for Germany in 2018 to the Tree cover density (TCD) product from Copernicus HRL (Copernicus HRL TCD, 2018) highlights that there is a general offset among the two products. The prediction of lower values in canopy cover for the Germany product compared to the TCD product amounts to a RMSE of 25.4 %. The continuous offset of the two products, specifically in the range of value from 60 % to 100 % according to the TCD product, is expressed in the Pearson's correlation coefficient amounting to 0.73 (a moderate to high correlation).

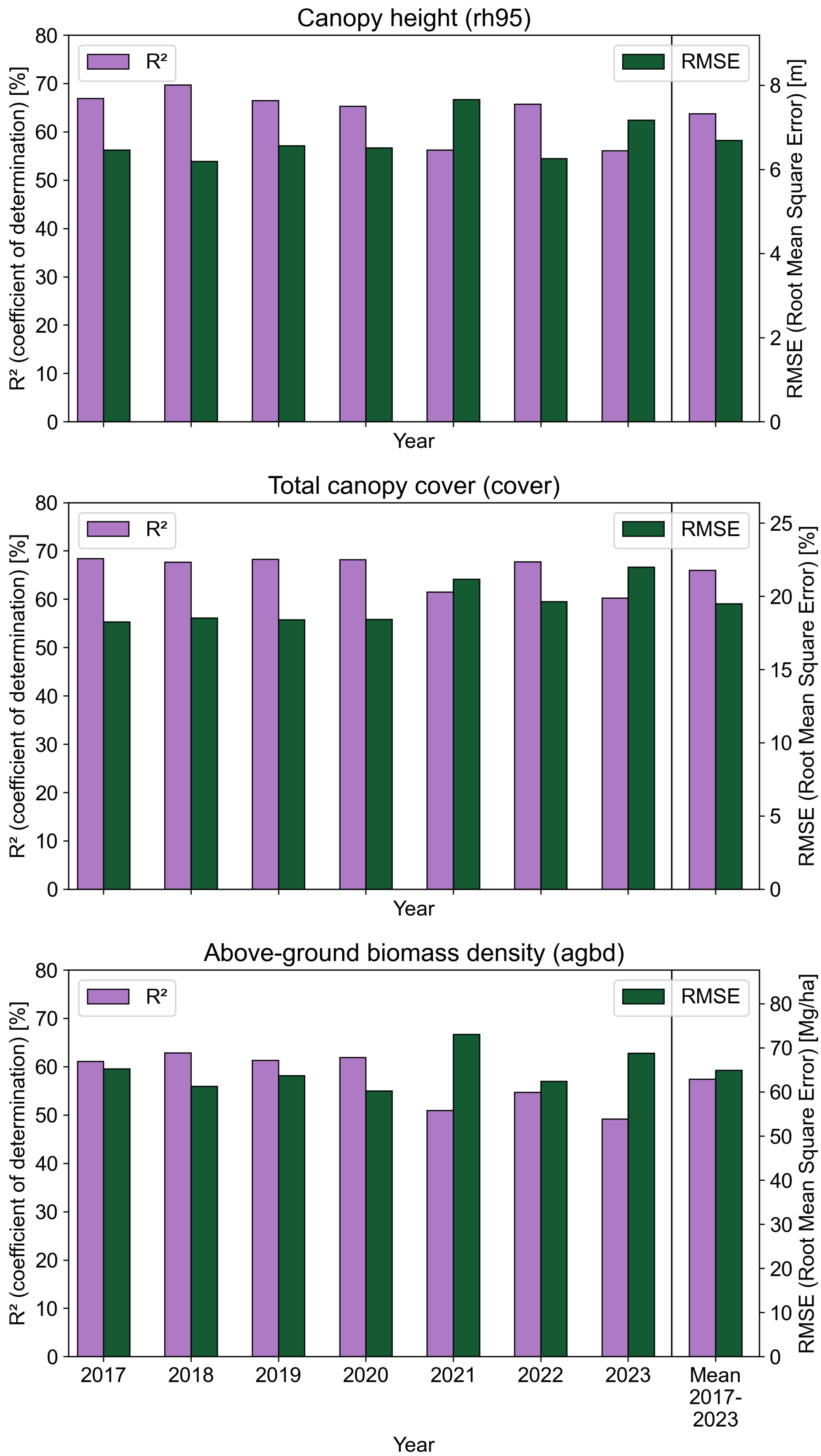

Figure 4.9: Accuracy assessment of forest structure modeling for modeled canopy height, total canopy cover, and above-ground biomass density according to R² and RMSE.

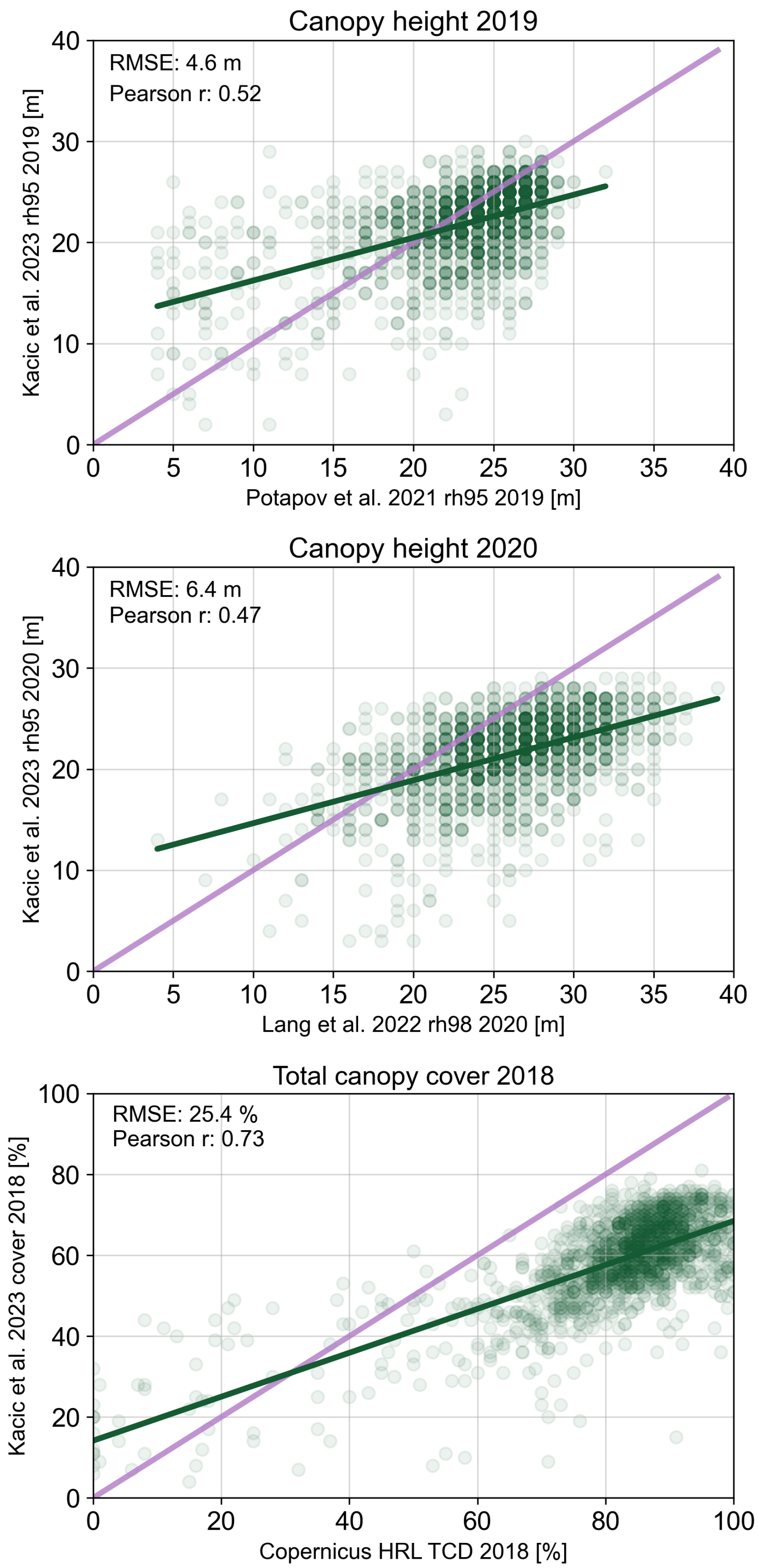

Figure 4.10: Comparison of forest structure modeling results to other published products: Potapov et al. (2021), Lang et al. (2023), Copernicus HRL TCD (2018).

4.4 Discussion

The discussion section begins with an elaboration of the multi-annual forest structure dynamics in Germany (section 4.4.1). In the following, the potentials and drawbacks of spaceborne forest structure modeling are discussed (section 4.4.2).

4.4.1 Multi-annual Forest Structure Dynamics in Germany

The modeling workflow integrating radar, multispectral, and Lidar enables the generation of the first consistent and multi-annual forest structure products for Germany based on spaceborne data. By combining temporal spectral metrics of the mapping missions Sentinel-1 and Sentinel-2, as well as sampling data from GEDI, forest canopy height, forest total canopy cover, and forest above-ground biomass characterize the recent forest structure dynamics in Germany from 2017 to including 2023.

The derived products of the machine learning workflow using random forest models present changes in forest structure as annual-products at the national-level and at the regional-level for Germany. The complementary attributes of forest structure focusing on different vertical and horizontal properties allow for a multi-faceted analysis of forest structure. Maps of canopy height are indicators of the vertical structure of forests providing an assessment of specifically high and low forests. Changes in canopy height are likely to influence changes in other forest structure attributes, such as canopy cover and above-ground biomass density. Information on total canopy cover is an indicator of vegetation cover measured as the vertical projection of vegetation cover from a top-of-canopy perspective, thus aggregating vegetation cover from multiple height-levels. Differences in total canopy cover over time can be attributed particularly to changes in the top-of-canopy vegetation cover since it is the densest vegetation cover across the vertical height distribution. The third derived attribute of forest structure from GEDI data is above-ground biomass density which aggregates structural information from both vertical and horizontal properties. Major changes in above-ground biomass density characterize differences in the forest carbon stock indicating stand-replacing disturbances, i.e. not only dynamics in canopy cover (leaf material).

The multi-annual analysis of forest structure attributes at the national-level present several hotspots of forest structure changes. The hotspots, such as the Harz and Thuringian forest are located in central Germany. Since 2018, repeated drought years in combination with heatwaves have impacted the forest conditions negatively, not only in Central Germany, but Central Europe (Buras et al., 2021; Rakovec et al., 2022). Increasing disturbances, such as windthrows, as well as cascading effects (e.g insect infestation) have predominantly affected coniferous stands. The dominance of stand-replacing disturbances through salvage logging as post-disturbance management practice following the natural disturbance are a common practice in German silvicultural management. Salvage logging comes along with various negative impacts on forest biodiversity: it not only changes the diversity and composition of recent species, but also strongly changes future forest habitats, thus limiting long-term forest resilience (Thorn et al., 2018). The presented large-scale changes in forest structure attributes for the Harz and Thuringian forest are matching the spatial patterns found of canopy cover loss (Thonfeld et al., 2022). The areas of canopy cover loss found by Thonfeld et al. (2022) are characterized by decreased canopy height, open canopy cover, and major reductions in above-ground biomass density. The finding of strong losses in the three forest structure attributes is an indicator of stand-replacing disturbances. Therefore, the novel products of multiple forest structure attributes for Germany demonstrate the potential to further characterize and understand pre- and post-disturbance structures. In addition, the assessment of differences in post-disturbances structures (e.g. stand-replacing and non-stand-replacing disturbances) has implications of potential future forest recovery and resilience.

The assessment of model accuracy shows that there is a general potential for spaceborne modeling of forest structure attributes combining Sentinel-1, Sentinel-2, and GEDI data (Figure 4.9). The mean value across-years of model accuracy for canopy height in Germany (R^2 = 63.8 %) is similar or higher to previous studies by Potapov et al. (2021) (R^2 = 61.0 %; global canopy height model for 2019 based on GEDI and Landsat data), Sothe et al. (2022) (R^2 = 58.0 %; canopy height modeling in 2020 for Canada based on GEDI, Sentinel-1, Sentinel-2, Phased Array L-band Synthetic Aperture Radar (PALSAR), Ice, Cloud, and land Elevation Satellite-2 (ICESat-2)), and Kacic et al. (2021) (R^2 = 64.0 %; canopy height modeling for the Paraguayan Chaco based on GEDI, Sentinel-1, Sentinel-2). In addition, selected products of forest structure attributes that match the temporal period of existing products were validated. The findings from the comparative canopy height models for 2019 (canopy height for Germany and canopy height based on Potapov et al. (2021)) and 2020 (canopy height for Germany and canopy height based on Lang et al. (2023)) present a general agreement of the different models in terms of values in the range of 15 m to 25 m (Figure 4.10). Strongest differences are found for 2019 for low canopy height values (below 10 m) which show deviations in both directions (over- and underestimation) of up to 15 m. For modeled canopy height in 2020, the product of Lang et al. (2023) generally presents higher values for values in a range of 25 m to 35 m. This findings can be attributed to the fact, that the modeled canopy height for Germany is based on th 95 th percentile of canopy height, in comparison to Lang et al. (2023) modeling the 98 th percentile of canopy height derived from GEDI. For modeled total canopy cover in 2017 for Germany a general offset of about 20 % was found when compared to the HRL TCD product 2018. The assessment of vegetation cover from different sensors (HRL TCD product 2018 is based on Sentinel-2 data only) might influence the value range of canopy cover leading to higher values at pixel-value compared to Lidar footprints from GEDI. Nevertheless, the high Pearson's correlation coefficient (r = 0.73) demonstrates a high correlation of the two products. A validation of the total canopy cover products for Germany against a reference product also based on GEDI data was not possible, since comparative products do not yet exist for Germany. Similarly, modeled above-ground biomass density for Germany could not be validated against other products of forest biomass, since existing products come with the limitation of a coarse spatial resolution (e.g. GEDI L4B Gridded Aboveground Biomass Density, Version 2.1 in 1 km, Dubayah et al. (2023)) that does not match the high spatial resolution (10 m) of the presented forest structure products for Germany.

The presented multi-annual products for Germany on canopy height, total canopy cover, and above-ground biomass density are based on all available GEDI data for the summer period (June to including August of 2019, 2020, 2021, 2022). Therefore, the annual products on forest structure for 2017, 2018, and 2023 are based on models trained using GEDI data from 2019 (2017, 2018) and 2022 (2023) combined with Sentinel-1 and Sentinel-2 temporal spectral metrics from 2019 and 2022, respectively. Therefore, there is a temporal match of the response and predictor variables (2019, 2022). In addition, only GEDI samples were considered that did not experience any canopy cover loss (Thonfeld et al., 2022) in 2017, 2018 for training the 2019 model and 2022 for training the 2023 model. When applying the trained models from 2019 on 2017 and 2018 continuous temporal-spectral metrics from Sentinel-1 and Sentinel-2, as well as from 2022 on 2023 continuous temporal-spectral metrics from Sentinel-1 and Sentinel-2, a modeling procedure was conducted that allows modeling forest structure for years without GEDI data. By considering samples without forest disturbances and training the models based on temporally matching GEDI, Sentinel-1, and Sentinel-2 data, the efficiency criteria on model accuracy for 2017, 2018, and 2023 are in the range of model accuracy for years with GEDI data (2019, 2020, 2021, 2022, Figure 4.9).

4.4.2 The Potential of Spaceborne Forest Structure Modeling

The analysis of forest structural characteristics from a spaceborne perspective is a relatively new development in the field of forest remote sensing (Coops et al., 2021; Aguilar et al., 2024). Following the start of the GEDI mission, the first full-waveform Lidar data was derived from space in order to measure vertical and horizontal structures on the earth's surface. GEDI is the first spaceborne Lidar sensor that was specifically developed for the characterization of forest structure. In comparison, previous spaceborne Lidar sensors by NASA, namely Ice, Cloud, and land Elevation Satellite (ICESat) and ICESat-2, were designed for the analysis of the assessment of structural properties of snow and ice. Since GEDI operates in the near-infrared, it holds a high sensitivity to measure structural characteristics of vegetation (Dubayah et al., 2020). In addition, since GEDI is not a satellite, but a spaceborne sensor attached to the ISS, a extended mission duration could be guaranteed due to fewer limitations in terms of energy consumption, as well as a above-average sensor condition (GEDI-Science-Team, 2025).

The GEDI sensor has the potential of near-global sampling of various forest structure attributes: canopy height as percentiles (GEDI L2A data set), canopy cover estimates (total canopy cover, Plant-Area-Index (PAI), GEDI L2B data set), above-ground biomass density (GEDI L4A data set), and vertical structural diversity and complexity (Foliage-Height-Diversity-Index (FHDI): GEDI L4C data set, Waveform-Structural-Complexity-Index (WSCI): GEDI L4C data set). The sampling scheme of GEDI enables transect analysis, as well as modeling approaches based on sparse sampling data. By combining GEDI samples with continuous data from mapping missions, such as Sentinel-1, Sentinel-2, and Landsat, wall-to-wall maps of forest structure attributes can be generated. Different quality assessments have revealed that it is crucial to conduct multiple pre-processing steps in order to derive high-quality samples without degradation and low sensitivity (Moudry et al., 2024). In addition, in mountainous areas, a filtering removing samples in steep terrain (e.g. slope greater than 35 °) should be conducted (Adam et al., 2020; Hirschmugl et al., 2023). Since GEDI operates in the near-infrared, the signal emitted by the sensor is sensitive to atmospheric artifacts, such as clouds and haze, which limits high data volume of quality filtered samples in the tropics.

Recent products of modeled forest structure based on spaceborne Lidar come with the limitation that extreme values are underrepresented. On the one hand, small-scale gaps in forests are unlikely to be sampled to a similar proportion as elevated values in canopy height, thus requiring a balancing of samples according to minimum and maximum values or integration of samples of ecosystems outside forests holding structures that are similar e.g. to minimum values (of canopy height, i.e. grasslands). On the other hand, there are sensor limitations challenging the accurate delineation of low vegetation and the ground level for an accurate measurement of low canopy heights. Furthermore, modeling approaches integrating spaceborne samples on forest structure as response predicted by satellite radar (e.g. Sentinel-1) and multispectral satellite data (e.g. Sentinel-2) brings further uncertainty: since Sentinel-1 radar can only penetrate the canopy to a limited extent (depending on density of canopy material) and multispectral measurements from Sentinel-2 assess top-of-canopy properties (if a canopy is present), there is only an indirect link between the forest structural measurements from spaceborne Lidar and the data from mapping missions (e.g. Sentinel-1 and Sentinel-2). In addition, machine learning models face the challenge of averaging-out extreme values as presented in Potapov et al. (2021). Moreover, modeled canopy height values in the upper quartile are likely to increased errors (Potapov et al., 2021; Kacic et al., 2021; Lang et al., 2023).

Spatial constraints of GEDI due to its orbit following the ISS limit the sampling of forest structure characteristics to most temperate and all tropical forests, i.e. within about 52 ° north and south. Therefore, for the study of German forest structure, GEDI samples are only available southern of the Harz forest. Since the forest structural characteristics of northern Germany are similar to the forest structural characteristics (e.g. minimum and maximum vertical structures, presence of tree species) of Central and southern Germany, no major gaps in sampling specific forest structural characteristics are to be expected. In addition, the temporal limitations, i.e. GEDI data availability, can be overcome as presented in the present study and other studies (Turubanova et al., 2023) since forest structural attributes were modeled with a similar model accuracy to years with GEDI data (Figure 4.9).

4.5 Summary

Continuous information on different forest structure attributes enables a quantitative assessment of forest condition and potential resilience. In addition, the generation of multi-annual products facilitates the characterization of change dynamics in vertical and horizontal structural properties of forests. Monitoring approaches integrating spaceborne data have the potential to provide consistent datasets as wall-to-wall products.

By combining data of complementary spaceborne sensors, namely GEDI (spaceborne Lidar), Sentinel-1 (radar satellites), and Sentinel-2 (multispectral satellites), the first spaceborne-derived products on forest canopy height, total canopy cover, and above-ground biomass density were generated for Germany. All available GEDI data on forest structure for the summer months (2019, 2020, 2021, 2022) were integrated as response variables in machine learning models based on predictive metrics derived from Sentinel-1 and Sentinel-2 time-series. Temporal-spectral metrics of the two mapping missions demonstrate the potential of radar and multispectral satellites to accurately model samples on forest structure attributes derived from spaceborne Lidar.

The annual products on forest canopy height, total canopy cover, and above-ground biomass density for Germany spanning the period from 2017 to including 2023 characterize the recent dynamics of forest structure change. The impacts of multi-annual drought years in combination with heatwaves since 2018 have led to large-scale changes in forest structure which were assessed at national and regional-level. At the national-level, multiple hotspots of forest structure change were identified: changes in forest structure were present not only for canopy height, but also total canopy cover, and above-ground biomass density, suggesting major changes (e.g. stand-replacing disturbances). The increasing areas of low canopy height, open canopy cover, and reduced above-ground biomass density were in particularly present in Central Germany, e.g. the Harz and Thuringian forests. The analysis of regional dynamics for the Harz and Thuringian forest reveal first small-scale changes from 2018 to 2020. Since 2021, landscapes of previously high forests with dense canopy covers being rich in above-ground biomass have changed to fragmented forests of different structural characteristics. Difference maps per forest structure attribute quantified losses in forest structure at regional-level and high spatial resolution (10 m): for both regions, large-scale areas show a reduction in canopy height of more than 20 m, total canopy cover exceeding 50 %, and above-ground biomass density of up to 200 Mg/ha. Those quantitative findings characterize the post-disturbance developments which are predominantly shaped by silvicultural management practices (e.g. salvage logging). Another similarity of the two regions is the fact that the losses in forest structure are mostly present in coniferous stands. Overall, broad-leaved stands experience little negative impact.

Based on the novel forest structure products for Germany, previously mapped areas of canopy cover loss as response to repeated drought years can be quantitatively characterized by canopy height, total canopy cover, as well as above-ground biomass density. Therefore, an improved understanding of post-disturbance structures is possible, e.g. to delineate stand-replacing and non-stand-replacing disturbances. This task is essential, since non-stand-replacing disturbances hold a higher potential to provide sufficient habitats for forest species, thus supporting biodiversity and avoiding further degradation processes. In addition, the characterization of disturbance structures and undisturbed areas enables the assessment of potential future forest resilience in order to understand which forest structural characteristics are beneficial to reduce impacts of future disturbances.

To sum up, spaceborne-derived information on forest structure has the potential to inform silvicultural management in order to safeguard forest biodiversity. In addition, the multi-variate characterization of forest structure can support the identification of forested areas which are on the one hand susceptible towards future forest disturbance, and on the other hand resilient due to complex forest structures.

Chapter 5

*A new Framework to assess enhanced Forest structural complexity**

This chapter presents the development and results of a new methodological framework to assess enhanced structural complexity in forests based on satellite time-series. The monitoring of different levels of structural complexity is a critical task for the assessment of current and potential future habitat characteristics, since the structural complexity of forests is closely linked to biodiversity and resilience. In the context of the interdisciplinary research project BETA-FOR, experimental silvicultural treatments were implemented in broad-leaved dominated forests in Germany (Figure 3.3). Through aggregated (gap felling) and distributed treatments (selective removal of trees) in combination with different dead-wood structures, an enhancement of the structural complexity of six forest regions was targeted. The following analysis are limited to the focus region of the BETA-FOR project since it holds an increased variety of treatments. In addition, the implementation of treatments was conducted in winter 2018/2019 (the treatments in the other regions were implemented earlier, i.e. in winter 2015/2016 and 2016/2017), thus allowing for a sufficient time-series for both pre- and post disturbance (treatment implementation) period.

The standardized design of experimental silvicultural treatments enables the assessment to which extent satellite time-series can identify the changes in forest structure through silvicultural management practices. The study makes use of dense radar (Sentinel-1) and multispectral (Sentinel-2) satellite time-series (section 5.1). The initial processing step of the methodological framework (section 5.2) comprises different correction techniques and artifact removals in order to derive analysis-ready time-series data (section 5.2.1). In the following, all listed indices from a standardized catalog are calculated for Sentinel-1 (n = 12) and Sentinel-2 (n = 129) time-series (section 5.2.2). At the patch-level (area of individual

*Parts of this chapter have been published in Kacic et al. (2024).

treatment), the time-series data of indices is aggregated as different spatial statistics per time-step to assess extreme, average, and heterogeneity statistics (section 5.2.3). Based on bayesian time-series decomposition models, the calculated metrics (combination of index and spatial statistic) are assessed in terms of change points and change point probabilities (section 5.2.4). Therefore, the original time-series are decomposed into seasonal and trend components characterizing the forest structural conditions for the treatments over time. In the results section (section 5.3), the potential of calculated time-series metrics is evaluated in terms of accurate assessment of the treatment implementation event (change in forest structure) based on change point dates and probabilities. Starting with the assessment of indices and spatial statistics, specific indices and spatial statistics were identified that demonstrate a great potential for monitoring the implementation of specific experimental silvicultural treatments. In addition, indices are listed that do not assess the forest structural changes accurately due to the treatment implementation (section 5.3.1). Exemplary time-series in section 5.3.2 show the differences among selected Sentinel-1 and Sentinel-2 time-series for aggregated and distributed treatments in comparison to control treatments (unaltered forest structure). The results section ends with the assessment of the general potential of radar and multispectral time-series for monitoring changes in forest structure due to experimental silvicultural treatments. Comparative statistics for Sentinel-1 and Sentinel-2 highlight selected indices and spatial statistics, as well as time-series components for a consistent monitoring of silvicultural management (section 5.3.3). In the discussion section (section 5.4), the potential of satellite time-series for the characterization of experimental silvicultural treatments is elaborated (section 5.4.1). In addition, the application of the time-series change detection framework for forest structure monitoring is discussed (section 5.4.2). The chapter ends with a summary of the developed methodological framework and applications (section 5.5).

5.1 Satellite Data

The satellite time-series analysis on forest structure changes in the context of experimental silvicultural treatments is based on data from Sentinel-1 radar and Sentinel-2 multispectral sensors. Both sensors have a high spatial resolution (10 m) and dense time-series observations which make them specifically suitable for the small-scale characterization of silvicultural treatments at high temporal resolution. In addition, the comparative analysis of satellite radar and multispectral time-series supports an improved understanding of sensor specific sensitivity towards forest structure characteristics over time.

5.1.1 Radar Data

The satellite radar data is based on the Sentinel-1 GRD product provided by ESA (Drusch et al., 2012). Data from both polar-orbiting satellites, namely Sentinel-1A (data available since October 2014) and Sentinel-1B (data available since October 2016 to December 2021), was used for the time-series characterization of forest structure. Time-series observations since October 2014 to October 2023 were considered for analysis. Please find more detailed information on sensor characteristics in section 4.1.1.

5.1.2 Multispectral Data

The multispectral satellite observations are based on data from ESA's Sentinel-2 mission (Berger et al., 2012). The satellite constellation is comprising polar-orbiting satellites: two often them are fully operational, i.e. since June 2015 (Sentinel-2A) and March 2017 (Sentinel-2B). The combined mapping of the two satellites increases the temporal revisit time since the satellites do not follow the same orbit. In the present study, time-series observations spanning the period from June 2015 to October 2024 were analyzed for the assessment of forest structure changes. Please find more detailed information on sensor characteristics in section 4.1.2.

5.2 Methodological Framework

The analysis of change in forest structure contextualized to experimental silvicultural treatments is based on a methodological framework comprising several data processing steps (Figure 5.1). Satellite time-series are pre-processed (section 5.2.1) in order to calculate all available radar indices for Sentinel-1 data (n = 12) and vegetation and water indices for Sentinel-2 data (n = 129, section 5.2.2) by making use of a standardized catalog of remote sensing indices (Montero et al., 2023). The calculation of patch-level metrics (single metric characterizing the area of an individual experimental silvicultural treatment) is conducted for each index as spatial statistic (section 5.2.3). The resulting time-series metrics for Sentinel-1 (n = 98: 12 indices and two polarizations aggregated as seven spatial statistics) and Sentinel-2 (n = 903: 129 vegetation and water indices aggregated as seven spatial statistics) are analyzed using time-series decomposition models, namely Bayesian Estimator of Abrupt change, Seasonal change, and Trend (BEAST) (section 5.2.4). The probabilistic models enable the identification of change points in the two components seasonality and trend. The change points are further attributed by change point date and change point probability, thus supporting the assessment if change points are characterizing the treatment implementations timely and accurately (high probability of change).

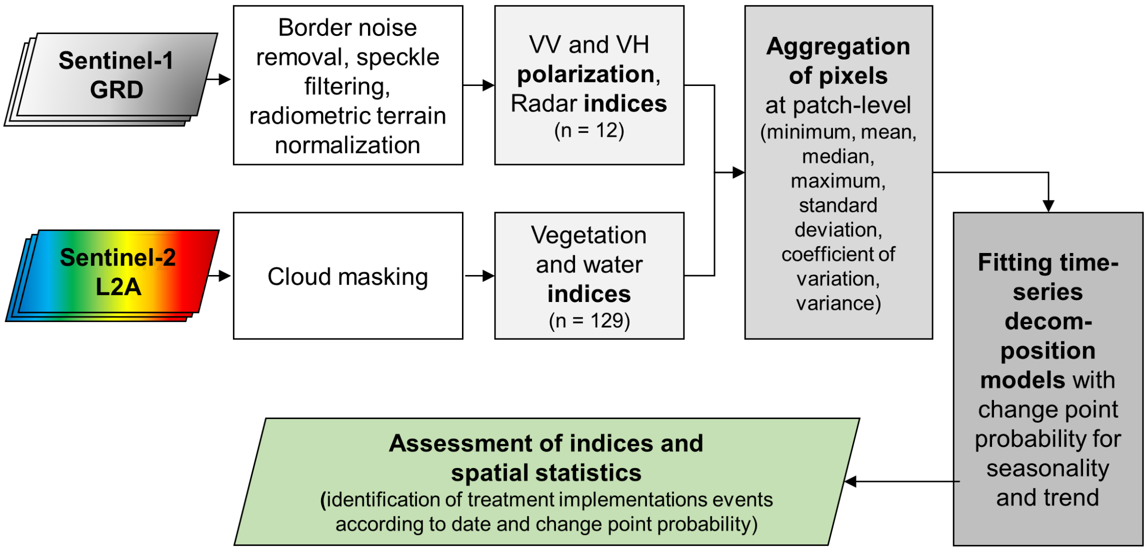

Figure 5.1: Workflow chart of Sentinel-1 and Sentinel-2 processing for time-series decomposition and statistical assessment of indices and spatial statistics identifying BETA-FOR treatment implementation events.

The pre-processing of Sentinel-1 and Sentinel-2 data was implemented in GEE using the Python API (modules: ee (Gorelick et al., 2017), eemont (Montero et al., 2023), geemap (Wu, 2020)). The following analysis steps were conducted in Python (modules: numpy (Oliphant et al., 2006), pandas (McKinney, 2012), geopandas (Rajamani and Iyer, 2023), shapely (Gillies, 2013), and xarray (Hoyer and Hamman, 2016)).

5.2.1 Pre-processing

Pre-processing satellite data is for both radar and multispectral data an important step in order to derive data that truly assesses dynamics (e.g. forest structure change) not influenced by artifacts. Therefore, the removal of border noise, filtering speckle, and normalizing the data for radiometric terrain effects is necessary for Sentinel-1 radar data. For Sentinel-2 data, the masking of clouds and other atmospheric artifacts (e.g. cloud shadows, haze) is an essential task to characterize earth surface properties.

5.2.1.1 Sentinel-1

The Sentinel-1 data was pre-processed following the analysis-ready workflow by Mullissa et al. (2021) comprising border noise removal, speckle filtering, and radiometrics terrain normalization. After the different pre-processing steps, the data was filtered to the VV (vertical transmit and vertical receive) and VH (vertical transmit and horizontal receive) polarization bands. Both bands hold a spatial resolution of 10 m. The data pre-processing in GEE ends with the export of analysis-ready Sentinel-1 time-series data which will be further processed in Python 3.12.4 (van Rossum, 1995).

5.2.1.2 Sentinel-2

The Sentinel-2 surface reflectance time-series was processed in GEE in order to remove atmospheric artifacts. The integration of the Sentinel-2 cloud probability collection enables an accurate detection of clouds, cloud shadows, and haze. For all scenes of the time-series, atmospheric artifacts were masked. The data was further filtered by bands in order to only consider the bands with a spatial resolution of 10 m and 20 m (please see section 4.1.2 for further details). Since single masked pixels of a patch can lead to bias of the spatial statistics that are calculated in following data processing steps in order to derive patch-level metrics of forest structure for various spectral indices, only observations were considered if all pixels within the individual patch are unmasked, i.e. free of masked artifacts. The data pre-processing in GEE ends with the export of analysis-ready Sentinel-2 time-series data which will be further processed in Python 3.12.4 (van Rossum, 1995).

5.2.2 Calculation of Indices based on a standardized Catalog

In remote sensing data analysis, the assessment of indices is highly informative since it allows the characterization of specific properties, e.g. photosynthetic activity of vegetation (Huete et al., 2002). The combination of different spectral bands for the calculation of spectral indices enables the identification of spectral wavelengths (spectral bands) that show a high sensitivity towards a certain phenomenon. For the analysis of vegetation conditions, a great variety of spectral indices has been developed with a focus on spectral indices derived from optical remote sensing sensors, e.g. multispectral and hyperspectral sensors (Zeng et al., 2022). Typically the term spectral index is used to describe indices that were derived from optical remote sensing data (Huete et al., 2002; Huete, 2012). Since the calculation of band-wise indices is not only limited to optical data, but also gains in importance for the calculation of indices e.g. from satellite radar data, in the following, the term indices is used to consider both spectral indices, as well as radar indices (Montero et al., 2023).

The recent publication by Montero et al. (2023) presents a comprehensive and standardized catalog of remote sensing indices for different remote sensing sensors. It holds a collection on indices for different application domains (e.g. sensors or ecosystem foci). The collection not only considers highly popular indices, such as the NDVI (Rouse et al., 1974), which was one on the first vegetation indices developed based on Landsat imagery in the 1970s, but also indices which are not yet established (Zeng et al., 2022; Montero et al., 2023).

The standardized catalog holds a great potential for an explorative analysis in order to test the performance of different indices. All available radar indices for Sentinel-1 time-series (n = 12), as well as all available vegetation and water indices for Sentinel-2 time-series (n = 129), were calculated as time-series data to assess to which extent the different indices are capable of identifying changes in forest structure, i.e. the treatment implementation event. Therefore, the calculation of indices was conducted for each time-step of the time-series data, thus generating time-series of different indices which characterize different characteristics of forest structure.

Since Sentinel-2 holds a great variety of spectral bands at high spatial resolution (10 m and 20 m, section 4.1.2), a high number of indices can be calculated being sensitive to very different characteristics of forest structure change. Previous studies on Sentinel-2 derived indices have demonstrated the informative content of the red edge bands being particularly sensitive towards vegetation vitality (chlorophyll content, Bhattarai et al. (2020); Delegido et al. (2011); Sun et al. (2020)). Based on Sentinel-1 data, the integration of VV (vertical transmit and vertical receive) and VH (vertical transmit and horizontal receive) polarization bands is a common practice for forest structure modeling (Kacic et al., 2021, 2023), drought susceptibility assessment in forests (Kaiser et al., 2022), and assessing forest structure-biodiversity relationships (Bae et al., 2019; Heidrich et al., 2020). Therefore, for Sentinel-1, not only 12 radar indices are considered, but also the two polarization bands.

The following tables present the characteristics of indices (short names, long names, formula) which are mentioned in the text, tables, and figures. Therefore, the tables only show a selection of indices considered for analysis. Sentinel-1 derived polarization bands and indices are listed in Table 5.1. Information on Sentinel-2 based vegetation indices is summarized in Table 5.2, 5.3, 5.4. Water indices derived from Sentinel-2 data are presented in Table 5.5. A table on all calculated indices can be found in the supplementary material of Kacic et al. (2024).

Table 5.1: Sentinel-1 radar indices and polarizations considered for time-series analysis according to Montero et al. (2023). The list shows the two polarization bands and all indices that were calculated. Band abbreviations: VV = Vertical transmit Vertical receive, VH = Vertical transmit Horizontal receive.

Short name	Long name	Formula
DPDD	Dual-Pol Diagonal Distance	(VV + VH)/2.0 ** 0.5
DpRVIVV	Dual-Polarized Radar Vegetation Index VV	(4.0 * VH)/(VV + VH)
NDPoll	Normalized Difference Polarization Index	(VV - VH)/(VV + VH)
VDDPI	Vertical Dual De-Polarization Index	(VV + VH)/VV
VH	Vertical transmit, Horizontal receive	-
VHVVD	VH-VV Difference	VH - VV
VHVVP	VH-VV Product	VH * VV
VHVVR	VH-VV Ratio	VH / VV
VV	Vertical transmit, vertical receive	-
VVVHD	VV-VH Difference	VV - VH
VVVHR	VV-VH Ratio	VV / VH
VVVHS	VV-VH Sum	VV + VH

Table 5.2: Sentinel-2 vegetation indices (A-M) calculated for time-series analysis according to Montero et al. (2023). The list only shows indices that were mentioned in the text, tables and figures. The full list of calculated indices for analysis can be found in the supplementary material of Kacic et al. (2024). Band abbreviations: B=blue, g=green, r=red, RE1=red edge 1, RE2=red edge 2, RE3=red edge 3, N=near-infrared, N2=near-infrared 2, S1=short-wave infrared 1, S2=short-wave infrared 2. Information on further index parameters (e.g. constants) can be found in the Github repository of Montero et al. (2023): https://github.com/awesome-spectral-indices/awesome-spectral-indices (last access: 30.01.2025).

Short name	Long name	Formula
AFRI1600	Aerosol Free Vegetation Index (1600 nm)	(N - 0.66 * S1) / (N + 0.66 * S1)
AVI	Advanced Vegetation Index	(N * (1.0 - R) * (N - R)) ** (1/3)
BCC	Blue Chromatic Coordinate	B / (R + G + B)
CIRE	Chlorophyll Index Red Edge	(N / RE1) - 1
DVI	Difference Vegetation Index	N - R
FCVI	Fluorescence Correction Vegetation Index	N - ((R + G + B)/3.0)
GARI	Green Atmospherically Resistant Vegetation Index	(N - (G - (B - R))) / (N - (G + (B - R)))
GEMI	Global Environment Monitoring Index	((2.0*((N ** 2.0)-(R ** 2.0)) + 1.5*N + 0.5*R)/(N + R + 0.5))* (1.0 - 0.25*((2.0 * ((N ** 2.0) - (R ** 2)) + 1.5 * N + 0.5 * R)/ (N + R + 0.5)))-((R - 0.125)/ (1 - R))
GLI	Green Leaf Index	(2.0 * G - R - B) / (2.0 * G + R + B)
GOSAVI	Green Optimized Soil Adjusted Vegetation Index	(N - G) / (N + G + 0.16)
GRNDVI	Green-Red Normalized Difference Vegetation Index	(N - (G + R))/(N + (G + R))
IKAW	Kawashima Index	(R - B)/(R + B)
IPVI	Infrared Percentage Vegetation Index	N/(N + R)
MCARI705	Modified Chlorophyll Absorption in Reflectance Index (705 and 750 nm)	((RE2 - RE1) - 0.2 * (RE2 - G)) * (RE2 / RE1)
MGRVI	Modified Green Red Vegetation Index	(G ** 2.0 - R ** 2.0) / (G ** 2.0 + R ** 2.0)
MNLI	Modified Non-Linear Vegetation Index	(1 + L)*((N ** 2) - R)/ ((N ** 2) + R + L)
MSI	Moisture Stress Index	S1/N
MSR	Modified Simple Ratio	(N / R - 1) / ((N / R + 1) ** 0.5)
MTVI1	Modified Triangular Vegetation Index 1	1.2 * (1.2 * (N - G) - 2.5 * (R - G))

Table 5.3: Sentinel-2 vegetation indices (N-S) calculated for time-series analysis according to Montero et al. (2023) (continued). The list only shows indices that were mentioned in the text, tables and figures. The full list of calculated indices for analysis can be found in the supplementary material of Kacic et al. (2024). Band abbreviations: B=blue, g=green, r=red, RE1=red edge 1, RE2=red edge 2, RE3=red edge 3, N=near-infrared, N2=near-infrared 2, S1=short-wave infrared 1, S2=short-wave infrared 2. Information on further index parameters (e.g. constants) can be found in the Github repository of Montero et al. (2023): https://github.com/awesome-spectral-indices/awesome-spectral-indices (last access: 30.01.2025).

Short name	Long name	Formula
NDII	Normalized Difference Infrared Index	(N - S1)/(N + S1)
NDMI	Normalized Difference Moisture Index	(N - S1)/(N + S1)
NDPI	Normalized Difference Phenology Index	(N - (alpha * R + (1.0 - alpha) * S1))/ (N + (alpha * R + (1.0 - alpha) * S1))
NDREI	Normalized Difference Red Edge Index	(N - RE1) / (N + RE1)
NDVI	Normalized Difference Vegetation Index	(N - R)/(N + R)
NDYI	Normalized Difference Yellowness Index	(G - B) / (G + B)
NIRv	Near-Infrared Reflectance of Vegetation	((N - R) / (N + R)) * N
NMDI	Normalized Multi-band Drought Index	(N - (S1 - S2))/ (N + (S1 - S2))
RCC	Red Chromatic Coordinate	R / (R + G + B)
REDSI	Red-Edge Disease Stress Index	((705.0 - 665.0) * (RE3 - R) - (783.0 - 665.0) * (RE1 - R)) / (2.0 * R)
RGBVI	Red Green Blue Vegetation Index	(G ** 2.0 - B * R)/ (G ** 2.0 + B * R)
SARVI	Soil Adjusted and Atmospherically Resistant Vegetation Index	(1 + L)*(N - (R - (R - B))) / (N + (R - (R - B)) + L)
SAVI2	Soil-Adjusted Vegetation Index 2	N / (R + (slb / sla))
SR	Simple Ratio	N/R
SR2	Simple Ratio (800 and 550 nm)	N/G
SR3	Simple Ratio (860, 550 and 708 nm)	N2/(G * RE1)

Table 5.4: Sentinel-2 vegetation indices (T-W) calculated for time-series analysis according to Montero et al. (2023) (continued). The list only shows indices that were mentioned in the text, tables and figures. The full list of calculated indices for analysis can be found in the supplementary material of Kacic et al. (2024). Band abbreviations: B=blue, g=green, r=red, RE1=red edge 1, RE2=red edge 2, RE3=red edge 3, N=near-infrared, N2=near-infrared 2, S1=short-wave infrared 1, S2=short-wave infrared 2. Information on further index parameters (e.g. constants) can be found in the Github repository of Montero et al. (2023): https://github.com/awesome-spectral-indices/awesome-spectral-indices (last access: 30.01.2025).

Short name	Long name	Formula
TCARIOSAVI705	TCARI/OSAVI Ratio (705 and 750 nm)	(3 * ((RE2 - RE1) - 0.2 * (RE2 - G) * (RE2 / RE1))) / (1.16 * (RE2 - RE1) / (RE2 + RE1 + 0.16))
TriVI	Triangular Vegetation Index	0.5 * (120 * (N - G) - 200 * (R - G))
TTVI	Transformed Triangular Vegetation Index	0.5 * ((865.0 - 740.0) * (RE3 - RE2) - (N2 - RE2) * (783.0 - 740))
VIG	Vegetation Index Green	(G - R) / (G + R)
WDRVI	Wide Dynamic Range Vegetation Index	(alpha * N - R) / (alpha * N + R)
WDVI	Weighted Difference Vegetation Index	N - sla * R

Table 5.5: Sentinel-2 water indices calculated for time-series analysis according to Montero et al. (2023). The list only shows indices that were mentioned in the text, tables and figures. The full list of calculated indices for analysis can be found in the supplementary material of Kacic et al. (2024). Band abbreviations: B=blue, G=green,Rr=red, N=near-infrared, S1=short-wave infrared 1, S2=short-wave infrared 2. Information on further index parameters (e.g. constants) can be found in the Github repository of Montero et al. (2023): https://github.com/awesome-spectral-indices/awesome-spectral-indices (last access: 30.01.2025).

Short name	Long name	Formula
AWEIsh	Automated Water Extraction Index with Shadows Elimination	B + 2.5 * G - 1.5 * (N + S1) - 0.25 * S2
LSWI	Land Surface Water Index	(N - S1)/(N + S1)
MBWI	Multi-Band Water Index	(omega * G) - R - N - S1 - S2
MLSWI26	Modified Land Surface Water Index (MODIS Bands 2 and 6)	(1.0 - N - S1)/(1.0 - N + S1)
MLSWI27	Modified Land Surface Water Index (MODIS Bands 2 and 7)	(1.0 - N - S2)/(1.0 - N + S2)
MNDWI	Modified Normalized Difference Water Index	(G - S1) / (G + S1)
NWI	New Water Index	(B - (N + S1 + S2))/ (B + (N + S1 + S2))
SWM	Sentinel Water Mask	(B + G)/(N + S1)
WRI	Water Ratio Index	(G + R)/(N + S1)

5.2.3 Calculation of spatial Statistics for Patch-Level Characterization

Since the implementation of experimental silvicultural treatments affects the full patch-area (50 m x 50 m, section 3.3), the time-series of data of radar, vegetation and water indices needs to be aggregated to patch-level metrics. Through an aggregation of the pixels intersecting with the individual patches, single metrics are derived per index. For each index the following spatial statistics were calculated (n = 7):

- extreme value statistics: minimum, maximum
- average value statistics: mean, median
- heterogeneity value statistics: standard deviation (std), variance (var), coefficient of variation (cv)

By considering different spatial statistics, complementary forest structure conditions are assessed at patch-level (extreme, average, and heterogeneity). The derived metrics (combination of index and spatial statistic) per patch are calculated as time-series statistics, i.e. for each time-step an index was aggregated spatially. Therefore, 98 metrics were calculated for Sentinel-1 and 903 metrics for Sentinel-2, allowing for a detailed cross-sensor comparison for the accurate identification of changes in forest structure due to experimental silvicultural treatments.

5.2.4 Time-Series Analysis to identify Implementation Events of experimental silvicultural Treatments

In the following, the time-series analysis to identify the implementation events of experimental silvicultural treatments is explained. Based on BEAST models, the time-series metrics of radar, vegetation, and water indices are evaluated in terms of change point properties. Change points in the period of treatment implementations (November and December 2018) with a high probability (greater than 90 %) are considered as detected changes in forest structure in the context of treatment implementation. For the analysis of treatment implementations, 60 patches of the BETA-FOR focus region (University Forest, Figure 3.5) are considered since they were all implemented in the aforementioned period.

The following sections provide insights on the one hand on model specifications of the BEAST algorithm to decompose the original time-series into trend and seasonality components (section 5.2.4.1). On the other hand, criteria are defined based on which change points in the time-series are considered to be the treatment implementation event (section 5.2.4.2).

5.2.4.1 Bayesian Time-Series Decomposition Modeling

The analysis of change points based on satellite time-series comprises different algorithms holding specific model configurations and characteristics to identify changes. In general, change points are sub-divided by the change dynamic, i.e. abrupt changes or gradual changes. In the following, there is a focus on the detection of abrupt changes, since this is the characteristic change dynamic in the context of the implementation of experimental silvicultural treatments. The changes in forest structure are considered to be abrupt because of the complete removal of single trees (distributed treatments) or tree groups (aggregated treatments). Therefore, there is an immediate change in light structures (Figure 3.6).

One of the most popular algorithms for satellite time-series change detection was published by Verbesselt et al. (2010). The Breaks for Additive Season and Trend (BFAST) algorithm has gained high popularity for different applications (e.g. satellite sensors, ecosystem focus) of change detection due to its robust approach decomposing the original time-series into the following three components: trend, seasonal, and residuals. Further publications have presented temporal segmentation approaches (e.g. LandTrendr by Kennedy et al. (2018)) or break detection based on spectral-trend information (Ghaderpour and Vujadinovic, 2020). Previously mentioned algorithms hold different limitations that were addressed by the BEAST algorithm which was published by Zhao et al. (2019). The BEAST algorithm is not based on a single model which can be prone to overfitting, but comprises a Bayesian modeling approach making use of Bayesian model averaging. Therefore, multiple models are generated iteratively in order to generate a final time-series model which is based on ensemble characteristics: limited restrictions of the fitted model to assess temporal dynamics are one benefit, i.e. no criterion-based decision on change point thresholds. The multi-model approach of BEAST facilitates the characterization of change points holding different likelihoods of changes. Therefore, the change points which are assessed for both seasonal and trend components are attributed with change point probabilities. BEAST is a generic approach capable of analyzing both regular and irregular time-series. In addition, no apriori specification of a training (period of temporal dynamics without abrupt and gradual changes) and monitoring period (period of temporal dynamics with expected abrupt and gradual changes) is needed which makes the BEAST model highly flexible.

Multiple studies (Zhao et al., 2019; Cai et al., 2020; Li et al., 2022) have demonstrated the increased performance of BEAST in comparison to other time-series change detection approaches. Therefore, the BEAST model was chosen for the assessment of Sentinel-1 and Sentinel-2 derived metrics in order to identify the treatment implementation event as change point in time-series.

5.2.4.2 Change Point Analyses

The assessment of change points in time-series of Sentinel-1 and Sentinel-2 metrics considers both change points in the trend and seasonal component. For each metric derived from Sentinel-1 and Sentinel-2 time-series, a BEAST model was trained and evaluated. Therefore, for each calculated metric, time-series characteristics are assessed. The following time-series derived characteristics need to be fulfilled so that identified change points are considered to characterize the treatment implementation event:

- Change point date: within the period from beginning of November to the end of December 2018 (treatment implementation period).
- High change point probability: the change point needs to hold a change point probability of greater than 90 %. The change in forest structure due to the treatment implementation event is a significant change in forest structure that needs to be assessed robustly, i.e. with a high probability.
- Maximum change point probability: the identified change point needs to hold the maximum change point probability among all assessed change points of a specific time-series. Therefore, the change in forest structure in the context of the treatment implementation event is the most pronounced change in forest structure, thus exceeding the changes associated with other natural disturbances. Based on expert knowledge, no significant natural disturbance events are known for the study area in the period of satellite data.

In the following, the Sentinel-1 and Sentinel-2 time-series characteristics are assessed for the metrics holding change points that fulfill the aforementioned criteria. In addition, the identified change points characterizing the treatment implementation events are assessed by change point type (change detection in the trend and/or seasonal component) and per individual treatment type. Therefore, sensor-specific assessments about the detection of forest structural changes due to tree removal (distributed and aggregated treatments) and presence/absence of deadwood structures (removal or generation of specific structures) are conducted.

5.3 Results

The results section is sub-divided into three sections: in the first section, a general assessment of indices and spatial statistics is provided in order to evaluate the potential for the detection of change points characterizing the treatment implementation event (section 5.3.1). In the following, exemplary time-series of Sentinel-1 and Sentinel-2 metrics are shown that demonstrate the accurate detection of treatment implementation events for selected treatments (section 5.3.2). In the final results section, specific spectral indices and spatial statistics are presented that are particularly suited for the detection of forest structural changes in the context of experimental silvicultural treatments. In addition, the potential of the derived time-series components (trend and seasonality) is evaluated. Furthermore, summary statistics on the identified accurate change points per individual treatment for both Sentinel-1 and Sentinel-2 are given (section 5.3.3).

5.3.1 Assessment of Indices and spatial Statistics

The assessment of spectral indices which identify the treatment implementation event are presented in Table 5.6. Based on the listed indices, the treatment implementation could be assessed accurately (following the change point criteria in section 5.2.4.2) and consistently, i.e. for all individual treatments of a specific treatment type (Figure 3.6). Each treatment type (e.g. AW = aggregated removal of trees with remaining stumps) was implemented three times. The distributed treatment of selective thinning leaving the remaining stumps was established more than three times as specific control for random single tree removal.

Table 5.6 highlights that only a selection of Sentinel-1 and Sentinel-2 indices have the potential to identify the changes in forest structure. The treatment specific statistics reveal that only aggregated treatments are assessed accurately and consistently. In addition, not all individual aggregated treatment types could be identified by either Sentinel-1 or Sentinel-2. For example, aggregated snags (AS) could only be assessed by Sentinel-1 indices, in comparison to aggregated total tree removal treatments (AR) which were only identified by Sentinel-2 indices. Furthermore, some indices present accurate and consistent results for multiple treatment types: Sentinel-1 (VH; VV-VH Sum (VVVHS)) and Sentinel-2 (e.g. Normalized Difference Red Edge Index (NDREI); NMDI).

In Table 5.7, Sentinel-1 and Sentinel-2 metrics are listed that identify consistently accurate change points (treatment implementation events). All listed indices were aggregated at patch-level as heterogeneity statistics, i.e. cv, std, and var. Only in two cases, indices with two spatial statistics each identified the treatment implementation event for each individual treatment accurately: Land Surface Water Index (LSWI) std, and LSWI var, as well as Moisture Stress Index (MSI) cv, and MSI std.

For both sensors, namely Sentinel-1 and Sentinel-2, there are indices that did not identify a single accurate change point for the treatment implementation event. From all calculated indices for Sentinel-1 (n = 12, the two polarizations are not considered), two indices (17 %

Table 5.6: Sentinel-1 and Sentinel-2 spectral indices that identify consistently (for all individual patches of a treatment) accurate change points according to previously defined criteria (section 5.2.4.2).

Treatment	Sentinel-1	Sentinel-2
AW (Aggregated stumps)	VH	CIRE, DVI, GOSAVI, LSWI, MSI, MTVI1, NDII, NDMI, NDPI, NDREI, NIRv, NMDI, WDVI
AL (Aggregated logs)	-	MBWI, NDPI, NDREI, SARVI
AS (Aggregated snags)	DPDD, VHVVP, VVVHS	-
AB (Aggregated logs and snags)	VH	AVI, AWEIsh, FCVI, GEMI, MBWI, MLSWI26, MSI, NMDI, TriVI
AR (Aggregated total tree removal)	-	MSI, NDREI, NMDI
AK (Aggregated crowns)	VVVHS	AWEIsh, MBWI, MNDWI, MSI, NDMI, NDPI, SR3
AH (Aggregated habitat trees)	-	NMDI

of all radar indices) are insensitive towards the change in forest structure: Vertical Dual De-Polarization Index (VDDPI) and VH-VV Ratio (VHVVR). About 19 % (n = 25) of all calculated Sentinel-2 vegetation and water indices are not capable to assess a treatment implementation event accurately. The list comprises also popular spectral indices, namely the NDVI or Simple Ratio (SR).

Table 5.7: Sentinel-1 and Sentinel-2 metrics that identify consistently (for all individual patches of a treatment) accurate change points according to previously defined criteria (section 5.2.4.2).

Treatment	Sentinel-1	Sentinel-2
AW (Aggregated stumps)	VH cv	CIRE std, LSWI std, LSWI var, MSI cv, MSI std, NDII std, NDWI std, NDMI var, NDREI std, NDPI var, NMDI cv,
AL (Aggregated logs)	-	MBWI cv, NDPI std, NDREI std
AS (Aggregated snags)	DPDD cv, VHVVP cv, VVVHS cv	-
AB (Aggregated logs and snags)	-	MBWI cv, MLSWI26 var
AR (Aggregated total tree removal)	-	NDREI var, NMDI cv
AK (Aggregated crowns)	VVVHS cv	NDPI var, SR3 cv
AH (Aggregated habitat trees)	-	NMDI var

Table 5.8: Sentinel-1 and Sentinel-2 indices not assessing any accurate change point identifying BETA-FOR treatment implementations according to previously defined criteria (section 5.2.4.2).

Sensor	Sentinel-1	Sentinel-2
n indices (% of all calculated indices per sensor)	2 (17 %)	25 (19 %)
Indices	VDDPI, VHVVR	BCC, GARI, GLI, GRNDVI, IKAW, IPVI, MCARI705, MGRVI, MNLI, MSR, NDVI, NDYI, NWI, RCC, REDSI, RGBVI, SAVI2, SR, SR2, SWM, RCARIOSAVI705, TTVI, VIG, WDRVI, WRI

5.3.2 Exemplary Time-Series

The availability of multi-annual time-series from both Sentinel-1 and Sentinel-2 enables a sensor comparison for the identification of changes in forest structure. Based on patch-level time-series, the pre- and post-disturbance conditions of forest structure, as well as the disturbance event (treatment implementation) can be assessed. A great benefit of the experimental treatment design (Figure 3.5,3.6) is the standardized establishment of different treatments at the same time (November and December 2018). For a comparative visualization of Sentinel-1 and Sentinel-2 time-series for three exemplary treatment types (control, aggregated, and distributed treatment) the temporal dynamics are shown. The time-series are sub-divided into the original time-series which were decomposed into trend and seasonality components. For both components detected change points in the context of the treatment implementation event are depicted.

The Sentinel-1 time-series (Figure 5.2) is based on VH cv patch-level metrics calculated for a control treatment (CC), an aggregated treatment (AW = aggregated removal of trees with stumps remaining), and a distributed treatment (DR = distributed total tree removal). The metric Sentinel-1 VH cv was chosen since it presented a general potential for the detection of the treatment implementation event (section 5.3.1). All detected change points with a probability of greater than 90 % are shown. The assessment of change points shows that only for the aggregated treatment an accurate detection of the implementation event was conducted in the trend component. For the control and the distributed treatment, no change points were found. In the case of the control treatment, the absence of change points confirms the performance of the BEAST algorithm since no changes in forest structure were expected. For the distributed treatment, no changes in the trend or seasonality component can be detected.

The time-series for Sentinel-2 (Figure 5.3) were calculated for the identical treatment patches as conducted for Sentinel-1. The dynamics in forest structure change are characterized by the Sentinel-2 derived NMDI cv metric which was found to be sensitive for the detection of different treatment implementations (section 5.3.1). Similar to the Sentinel-1 time-series for the aggregated treatment, a change point was detected in the period of the treatment implementation event. The change points were detected in both the trend and seasonal component. After the change in forest structure, an increase in the trend component, as well as an increased amplitude of the seasonality component are apparent. The control and distributed treatment do not hold any change point. In addition, no significant change dynamics are found in the context of the treatment implementation event.

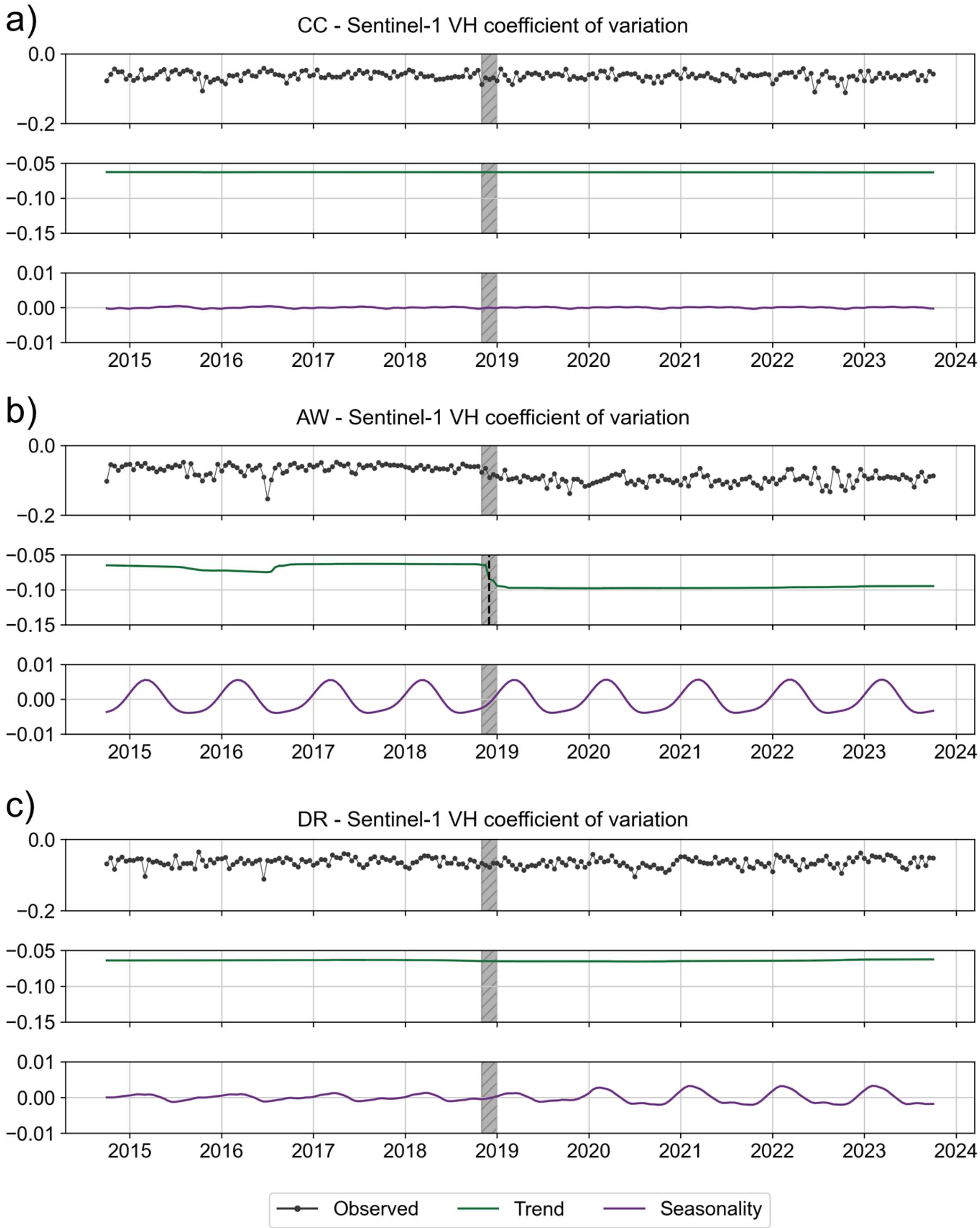

Figure 5.2: Exemplary Sentinel-1 VH coefficient of variation (cv) time-series for different BETA-FOR treatment patches. The grey area represents the treatment implementation period. All change points with a probability of greater than 90 % are shown. All change points with a probability of greater than 90 % are shown. The treatments are identical to the treatments shown for Sentinel-1 time-series (Figure 5.3).

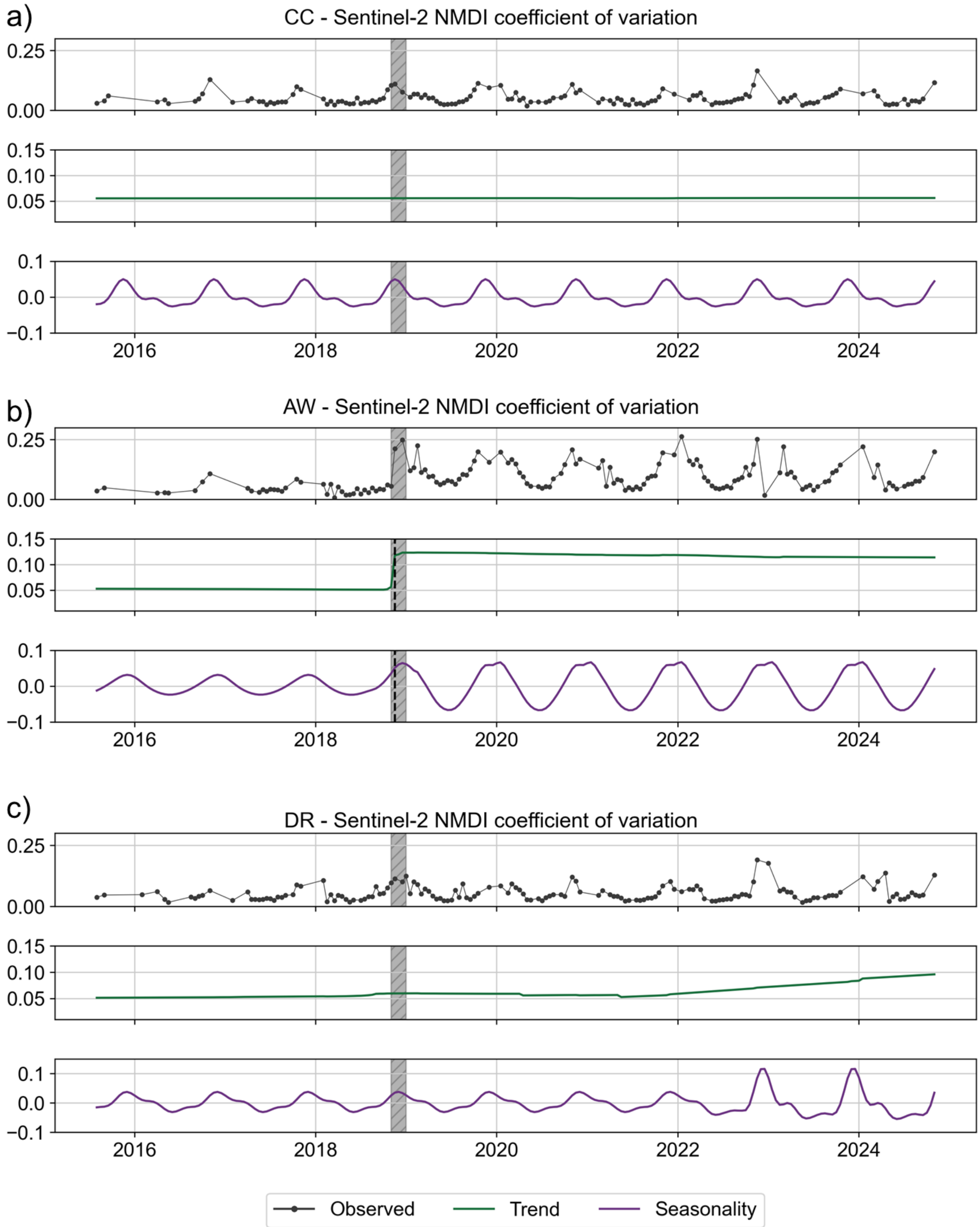

Figure 5.3: Exemplary Sentinel-2 NMDI coefficient of variation (cv) time-series for different BETA-FOR treatment patches. The grey area represents the treatment implementation period. All change points with a probability of greater than 90 % are shown. The treatments are identical to the treatments shown for Sentinel-1 time-series (Figure 5.2).

5.3.3 Identification of Implementation Events of experimental silvicultural Treatments

The comparative statistics of Sentinel-1 and Sentinel-2 indices assessing accurate change points of the treatment implementation events present a varying performance of the indices (Figure 5.4). The statistics consider all calculated spatial statistics that were calculated for all indices. In addition, the statistics account for all change point types, i.e. one trend and one seasonality change point. Furthermore, the accurate assessment of abrupt changes points characterizing the treatment implementation event was considered for all experimental silvilcultural treatments. Therefore, the percentage statistics of an index do not only account for the different spatial statistics, but also the change point type and the number of individual experimental silvicultural treatments that were implemented.

A general finding of the comparative statistics of Sentinel-1 polarizations/indices and Sentinel-2 indices identifying the treatment implementation events accurately is the lower maximum percentage value of the best Sentinel-1 polarization (VH, about 3 %) compared to the Sentinel-2 indices. The Sentinel-2 index assessing most treatment implementation events is the NMDI with about 6 %.

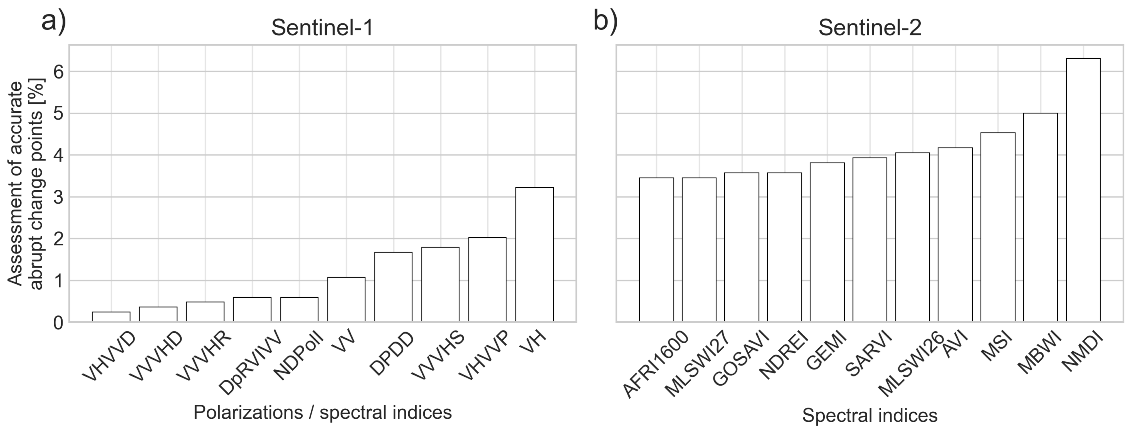

Figure 5.4: Comparative statistics of Sentinel-1 and Sentinel-2 indices identifying accurate change points assessing the treatment implementation event. Please find the long names of indices in tables 5.1, 5.2, 5.3, 5.4, 5.5.

Similar to the statistics of Sentinel-1 and Sentinel-2 indices, the comparative statistics of spatial statistics account for all calculated polarizations/indices, change point types, and experimental treatment implementation events. The spatial statistic assessing most treatment implementation events based on Sentinel-1 is the cv (Figure 5.5). The cv outperforms all other spatial statistics for Sentinel-1 since it identifies about 4 % of all theoretically change points of treatment implementation events. The second best spatial statistic (std) also reaches about 1 %. For spatial statistics calculated for Sentinel-2 indices, the heterogeneity statistics (cv, std, var) present rather similar performances for the identification of forest structure changes in the context of treatment implementation events. The best spatial statistic, namely cv, amounts to about 2.5 %.

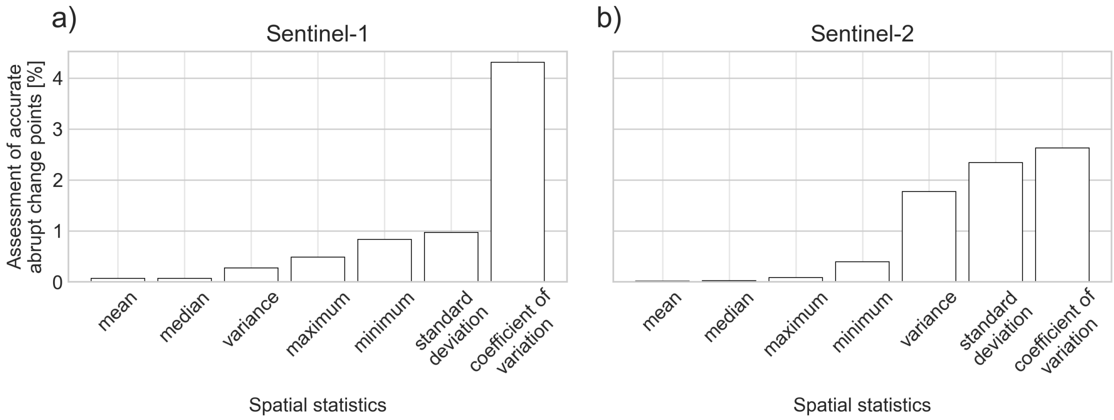

Figure 5.5: Comparative statistics of Sentinel-1 and Sentinel-2 spatial statistics assessing accurate change points for the treatment implementation events.

The results of the spatial statistics are that heterogeneity statistics, in particular the cv, hold a greater potential for the identification of treatment implementation events than average or extreme statistics. This result explains the relatively low percentage values of indices (Figure 5.4).

The statistics of trend and seasonality change points characterizing the treatment implementation event, assessed for Sentinel-1 and Sentinel-2 time-series, present a further influencing factor on the statistics of indices and spatial statistics (Figure 5.6). For both Sentinel-1 and Sentinel-2, most change points were identified based on the trend component. More than 95 % of all Sentinel-1 derived change points of treatment implementation events are trend change points. In addition, the few change points (lower than 5 %) which were identified as seasonality change points, were also assessed as trend change points. A similar proportion of seasonality change points which were also identified in the trend component (about two third) are assessed for Sentinel-2 change points. For Sentinel-2 change points of treatment implementation events more than 80 % of all change points are trend change points. Therefore, a greater proportion of seasonality change points (about 15 %) was assessed for Sentinel-2 compared to Sentinel-1.

Similar to previous statistics on indices and change points, the comparative statistics of trend and seasonal change points for Sentinel-1 and Sentinel-2 highlight that most change points of treatment implementation events are detected in the trend component. This finding

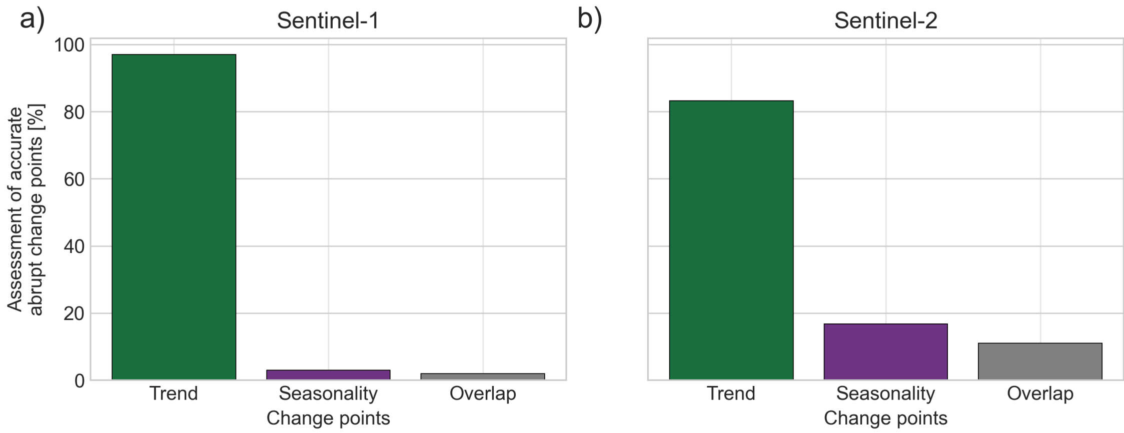

Figure 5.6: Comparative statistics of Sentinel-1 and Sentinel-2 accurately assessed change points of treatment implementation events.

constitutes another influential factor on the relatively low percentage values of accurately assessed change points in Figure 5.4, 5.5.

The comparative statistics of Sentinel-1 and Sentinel-2 metrics assessing accurate change points grouped by treatment shows that there is a higher potential to identify aggregated treatments (Figure 5.7). The statistics are based on all calculated metrics of Sentinel-1 (Table 5.1) and Sentinel-2 (please find a selection of indices in Table 5.2,5.3,5.4,5.5; please find a full list of calculated indices in the supplementary material of Kacic et al. (2024)). Metrics based on Sentinel-1 and Sentinel-2 indices only detected few treatment implementation events of distributed treatments accurately. Furthermore, there is a absence of false positive change point detections for control treatments.

The summary statistics of identified change points (treatment implementation events) per treatment type considers different characteristics: the statistics take into account all theoretical change points for each individual treatment patch, the two change point types, and all calculated metrics. There are no clear advantages to identify a specific treatment type (i.e. benefits to detect one specific aggregated treatment) which is consistent for both Sentinel-1 and Sentinel-2 metrics. For Sentinel-1, accurate assessments of the treatment implementation events were conducted for seven treatment types (DR, AK, AR, AB, AS, AL, AW; please find the long names in Figure 5.7). The number of identified treatment types based on Sentinel-2 metrics amounts to eleven treatment types (DK, DB, DS, DW, AH, AK, AR, AB, AS, AL, AW; please find the long names in Figure 5.7). Therefore, the following treatment types were not assessed as change points characterizing the treatment implementation event based on Sentinel-1 metrics, but based on Sentinel-2 metrics: DK, DB, DS, DW, AH. All those treatment types were only assessed by few metrics since the percentage frequency values are lower than 1 % (Figure 5.7).

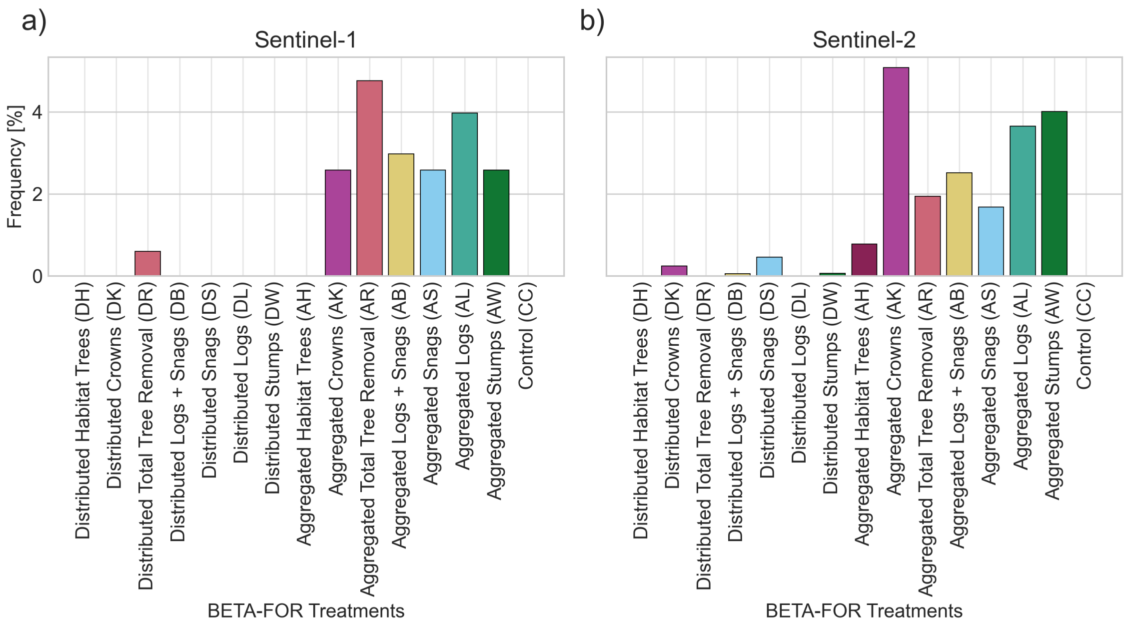

Figure 5.7: Comparative statistics of Sentinel-1 and Sentinel-2 metrics assessing accurate change points of the treatment implementation events grouped by treatment.

5.4 Discussion

The developed framework to assess enhanced forest structural complexity through experimental silvicultural treatments makes use of dense satellite time-series, a standardized catalog of indices, and the probabilistic BEAST algorithm. In the first chapter of the discussion, the potential to characterize experimental silvicultural treatments based on satellite time-series is elaborated (section 5.4.1). In the following, the application of the time-series change detection framework for forest structure monitoring is discussed (section 5.4.2).

5.4.1 Characterizing experimental silvicultural Treatments based on Satellite Time-Series

Assessing enhanced forest structural complexity through the implementation of novel experimental silvicultural treatments is a critical task of forest monitoring activities (Skidmore et al., 2021). The recent structural conditions of German forests are generally homogeneous in terms of age structure, canopy height, canopy cover, and structural complexity (Dieler et al., 2017; Mueller et al., 2022a). The need to alter the forest structure towards enhanced structural complexity can provide several benefits, such as increased biodiversity, improved ecosystem functioning, and enhanced resilience towards disturbances (Messier et al., 2021). Implementing and testing the environmental consequences of novel silvicultural management practices has gained in relevance in particular with the increasing frequency and intensity of forest disturbances (Müller et al., 2018). Within the context of the BETA-FOR project (Mueller et al., 2022b), standardized silvicultural treatments have been implemented in German broad-leaved forests. The combination of aggregated (gap felling) and distributed treatments (selective tree removal), as well as the establishment of different deadwood structures has the potential to ensure the logging of trees while enhancing the structural complexity. Monitoring the implementation of those novel experimental silvicultural treatments is indispensable in order to characterize the changes in forest structure and future conditions (Camarretta et al., 2020; Nabuurs et al., 2022).

Based on satellite time-series, various metrics of forest structure conditions were tested to which extent the implementation event of experimental silvicultural treatments was identified. From a standardized catalog (Montero et al., 2023), all available radar indices were calculated for Sentinel-1 time-series and all available vegetation and water indices for Sentinel-2 time-series. To identify change points in the satellite time-series different criteria were defined (section 5.2.4.2) serving as consistent time-series change detection characteristics of the implementation event of experimental silvicultural treatments. A general finding was the clear advantage to identify the treatment implementation event for aggregated treatments. Interestingly, aggregated treatments with various deadwood structures were assessed: aggregated treatments with no standing deadwood present, as well as aggregated treatments with downed deadwood or an absence of deadwood. This finding suggests that small-scale changes (area of an experimental treatment: 50 m x 50 m) characterized by an aggregated removal of trees can be characterized by both Sentinel-1 and Sentinel-2 time-series. Therefore, there is a potential to further develop recent binary forest disturbance change products, e.g. on forest canopy cover loss (Thonfeld et al., 2022), towards the assessment of non-stand replacing disturbances (remaining deadwood structures).

The analysis of various radar, vegetation, and water indices revealed that there are strong differences among indices to identify the treatment implementation event as change point using the BEAST algorithm. For both Sentinel-1 and Sentinel-2 derived indices, a significant share (Sentinel-1: 17 %, Sentinel-2: 19 %) of calculated indices did not assess any change point in the context of the treatment implementation event. In addition, for both Sentinel-1 and Sentinel-2 indices, there are indices which demonstrate an increased performance for the identification of the treatment implementation event of experimental silvicultural treatments, namely Sentinel-1 VH (polarization) and Sentinel-2 NMDI (Figure 5.4). The potential of Sentinel-1 VH for deforestation monitoring (Reiche et al., 2021), as well as modeling of forest structure (Kacic et al., 2023) has been previously emphasized. The high performance of the NMDI for monitoring forest structure change is a result that was not found by previous studies. The initial publication of the NMDI in the context of forests by Wang et al. (2008) stressed the applicability for monitoring risk to forest fires in arid regions. Following studies made use of the NMDI for the assessment of vegetation cover dynamics (Korhonen et al., 2017; de Oliveira Santos et al., 2021), as well as land surface temperature monitoring (Yang et al., 2017). Nevertheless, there are only few indices that assess the treatment implementation event consistently, i.e. for individual treatments of a treatment type (Table 5.6). This finding suggests, that multi-variate analysis of indices might outperform analysis based on single indices. A similar finding was stressed by Zeng et al. (2022) stating that the integration of multi-sensor derived indices should be best-practice.

The integration of the different spatial statistics on extreme, average, and heterogeneity conditions had a strong impact on the identification of change points contextualized to the implementation event of experimental silvicultural treatments (Figure 5.5). The choice of heterogeneity statistics clearly benefited the accurate detection of treatment implementation events assessed as change points. This finding suggests that the characterization of forest structure heterogeneity based on Sentinel-1 and Sentinel-2 metrics better describes the enhancement of structural complexity through the implementation of experimental silvicultural treatments. In addition, the combination of heterogeneity statistics with the trend component of Sentinel-1 and Sentinel-2 time-series has advantages over the usage of the seasonal component for both Sentinel-1 and Sentinel-2. Therefore, future analysis can focus on the trend analysis of forest structure dynamics using heterogeneity statistics of satellite time-series. Furthermore, the integration of the BEAST algorithm by Zhao et al. (2019) provided a great benefit for the analysis of forest structure dynamics due to the calculation of change point probabilities for both trend and seasonal change points. Since BEAST is a model that can solely be trained by a single metric (univariate), the derivation of change points and change point probabilities has a strong bias towards the selected metric. The novel proposed framework has shown that there are no single best metrics, but multiple metrics (different indices as heterogeneity statistics) should be considered.

Recently a novel time-series method, namely breakpoints-Detection algoRithm using MultivAriate Time series (DRMAT) by Li et al. (2024), was developed which is capable to integrate multi-variate time-series. DRMAT was published in December 2024, thus not yet available at the time of the development of the time-series change detection framework for forest structure monitoring. Future research on multi-variate time-series change detection analysis holds a great potential to better assess the multifaceted characteristics of forest structure. DRMAT outperformed an univariate algorithm (COntinuous monitoring of Land Disturbance (COLD), i.e. no comparison to BEAST was conducted) since multiple bands and/or indices can be integrated which are sensitive to e.g. the different temporal structures of forest structure change (e.g. disturbance event detection, recovery assessment).

5.4.2 Application of the Time-Series Change Detection Framework for Forest Structure Monitoring

The development of the time-series change detection framework for forest structure monitoring was conducted in the context of experimental silvicultural treatments to make use of the standardized design of various forest structures created by silvilcultural management. Thanks to the standardization of treatment patch sizes, land use history, forest composition characteristics, treatment types, as well as treatment implementation event timing, different satellite time-series metrics were consistently evaluated. Since the experimental silvicultural treatments are limited to broad-leaved forests, the identified metrics best assessing the treatment implementation events do not necessarily best characterize forest structure change in other forest types, e.g. mixed forests or conifer plantations.

The continuous availability of Sentinel-1 and Sentinel-2 time-series holds a great potential to apply the developed framework combining satellite time-series, a standardized catalog of indices, as well as the probabilistic BEAST model to identify change points including probability assessment, in different forest types. Therefore, satellite time-series metrics can be identified that are only sensitive to specific forest types, but also metrics that assess forest structural changes across forest types. In addition, time-series characteristics of the different experimental silvicultural treatments outside the regions of the experimental silvicultural treatments (Figure 3.5) can be compared. Temporal signatures of pre- and post-disturbance conditions can be evaluated in order to identify corresponding temporal signatures that link the experimental silvicultural treatment characteristics to forest structure conditions developed naturally or by management.

The developed framework can also be applied to benchmark existing change point detection algorithms based on satellite time-series. On the one hand, forest structural characteristics can be spatially aggregated (e.g. of mapped forest disturbance areas) as conducted in the context of the assessment of experimental silvicultural treatments. On the other hand, the developed framework can also be applied as pixel-based algorithm, e.g. as comparative analysis of threshold-based change detection algorithms of forest canopy cover loss (Thonfeld et al., 2022). The calculation of change point probability statistics for both trend and seasonal component enables a more in-depth understanding of temporal characteristics (e.g. the decomposition into additive trend and seasonality components). In addition, mapped areas of forest canopy cover loss can be attributed with change point probabilities which could be informative statistics for the delineation of abrupt and gradual changes (Zhao et al., 2019). Furthermore, a validation of the change point date, i.e. disturbance occurrence, is possible by comparing the change point dates in combination with change point probabilities derived from the BEAST algorithm. Lastly, the existing metric of univariate change detection methods, e.g. the Disturbance Index (DI) used for forest canopy cover loss mapping by Thonfeld et al. (2022), can be tested based on the BEAST algorithm. Not only the existing metric can be evaluated, but also further metrics suggested by other algorithms, such as Sentinel-1 VH by (Reiche et al., 2021) or multispectral indices based on Landsat data (Senf et al., 2020a, 2021), can be tested.

Overall, the developed framework for forest structural change detection based on satellite time-series provides a flexible opportunity to test various metrics derived from different sensors. In addition, existing change detection algorithms can be evaluated in terms of metric performance, change point date difference, as well as the comparison of contrasting change point probabilities. Furthermore, the post-disturbance forest structural conditions can be characterized by trend and seasonality analysis, e.g. change points identifying further vegetation degradation or recovery. Therefore, the developed framework supports the continuous monitoring of forest structure conditions at high spatio-temporal resolutions. The derived time-series information of forest structure condition can inform silvicultural management in order to guide management efforts towards increased forest resilience.

5.5 Summary

An automated forest structure change detection framework was developed based on radar and multispectral satellite time-series. The approach integrates Sentinel-1 radar indices (n = 12) and two polarization bands, as well as Sentinel-2 derived vegetation and water indices (n = 129) from a standardized catalog (Montero et al., 2023). To characterize the enhancement of forest structural complexity through experimental silvicultural treatments at patch-level, the time-series data of Sentinel-1 and Sentinel-2 was spatially aggregated as different statistics (extreme, average, heterogeneity statistics). The spatial aggregation enables the characterization at patch-level for each individual treatment covering an area of about 50 m x 50 m. The patch-level time-series metrics (combination of an index and spatial statistic) are assessed for each individual treatment to assess change points of the treatment implementation event. Based on probabilistic time-series models (BEAST, Zhao et al. (2019)), the time-series were decomposed into trend and seasonality components for which change points were derived. The probabilistic BEAST model holds the advantage that probabilities for each trend and seasonality change point are calculated, thus supporting the identification of abrupt forest structural changes as high probability change points.

Since the treatment implementation events of experimental silvicultural treatments were conducted in November and December 2018, a temporal assessment for the identified high probability change points (probability greater than 90 %) was carried out.

The statistical evaluations of indices, spatial statistics, and change point types (trend and seasonal change points) revealed that both Sentinel-1 and Sentinel-2 derived indices aggregated as spatial heterogeneity statistics have the potential to assess forest structural changes through aggregated silvicultural treatments (gap felling). The metrics Sentinel-1 VH (spatial aggregation: cv) and Sentinel-2 NMDI (cv) identified most change points of the treatment implementation events. Only in few cases, the implementation event of experimental silvicultural treatments characterized by a distributed removal of trees could be assessed. There are advantages for Sentinel-2 time-series to identify the treatment implementation event of distributed treatments. In addition, the treatment implementation event of aggregated treatments with an absence of standing deadwood, as well as aggregated treatments with different standing deadwood structures, are assessed for both Sentinel-1 and Sentinel-2 time-series. Furthermore, the detection of change points of the treatment implementation event was better based on the trend component for both satellite sensors (Sentinel-1: 97.0 %, Sentinel-2: 83.2 %).

Overall, both Sentinel-1 and Sentinel-2 time-series have the potential to characterize forest structure changes of small-scale aggregated tree removal. The high spatio-temporal resolution of the two satellite sensors facilitates timely and consistent monitoring of forest structure dynamics. The implementation of novel silvicultural management practices, such as the local enhancement of structural complexity through aggregated treatments, supports the diversification of forest habitat characteristics. Therefore, an increase in forest biodiversity and multifunctionality is expected which is why the transformation of homogeneous forest structures towards more complex forest structures is a critical task (Müller et al., 2018; Messier et al., 2021). The developed framework provides a methodological approach based on satellite time-series to monitor forest structure dynamics, as well as characterize forest structure changes due to silvicultural management.

Chapter 6

Comparative Analyses of Spaceborne and In-situ Forest Structure Indicators*

The analysis of forest structure based on in-situ and spaceborne measurements offers complementary perspectives on e.g. canopy height, vegetation cover, and structural complexity. In-situ remote sensing measurements by MLS or TLS assess the structural characteristics from a ground perspective, i.e. from sub-canopy. In comparison, spaceborne remote sensing sensors hold a top-of-canopy perspective, thus providing a different point of view to in-situ remote sensing. Therefore, comparative analysis of spaceborne and in-situ remote sensing indicators of forest structure are of high interest in order to understand to which extent the differently sensed forest structure measurements agree (Camarretta et al., 2020; Jetz et al., 2016). Analyzing forest structural complexity, i.e. the multi-dimensional complexity of vegetation arrangement, is of specific relevance since indicators of forest structural complexity have been proposed as key predictors of forest biodiversity (Bohn and Huth, 2017; Heidrich et al., 2020).

In the following, comparative analysis of spaceborne and in-situ remote sensing indicators of forest structural complexity are carried out in the context of experimental silvicultural treatments (section 3.3). The assessment of forest structural complexity is based on data from different platforms and sensors (section 6.1): in-situ measurements are derived from both MLS and TLS. Spaceborne measurements comprise satellite and spaceborne platforms, as well as three different sensor types. Satellite measurements of forest structural complexity are based on Sentinel-1 radar and Sentinel-2 multispectral data. The present analysis builds up on findings from the developed methodological framework to assess enhanced forest structural complexity (section 5). Therefore, Sentinel-1 and Sentinel-2 metrics were chosen that best characterize the change in forest structure due to experi-

*Parts of this chapter have been published in Kacic et al. (2025).

mental silvicultural treatments. In addition to satellite time-series metrics from Sentinel-1 and Sentinel-2, modeled attributes of forest structure based on GEDI, Sentinel-1, and Sentinel-2 data are integrated. The workflow to derive multi-annual products of forest structure attributes was presented in section 4. In the methods section (section 6.2) the following statistical analysis are explained in order to assess the agreement of in-situ and spaceborne remote sensing indicators of forest structural complexity: bi-variate correlations (section 6.2.1), multi-variate statistics (section 6.2.2), and unsupervised clustering analysis (section 6.2.3). The results section (section 6.3) starts with a visualization of spaceborne time-series to characterize forest structure change dynamics for the experimental silvicultural treatments (section 6.3.1). In the following, the findings from the bi-variate correlation analysis are shown as correlation heatmap (section 6.3.2). Multi-variate statistics of in-situ and spaceborne indicators present the characterization of forest structural differences among experimental silvicultural treatments (section 6.3.3). Based on unsupervised clustering analysis (section 6.3.4), the grouping of experimental silvicultural treatments according to remotely sensed indicators of forest structural complexity is assessed. The clustering analysis is on the one hand conducted only for spaceborne indicators (section 6.3.4.1), and on the other hand combined for in-situ and spaceborne indicators (section 6.3.4.2). Therefore, the potential to which extent the experimental silvicultural treatments can be delineated based on different remote sensing platforms and sensors. In the first section of the discussion section (section 6.4), intra and inter-platform correlations among spaceborne and in-situ indicators are elaborated (section 6.4.1). In the following, the general potential of remotely sensed forest structural complexity analysis is assessed (section 6.4.2), as well as the characterization of standing deadwood structures (section 6.4.3). The discussion ends with the examination of the ecological relevance to characterize forest structural complexity and its relationship to biodiversity (section 6.4.4). Lastly, the findings of the comparative analysis of spaceborne and in-situ remote sensing indicators of forest structural complexity are summarized (section 6.5).

6.1 Data of Forest structural complexity Indicators

The comparative analysis of forest structural complexity is based on data from spaceborne and in-situ remote sensing sensors. Spaceborne data on forest structural complexity comprises satellite radar (Sentinel-1) and satellite multispectral (Sentinel-2) data, as well as modeled spaceborne Lidar samples from GEDI based on Sentinel-1 and Sentinel-2 temporal spectral metrics. In-situ sensors are ground-based measurements that characterize forest structural complexity from a sub-canopy perspective. In-situ remote sensing data from both MLS and TLS was considered for analysis. Table 6.1 provides an overview of data characteristics, i.e. sensor name, sensor type, year of data acquisition, calculated forest structural indicators, and assessed forest structural attributes.

Table 6.1: Overview of remote sensing metrics on forest structural complexity.

Sensor name	Sensor type	Year	Structural indicators	Structural attributes
Mobile Laser Scanning (MLS)	handheld Lidar	2023	box dimension, canopy cover	structural complexity (box dimension), cover and openness (canopy cover)
Terrestrial Laser Scanning (TLS)	static Lidar	2023	stand structural complexity (SSCI), understory complexity index (UCI), canopy openness index (COI)	structural complexity (SSCI, UCI), cover and openness (COI)
Sentinel-1	radar satellite	2016-2023	VH coefficient of variation (cv)	heterogeneity of surface roughness and moisture
Sentinel-2	multispectral satellite	2016-2023	NMDI (Normalized Multi-band Drought Index) cv	heterogeneity of photosynthetic activity with sensitivity to drought stress
GEDI, Sentinel-1, Sentinel-2	spaceborne Lidar, radar satellite, multispectral satellite	2017-2023	rh95 (canopy height) cv, cover (total canopy cover) cv, agbd (above-ground biomass density) cv	heterogeneity of vertical and horizontal structure (rh95, agbd), cover and openness (cover)

Research on forest structural complexity based on remote sensing data is not yet based on a standardized understanding of forest structural complexity. There are different definitions of forest structural complexity which are in some studies differentiating between forest structural complexity, forest structural diversity, and forest structural heterogeneity (McElhinny et al., 2005). Other studies propose to treat forest structural complexity, forest structural diversity, and forest structural heterogeneity as synonyms (LaRue et al., 2023). In general, forest structure can be characterized based on different attributes which were summarized by Atkins et al. (2023), e.g. cover and openness, forest structural heterogeneity, structural complexity (more attributes of forest structure are defined but not relevant to the present analysis which is why they are omitted). The pioneering study by McElhinny et al. (2005) suggested to define stand structure characteristics using the term structural complexity instead of structural diversity. According to McElhinny et al. (2005), structural diversity is understood as an aggregation metric comprising various forest structural attributes that contribute to overall forest biodiversity. In the present study, experimental silvicultural treatments are assessed since manipulations of light conditions through tree removal and establishments of various deadwood structures were conducted. Therefore, an enhancement of forest structural complexity is assumed (Mueller et al., 2022a,b). Since the present analysis focuses on the characterization of the enhancement of forest structural complexity based on spaceborne and in-situ indicators of forest structural complexity, the term structural complexity is preferred. Nevertheless, the considered indicators represent different forest structural attributes (Table 6.1, column "Structural attributes") aiming to assess the enhancement of forest structural complexity. Therefore, the forest structural indicators of spaceborne and in-situ sensors are summarized under the term structural complexity, but will be elaborated based on the specific forest structural attributes which are assessed.

The present analysis is limited to the focus region University forest of the BETA-FOR project (Figure 3.5) since in-situ remote sensing was only available for this region. Furthermore, 84 patches of the region are considered for analysis with 18 control treatment patches, and three patches for each experimental silvicultural treatment (aggregated and distributed treatments, Figure 3.6). Due to data acquisition errors for the in-situ sensors, the aggregated treatment with crowns (AK) remaining can only be represented by two patches. For the distributed treatment with stumps remaining (DW) there are 28 patches.

6.1.1 Spaceborne Data

Spaceborne data to assess enhanced forest structural complexity comprises time-series data of Sentinel-1 and Sentinel-2. More specifically, Sentinel-1 and Sentinel-2 time-series indicators were calculated that were identified in the previous section 5 as specifically suited to characterize forest structural changes due to the treatment implementation events of experimental silvicultural treatments. Modeled data on forest structure attributes of GEDI stem from the previously introduced workflow (section 4) to derive multi-annual forest structure attributes combining GEDI, Sentinel-1, and Sentinel-2 data. Therefore, the present analysis makes use of previously developed methodologies to derive spaceborne forest structural indicators.

6.1.1.1 Sentinel-1

Satellite radar time-series based on Sentinel-1 data was considered for analysis. Based on a new methodological framework to assess enhanced forest structural complexity (section 5), various metrics based on Sentinel-1 GRD data were tested using the probabilistic BEAST models for time-series analysis. The metric Sentinel-1 VH cv outperformed other metrics (Figure 5.4a) to accurately detect the change in forest structure due to experimental silvicultural treatments. Therefore, for the present analysis, Sentinel-1 VH cv patch-level time-series were calculated as annual temporal aggregations (median of the months July to including September). The annual metrics (2016-2023) are considered as forest structural heterogeneity indicator for annual summer conditions. Sentinel-1 VH cv characterizes the structural heterogeneity (calculation of spatial cv) with a specific sensitivity to surface roughness and moisture. Since the original cv values are negative, absolute values were calculated for the patch-level mean in order to derive positive cv values, thus being aligned with the understanding that heterogeneity can only be positive (increasing values describe an enhancement of forest structural heterogeneity).

6.1.1.2 Sentinel-2

Satellite multispectral time-series from Sentinel-2 data are integrated for the comparative analysis of spaceborne and in-situ indicators of forest structural complexity. Previous analysis to assess enhanced forest structural complexity (section 5) have demonstrated the high performance of the NMDI as patch-level cv statistics derived from Sentinel-2 L2A surface reflectance data in order to assess forest structural changes in the context of experimental treatment implementations (Figure 5.4b). Similar to the Sentinel-1 time-series data processing, also for Sentinel-2 NMDI cv time-series annual summer conditions (2016-2023) were calculated (median of the months July to including September). Based on the Sentinel-2 NMDI cv the heterogeneity (cv) at patch-level of photosynthetic activity is quantified. The values of cv for Sentinel-2 NMDI are positive which is why an increase in forest structural heterogeneity is assessed as increasing values for Sentinel-2 NMDI cv.

6.1.1.3 Modeled Forest Structure Attributes of GEDI

Data on modeled forest structure attributes is based on a novel workflow to derive multi-annual forest structure attributes (section 4). Per patch of the experimental silvicultural treatments, the data of 2023 on forest canopy height (indicator abbreviation: rh95), total canopy cover (cover), and above-ground biomass density (agbd) was spatially aggregated as cv. Therefore, the different attributes of forest structure characterize forest structural heterogeneity as cv in the vertical dimension (canopy height), as well as vertical and horizontal dimension (total canopy cover, above-ground biomass density). Similar to the indicators on forest structure conditions based on Sentinel-1 and Sentinel-2 data, the cv values of modeled forest structure attributes present increasing forest structure heterogeneity as increasing values.

6.1.2 In-situ Data

In-situ remote sensing data was integrated from MLS and TLS. Both sensors characterize a ground-based perspective during leaf-on conditions in summer 2023.

6.1.2.1 Mobile Laser Scanning (MLS)

MLS data was obtained in July 2023 using a hand-held ZEB Horizon laser scanner (Geoslam Ltd., UK). The patch-level measurement of forest structure was conducted with an initial position at the patch center with following scanning orientation in concentric circles with increasing radius. Therefore, the patch center was surrounded about five to ten times being dependent on stand density. After reaching the outer-bound of the patch, the laser scanner was carried back to the patch center location and the scan was ended.

Multiple forest structure complexity indicators were calculated at patch-level from the original point cloud data: canopy cover and openness was measured as canopy cover [%] using 20 cm voxels (Höwler et al., 2024). The box dimension is a true forest structural complexity indicator since it considers the three-dimensional complexity of vegetation quantified as space filling (Seidel, 2018).

6.1.2.2 Terrestrial Laser Scanning (TLS)

TLS data was collected during leaf-on conditions in August 2023. The static close-range sensing of the laser scanner was conducted as single-scan from the center location of each patch. The TLS device was a FARO M70 system (Faro Technologies Inc., Lake Marry, USA).

The resulting point cloud for each scan (patch) was further processed as patch-level indicators of forest structural complexity. The forest structural attribute canopy cover and openness was quantified as COI. The COI derived from TLS is inverse to the MLS canopy cover measurement. Both MLS canopy cover and TLS COI are sensitive to open and closed forest canopies, e.g. aggregated and distributed tree removal (Zheng et al., 2012). Two additional indicators of forest structural complexity were calculated. The Stand Structural Complexity Index (SSCI) quantifies forest structural complexity and it is calculated based on fractal dimension, i.e. space filling of vegetation in three dimensions (Ehbrecht et al., 2017, 2021; Frey et al., 2019). In comparison to the SSCI which is considers vegetation structure characteristics of the full vertical strata, the Understory Complexity Index (UCI) focuses on the assessment of structural complexity of understory vegetation (e.g. recovery dynamics of low vegetation after disturbance) (Willim et al., 2019).

6.2 Methodological Approach

The comparative analysis of spaceborne and in-situ remote sensing indicators of forest structural complexity is based on three methodological approaches: bi-variate correlations (section 6.2.1), multi-variate statistics (section 6.2.2), and unsupervised clustering (section 6.2.3).

6.2.1 Bi-variate Correlations

Using bi-variate correlations, linear relationships are assessed among all calculated indicators. Therefore, the influence of remote sensing platform and sensor is assessed in the context of various forest structural attributes characterizing the enhancement of structural complexity in aggregated and distributed treatments. Bi-variate correlations were quantified as Pearson's correlation coefficient (r) delineating positive and negative correlations. Moderate correlations are present for absolute values in a range of 0.4 to 0.6 ($|r| > 0.4$ and $|r| < 0.7$). Correlations are considered to be strong for $|r| >= 0.7$.

6.2.2 Multi-variate Statistics

Multi-variate statistics are carried out in order to identify to which extent the different indicators of enhanced forest structural complexity assess the forest structural differences of aggregated, distributed, and control treatments. The multi-variate statistics are calculated on the one hand for spaceborne indicators as bi-temporal comparison for 2019 (first summer after the treatment implementation events) and 2023 (the fifth summer after the treatment implementation event). On the other hand, a multi-variate comparison of both spaceborne and in-situ indicators was conducted for 2023 in order to identify the influence of forest structural attributes, remote sensing platforms, as well as sensors to delineate aggregated, distributed, and control treatments. All indicators were rescaled to a range from 0 to 1 for simplified cross-comparison. The enhancement of forest structural complexity through experimental silvicultural treatments (aggregated and distributed treatments) is characterized by values close to 1. In comparison, low forest structural complexity is indicated by low values close to 0.

6.2.3 Clustering Analyses

Unsupervised clustering analyses were carried out to identify groups (patches) of similar forest structural characteristics. The analysis was first conducted exclusively for spaceborne indicators, and in a second step for both spaceborne and in-situ indicators combined. Based on the unsupervised method, the alignment of identified groups (patches) holding similar forest structural conditions is compared to the experimental design (grouping as aggregated, distributed, control treatments). Unsupervised clustering was calculated based on K-Means clustering with a definition of n = 3 clusters. Three clusters were defined in order to potentially cluster the patches based on their treatment group (aggregated, distributed, control treatment).

6.3 Results

The results section is sub-divided into four sections to present the findings of the different methodological approaches. In section 6.3.1, spaceborne time-series are visualized highlighting the temporal benefits of spaceborne data in order to characterize pre-disturbance and post-disturbance (after the treatment implementation event) forest structural conditions. The results of the correlation analysis of spaceborne and in-situ forest structural complexity indicators are presented in section 6.3.2. Multi-variate analysis to assess the differences in forest structural complexity by treatment groups (aggregated, distributed, control treatments) are conducted based on spaceborne indicators and combined spaceborne and in-situ indicators (section 6.3.3). Lastly, unsupervised clustering analyses were carried out in order to identify groups of patches with similar forest structural characteristics (section 6.3.4). The clustering analyses are presented based on spaceborne indicators only (section 6.3.4.1), as well as combined analysis of both spaceborne and in-situ indicators (section 6.3.4.2).

6.3.1 Spaceborne Time-Series Visualization

The following time-series visualizations are presented for spaceborne data since multi-annual observations exist. Therefore, time-series of Sentinel-1, and Sentinel-2, as well as multi-annual data on forest structure characterize forest structural complexity before (pre-disturbance) and after the treatment implementation event (post-disturbance). Since the data was temporally aggregated as annual summer conditions, years before 2019 present pre-disturbance conditions. After the treatment implementation event in November and December 2018, i.e. the years since 2019, post-disturbance conditions are characterized. The visualizations show all individual treatment patches grouped by treatment types (Figure 3.6).

Sentinel-1 VH cv time-series present similar forest structural conditions among treatments for the years 2016 to 2018 (Figure 6.1). With the enhancement of forest structural complexity through experimental silvicultural treatments (aggregated and distributed treatments), an increase in forest structural heterogeneity (most values are greater than 0.08;

except for AH, aggregated habitat trees) is depicted for aggregated treatments since 2019. In addition, increasing variance among individual treatment patches of aggregated treatments can be observed since 2021. Distributed treatments hold similar values for forest structural heterogeneity as control treatments for all years.

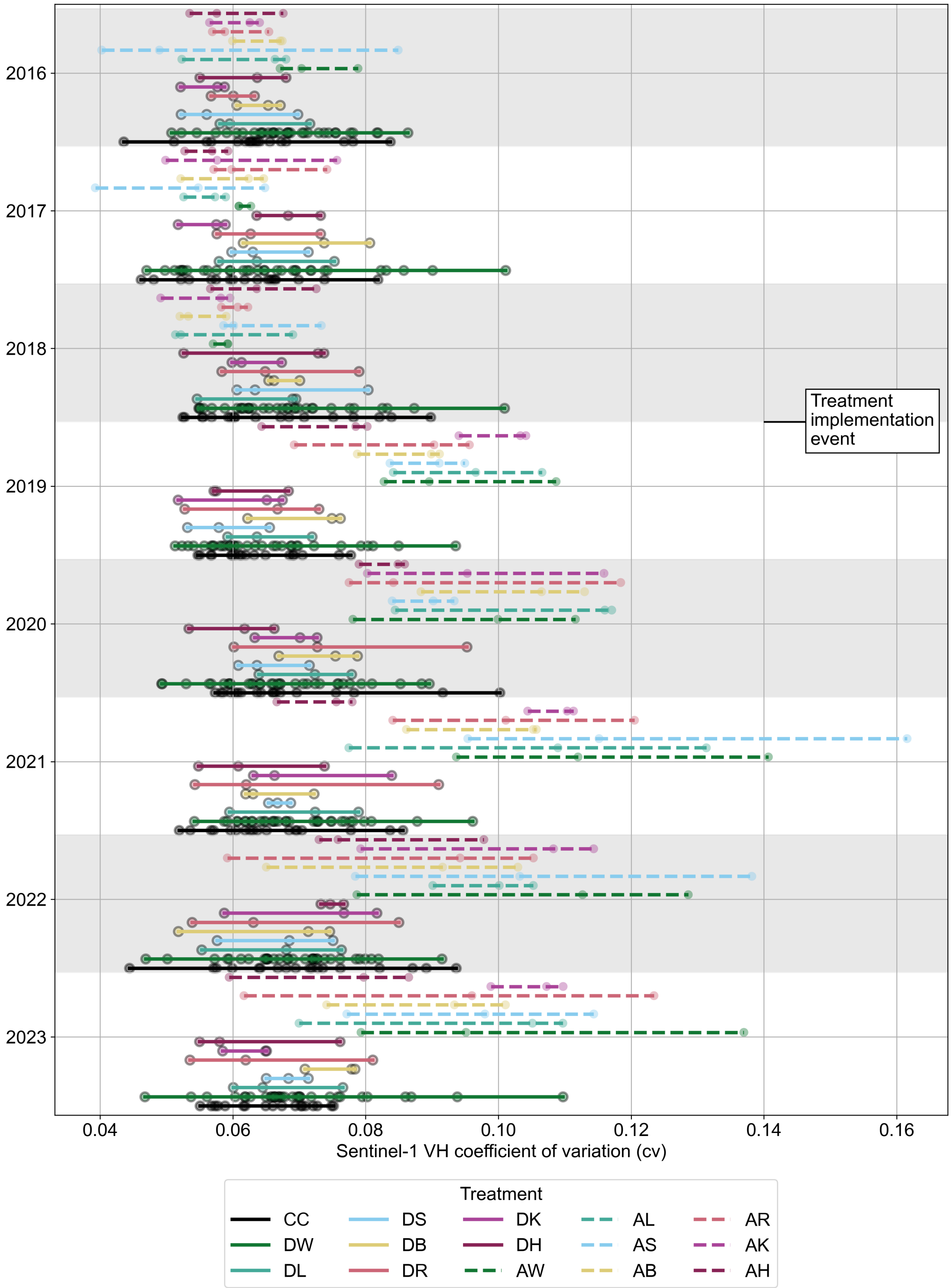

Figure 6.1: Sentinel-1 VH coefficient of variation (cv) time-series at patch-level of individual BETA-FOR patches from 2016 to 2023.

Sentinel-2 NMDI cv time-series (Figure 6.2) present similar temporal dynamics among treatments as observed for Sentinel-1 VH cv time-series. Before the treatment implementation event (2016 to 2018), a low forest structural heterogeneity (values lower than 0.06) is depicted for all treatments with only few patches indicating slightly increased heterogeneity (values greater than 0.06). After the treatment implementation event which enhanced the forest structural complexity, there is a strong increase in forest structural heterogeneity (values greater than 0.06 and mean values per treatment type of about 0.08) for all aggregated treatment types (except AH, aggregated treatment with habitat trees). Interestingly, the first two years after the treatment implementation event (2019 and 2020) present highest forest structural heterogeneity per treatment type of the full time-series. The years since 2021 still show increased forest structural heterogeneity for aggregated treatments (mean values per treatment type about 0.06) in comparison to distributed and control treatments (mean values per treatment type about 0.035). For all years of the time-series, assessed forest structural heterogeneity based Sentinel-2 NMDI cv of distributed treatments is similar to control treatments.

The multi-annual data of forest structure attributes is available from 2017 to 2023 characterizing summer conditions. As an example of modeled forest structure, the heterogeneity (cv) of total canopy (Figure 6.3) is presented in a similar way to Sentinel-1 and Sentinel-2 time-series. For the pre-disturbance years (2017 and 2018), there is a homogeneity (mean values per treatment types lower than 0.1) of forest structure conditions for aggregated, distributed, and control treatments. After the enhancement of forest structural complexity in November and December 2018, the post-disturbance years (2019 to 2023) depict increased forest structural heterogeneity for aggregated treatments compared to distributed and control treatments. From 2019 to 2023, there is a reduction in forest structural heterogeneity for aggregated treatments: in the first year after the treatment implementation event, highest values of forest structural heterogeneity are reached (mean values per treatment types greater than 0.23). The following years present declining forest structural heterogeneity. Nevertheless, the heterogeneity of total canopy cover in 2023 of aggregated treatments still holds higher values (mean values per treatment types of 0.07) than distributed and control treatments. Similar to the time-series results of Sentinel-1 and Sentinel-2, also for modeled total canopy cover cv there is a low heterogeneity for the aggregated habitat trees treatment for all years (values lower than 0.08). Furthermore, no increase of forest structural heterogeneity for distributed treatments after the treatment implementation can be observed. Therefore, there is a homogeneity of total canopy cover for distributed treatments which is similar to control treatments.

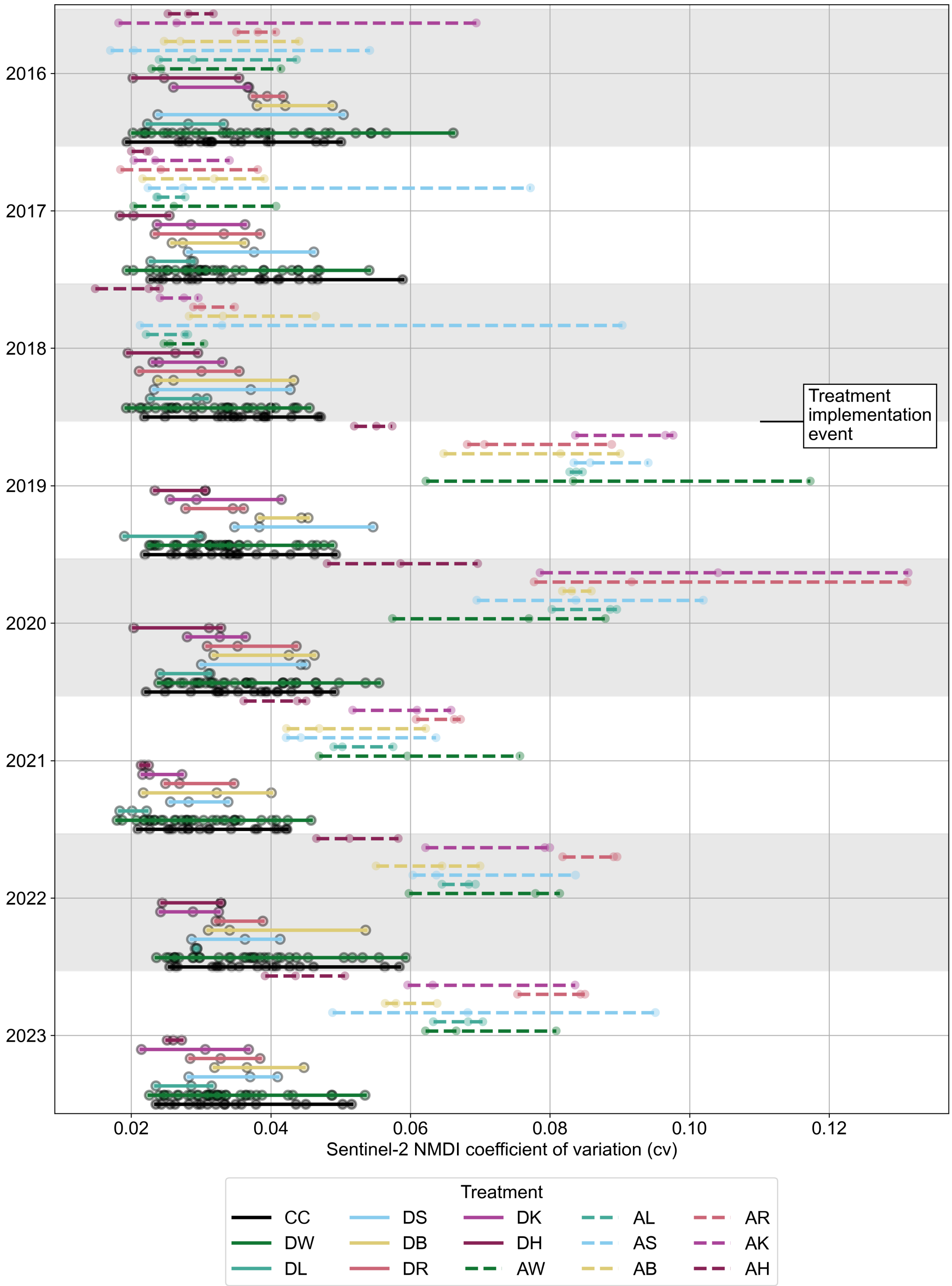

Figure 6.2: Sentinel-2 NMDI coefficient of variation (cv) time-series at the patch-level of individual BETA-FOR patches from 2016 to 2023.

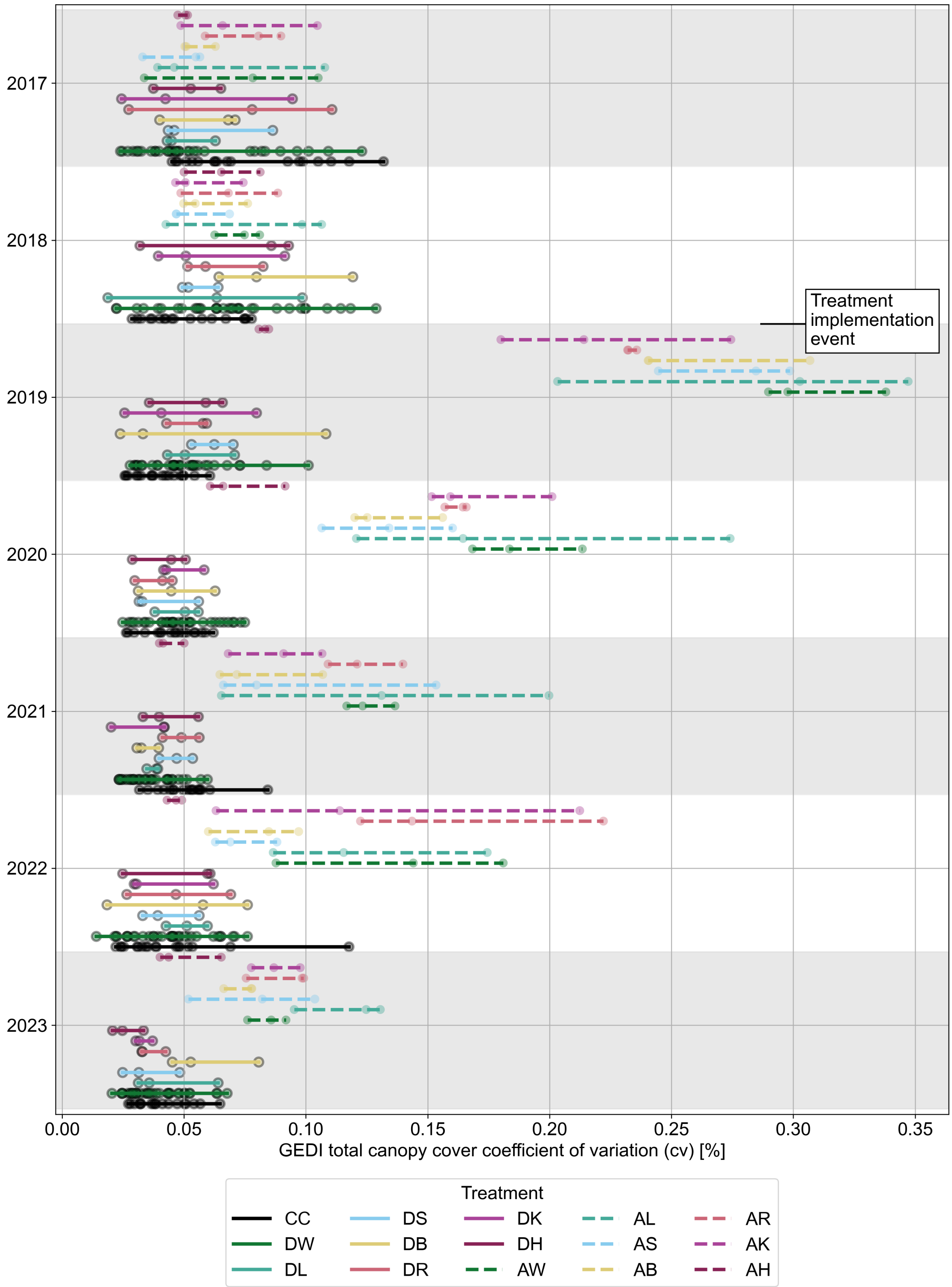

Figure 6.3: GEDI total canopy cover coefficient of variation (cv) time-series at patch-level from 2017 to 2023.

6.3.2 Correlation Analyses of Forest structural complexity Indicators

In the following, bi-variate correlations among spaceborne and in-situ forest structural complexity indicators are assessed. Pair-wise Pearson's correlations (r) are shown as heatmap in Figure 6.4.

Figure 6.4: Correlation matrix indicating the relationships among cross-platform and -sensor metrics of forest structural complexity.

Overall, there are moderate to strong positive and negative correlations. Strongest positive correlations (r >= 0.7) are found among indicators MLS box dimension and MLS canopy cover (r = 0.9), as well as for modeled GEDI total canopy cover (cover) cv and

Sentinel-2 NMDI cv (r = 0.8). Therefore, strong correlations among forest structural complexity indicators of the same platform were found for both spaceborne and in-situ based indicators. The indicators derived from TLS hold low to moderate correlations: highest correlations exist among TLS COI and TLS SSCI amounting to r = -0.6 (moderate negative correlation).

Strongest intra-platform correlations are present among MLS indicators and TLS COI (r = -0.8), as well as GEDI cover cv (r = -0.7), Sentinel-1 VH cv (r = -0.7), and Sentinel-2 NMDI cv (r = -0.7). Among spaceborne indicators derived from GEDI, Sentinel-1, and Sentinel-2 minimum absolute correlations amount to |r| >= 0.5. Lowest maximum cross-platform correlations are found for TLS SSCI (|r| <= 0.5) and GEDI agbd cv (|r| <= 0.5). Furthermore, there are strong intra-sensor correlations (|r| >= 0.7), i.e. among different sensor types, for MLS indicators (Lidar) and Sentinel-1 VH cv (radar), as well as Sentinel-2 NMDI cv (multispectral). In addition, cross-platform indicators on forest canopy cover (MLS canopy cover, TLS COI, GEDI cover cv) are highly correlated (|r| >= 0.7).

6.3.3 Multi-variate Comparison of experimental silvicultural Treatments

Based on multivariate statistics, differences in forest structural complexity among three treatment groups (aggregated, distributed, control treatments) of experimental silvicultural treatments are assessed. The statistics were calculated on the one hand for spaceborne indicators, and on the other hand based on all indicators (spaceborne and in-situ indicators).

The assessment of differences in forest structural complexity of aggregated, distributed, and control treatments was conducted as bi-temporal analysis for spaceborne indicators. In 2019, i.e. the first summer after the treatment implementation event in November and December 2018, all spaceborne indicators characterize a clear difference in forest structural complexity of aggregated treatments to distributed and control treatments (Figure 6.5). All spaceborne indicators present mean values for aggregated treatments greater than 0.6. In addition, there is no overlap of the standard deviations of aggregated treatments with distributed and control treatments.

The comparative analysis of spaceborne indicators from 2023, i.e. the fifth summer after the treatment implementation event in November and December 2018, shows a decrease in forest structural complexity for aggregated treatments (Figure 6.6). Only the spaceborne indicators GEDI cover cv and Sentinel-2 NMDI cv clearly delineate aggregated treatments from distributed and control treatments since there is no overlap of standard deviations. In addition, mean values GEDI cover cv and Sentinel-2 NMDI cv amount to values close to

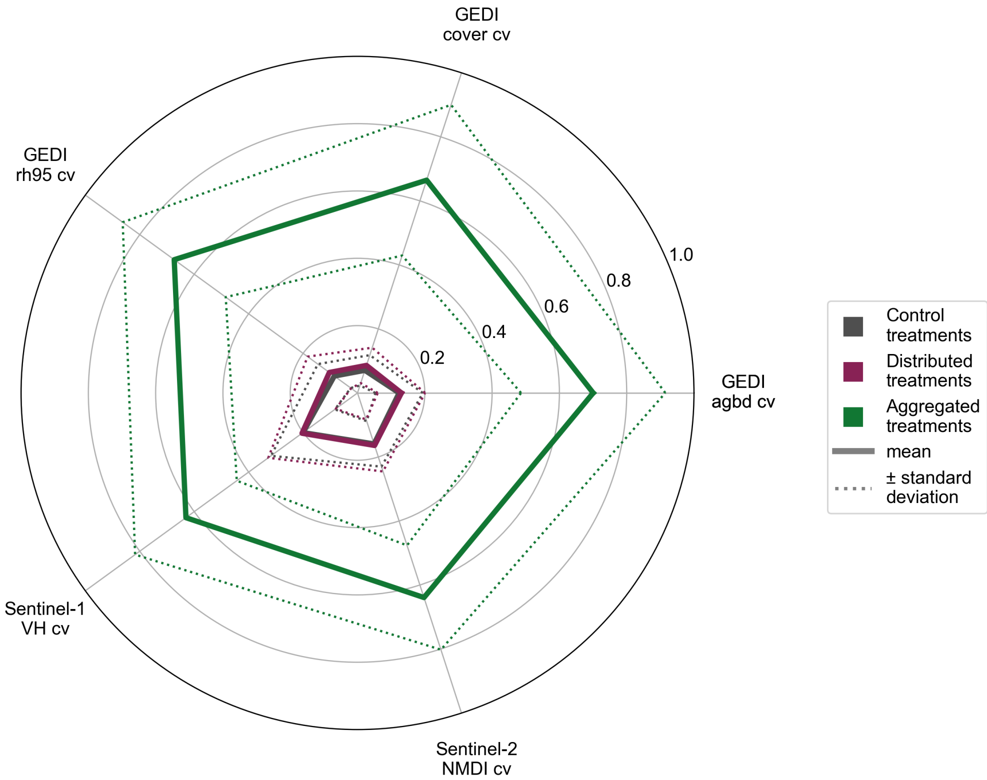

Figure 6.5: Spaceborne metrics of forest structural complexity for 2019 as multivariate comparison to assess differences in forest structural complexity among treatment groups.

0.6, i.e. similar to the conditions in 2019 (Figure 6.5). For the other spaceborne indicators, there is an overlap of standard deviations from aggregated treatments with standard deviations of distributed and control treatments. Nevertheless, according to mean values, aggregated treatments are different to distributed and control treatments. Similar to the multivariate comparison in 2019, there is no difference among distributed and control treatments in 2023.

Figure 6.7 depicts a multivariate comparison of aggregated, distributed, and control treatments based on spaceborne and in-situ indicators of forest structural complexity from 2023. Multiple spaceborne (Sentinel-1 VH cv, Sentinel-2 NMDI cv, GEDI cover cv) and in-situ indicators (MLS canopy cover, MLS box dimension, TLS SSCI) characterize the enhancement of forest structural complexity through aggregated treatments as mean values greater than 0.5. For all those indicators a clear separation of aggregated to distributed and control treatments is possible (no overlap of standard deviation), except for Sentinel-1 VH cv, TLS SSCI. Similar to the analysis of spaceborne indicators for 2023, the in-situ indicators of forest structural complexity do not present differences among distributed and control treatments.

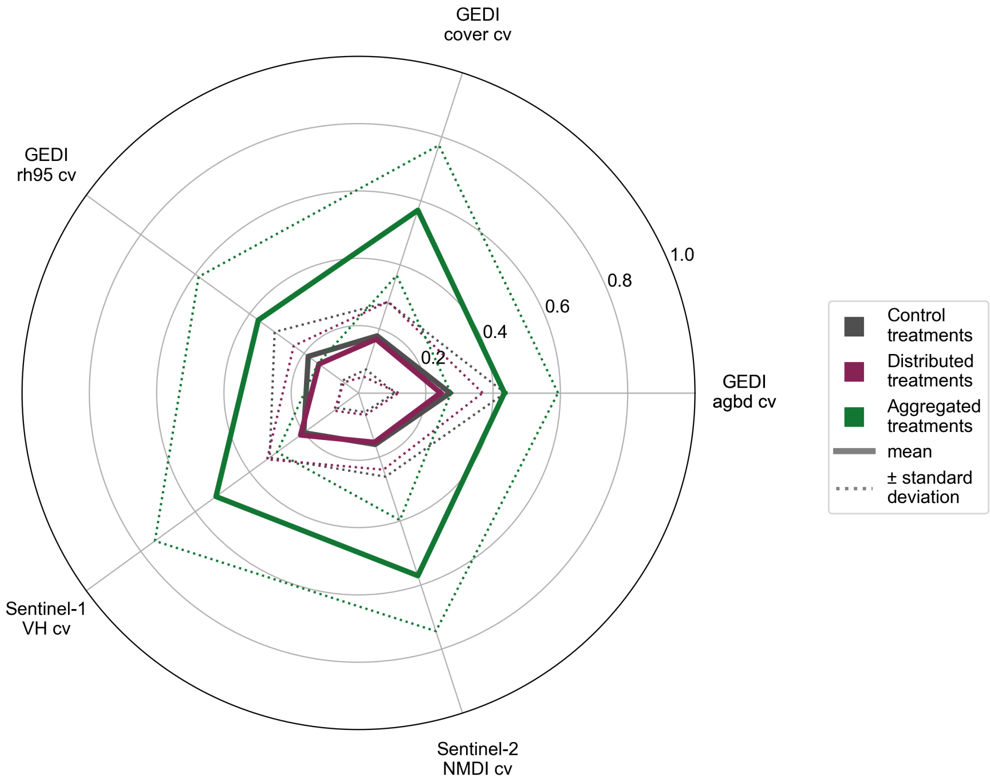

Figure 6.6: Spaceborne metrics of forest structural complexity for 2023 as multivariate comparison to assess differences in forest structural complexity among treatment groups.

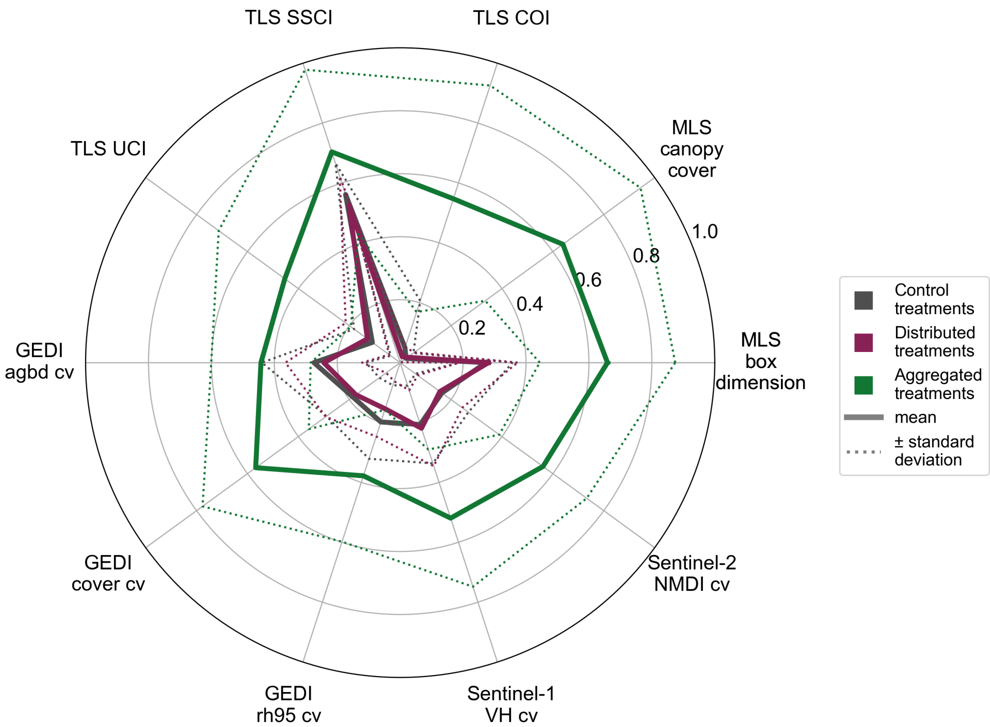

Figure 6.7: All metrics of forest structural complexity (2023) as multivariate comparison to assess differences in forest structural complexity among treatment groups.

6.3.4 Unsupervised Clustering Analyses

The assessment of differences in forest structural complexity based on unsupervised clustering aims to identify groups of patches (individual treatments) that hold similar characteristics according to remotely sensed indicators. By comparing the resulting clusters (groups of patches) from unsupervised clustering with the forest structural characteristics due to tree removal (aggregated, and distributed removal, or no removal in control treatments) and deadwood generation (standing structures, downed deadwood, no deadwood presence), the sensitivity of remotely sensed indicators to specific forest structure characteristics is analyzed. The analysis was conducted on the one hand for spaceborne indicators (separately for 2019 and 2023) (section 6.3.4.1), and on the other hand based on all indicators from both spaceborne and in-situ remote sensing (section 6.3.4.2).

6.3.4.1 Spaceborne Indicators

The unsupervised clustering analysis for 2019 presents that the majority (about 85 %) of all aggregated treatments are clustered separately (cluster 2) from distributed and control treatments (cluster 0 and 1) (Figure 6.8a). Only aggregated treatments with habitat trees (AH) are clustered differently, i.e. as cluster 0. Aggregated treatments with other standing deadwood structures, as well as aggregated treatments without standing deadwood structures are characterized by an increased forest structural heterogeneity according to Sentinel-2 NMDI cv and GEDI cover cv (Figure 6.8b). Distributed and control treatments are clustered in both cluster 0 and 1. In addition, distributed and control treatments hold values lower than 0.05 for Sentinel-2 NMDI cv and lower than 0.1 for GEDI cover cv.

Based on spaceborne data from 2023, there is a reduction in clustering aggregated treatments as separate cluster (cluster 2): 60 % of all aggregated treatments are clustered as cluster 2 (Figure 6.8c). Therefore, 40 % of aggregated treatments are clustered as cluster 0 or 1. Interestingly, only aggregated treatments with standing deadwood structures (AH: habitat trees, AB: standing and downed deadwood, AS: standing deadwood) are clustered as cluster 0 and 1, i.e. different to aggregated treatments without standing deadwood structures (cluster 2) (Figure 6.8d). Similar to the analysis based on spaceborne data from 2019 (Figure 6.8a,b), there is no clear separation of distributed and control treatments since both treatments are clustered as cluster 0 and cluster 1.

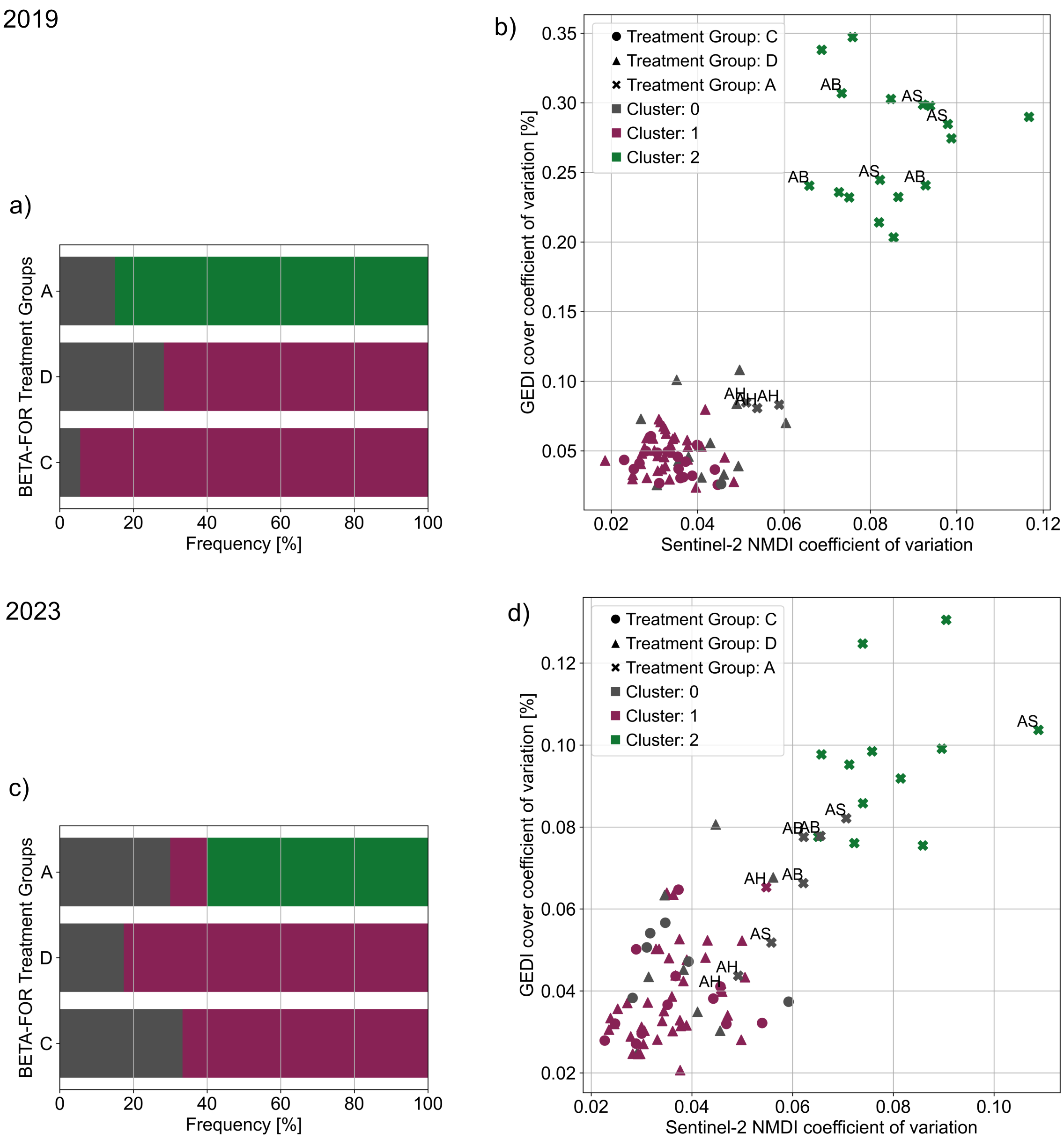

Figure 6.8: Clustering results based on all spaceborne metrics of forest structural complexity for 2019 and 2023. For aggregated treatments with standing deadwood structures the treatment abbreviations (AS=snags, AB=snags and downed deadwood, AH=habitat trees) are depicted. The colors of individual clusters of a) and b), as well as c) and d) are corresponding.

6.3.4.2 Combination of Spaceborne and In-situ Indicators

The unsupervised clustering analysis considering all spaceborne and in-situ indicators of forest structural complexity shows that there is a slight increase of aggregated treatments which are clustered separately to distributed and control treatments (Figure 6.9a). About 65 % of all aggregated treatments are clustered as cluster 2. Similar to the findings based on spaceborne data only (section 6.3.4.1), only aggregated treatments with standing deadwood structures are clustered as cluster 0 and 1 (Figure 6.9b). Aggregated treatments (AH) with habitat trees and standing deadwood (AB, AS) are more similar to distributed and control treatments based on spaceborne and in-situ indicators of forest structural complexity. Most of the aggregated treatments which are clustered in cluster 2 hold values lower than 2.3 for MLS box dimension and greater than 0.05 for GEDI rh95 cv (Figure 6.9b). The similarity of distributed and control treatments according to forest structural characteristics can be expressed by MLS box dimension values of greater than 2.3 and GEDI rh95 cv values lower than 0.06.

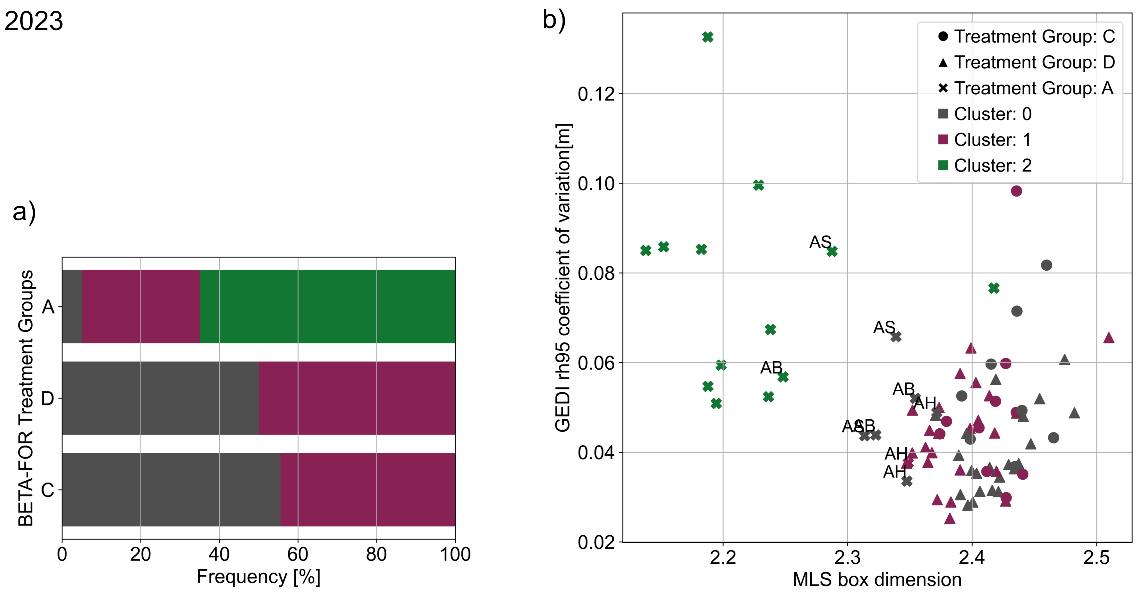

Figure 6.9: Clustering results based on all calculated metrics of forest structural complexity for 2023. For aggregated treatments with standing deadwood structures the treatment abbreviations (AS=snags, AB=snags and downed deadwood, AH=habitat trees) are depicted. The colors of individual clusters of a) and b) are corresponding.

6.4 Discussion

The discussion section is sub-divided into four sections. First, intra- and inter-platform correlations among spaceborne and in-situ indicators are assessed (section 6.4.1). Next, the general potential to analyze forest structural complexity based on spaceborne and in-situ remote sensing is elaborated (section 6.4.2). In the following, the characterization of standing deadwood structures from remote sensing is discussed (section 6.4.3). Lastly, there is an elaboration on the ecological relevance to characterize forest structural complexity and its relationship to biodiversity (section 6.4.4).

6.4.1 Intra- and inter-Platform Correlations among Spaceborne and In-situ Indicators

Indicators of forest structural complexity are valuable for the characterization of habitat structures and potential forest resilience towards disturbances (Mueller et al., 2022a). The comparative analysis of forest structure conditions based on in-situ and spaceborne observations is essential in order to better understand the potential of spaceborne data to characterize local forest structure, as well as to identify limitations and research gaps. Since in-situ measurements from close-range sensing techniques, e.g. MLS and TLS, assess sub-canopy perspectives on forest structure, there is a complementary perspective of top-of-canopy measurements derived from spaceborne sensors, e.g. Sentinel-1, Sentinel-2, GEDI (Camarretta et al., 2020). Therefore, the cross-validation of different forest structural attributes (Table 6.1) assessed from both spaceborne and in-situ remote sensing is indispensable.

The correlation analysis of spaceborne and in-situ indicators of forest structural complexity in the context of experimental silvicultural treatments shows that there are strong correlations among indicators from the same (intra-platform correlations) and complementary platform (inter-platform correlations). On the one hand, strong correlations ($|r| >= 0.7$) were found for intra-platform correlations, e.g. MLS box dimension and canopy cover or GEDI cover cv and Sentinel-2 NMDI cv. On the other hand, strong inter-platform correlations were found for different platform combinations: MLS (box dimension, canopy cover) and TLS (COI), MLS (box dimension, canopy cover) and spaceborne sensors (GEDI cover cv, Sentinel-1 VH cv, Sentinel-2 NMDI cv), TLS (COI) and spaceborne sensors (GEDI cover cv, Sentinel-2 NMDI cv). Therefore, indicators of different forest structural attributes are highly correlated independent of the platform. In addition, the highly correlated indicators of forest structural attributes are derived from different remote sensing sensors (Lidar: MLS, TLS, GEDI; SAR: Sentinel-1; multispectral: Sentinel-2).

6.4.2 Remotely sensed Forest structural complexity Assessment

Finding multiple strong correlations among spaceborne and in-situ indicators of forest structural complexity suggests that a remotely sensed assessment of forest structure conditions can be accurately conducted based on spaceborne data. The characterization of experimental silvicultural treatments (section 6.3.3) showed that both spaceborne and in-situ indicators of forest structural complexity have the potential to delineate aggregated treatments (gap felling) from distributed (selective tree removal) and control treatments (unaltered forest structure conditions). The spaceborne indicators GEDI cover cv, Sentinel-1 VH cv, and Sentinel-2 NMDI cv identified the strongest enhancement of forest structural complexity through aggregated treatments to a similar degree as in-situ indicators, e.g. MLS box dimension, MLS canopy cover, TLS COI, TLS UCI. The finding that neither in-situ nor spaceborne indicators hold the potential to delineate the difference in forest structural conditions of distributed to control treatments suggests that the forest structural conditions about five years after the treatment implementation event are relatively similar for control and distributed treatments. Therefore, the gap in the canopy due to the removed crown might have closed through overgrowth of surrounding trees.

6.4.3 Characterization of standing Deadwood Structures

Based on unsupervised clustering a sensitivity of spaceborne, as well as in-situ indicators, was found towards the presence of standing deadwood structures in aggregated treatments. In addition, a temporal influence was detected based on spaceborne bi-temporal comparisons (section 6.3.4.1). The aggregated treatments with and without standing deadwood structures are more similar, i.e. clustered in the same cluster, according to forest structural characteristics derived from spaceborne data of the first summer after the treatment implementation event. The aggregated habitat treatments are an exception which might be due to the presence of tilted trees instead of snags (standing deadwood cut at about four meters height which are present in the other aggregated treatments with standing deadwood). Four years later, i.e. the fifth summer after the treatment implementation event, the structural differences of some aggregated treatments with standing deadwood to distributed and control treatments is reduced. Therefore, instead of 85 % of aggregated treatments in 2019, only 60 % of aggregated treatments (mostly without standing deadwood) are clustered in the same cluster, i.e. 40 % of aggregated treatments (mostly with standing deadwood) are clustered in clusters with a dominance of distributed and control treatments.

The identification of temporal effects on differences among experimental silvicultural treatments emphasizes a timely monitoring of forest structure conditions. Since previous correlation analysis have demonstrated strong correlations among multiple spaceborne and in-situ indicators of forest structural complexity, spaceborne time-series hold a great potential to continuously characterize the dynamics of forest structure. In comparison to mono-temporal and cost-intensive in-situ measurements, the integration of spaceborne time-series facilitates the identification of standing deadwood structures. The assessment of standing deadwood structures in comparison to unaltered forest structure (e.g. control treatments) to gap felling (aggregated treatments) is important since the presence of standing deadwood strongly improves the habitat variety and enhanced resilience towards further degradation (Kortmann et al., 2018; Seibold et al., 2016a,b, 2019).

6.4.4 Ecological Relevance to characterize Forest structural complexity and its Relationship to Biodiversity

The assessment of forest structure characteristics was traditionally conducted based on ground-based measurements organized as field campaigns of inter-disciplinary research groups (Palmer, 1995; Palmer et al., 2002). With the technical advancements in sensor systems and automatized data processing, the field of in-situ remote sensing (i.e. close-range sensing techniques) further specialized and now constitutes an important reference perspective for airborne and spaceborne observations (Camarretta et al., 2020; Morsdorf et al., 2018). For an improved inter-disciplinary characterization of forest structure, a strengthening of collaborations among remote sensing data scientists and ecologists is needed (Jetz et al., 2016; Cavender-Bares et al., 2022; Burrascano et al., 2023).

Forest structure attributes, such as forest structural complexity, were found to be representative measurements for general levels of biodiversity and ecosystem functioning (Bohn and Huth, 2017; Heidrich et al., 2020). Therefore, there is a relevance from an ecological perspective to assess forest structural complexity. Joint analysis of ecologists and remote sensing data scientists hold a great potential to investigate recent knowledge gaps, such as scale dependency, temporal stability, and influences due to disturbances (Bae et al., 2019; Fassnacht et al., 2022; Graser et al., 2025).

The establishment of experimental silvicultural treatments enhancing the forest structural complexity through aggregated and distributed treatments was conducted in the context of an inter-disciplinary research unit (Mueller et al., 2022b,a). On the one hand forest structure conditions were measured based on in-situ and spaceborne remote sensing sensors holding strong correlations among multiple attributes of forest structure from different sensors and platforms (section 6.3.2). On the other hand, ecologists and biologists took measurements of volatilomes, sampled microbial communities in soils and deadwood, investigated interactions of plants and animals, characterized understory vegetation structure, and quantified multifunctionality and biodiversity of higher trophic levels (e.g. birds, mammals). Since all measurements were conducted in the context of experimental silvicultural treatments, multifaceted forest structure-biodiversity relationships can be assessed. The analysis of forest structure through spaceborne sensors in relation to multiple variables of biodiversity and ecosystem functioning is the focus of chapter 7.

Findings on forest structure-biodiversity relationships contextualized to the experimental silvicultural treatments have important implications for silvicultural management. The identification of specific variables of biodiversity and ecosystem functioning which are promoted by enhanced forest structural complexity through novel silvicultural practices (e.g.

small-scale distributed and aggregated tree removal, generation of various deadwood structures) is of high interest to foster future forest resilience through improved biodiversity and ecosystem functioning. In addition, the characterization of forest habitat structures through spaceborne remote sensing which are sensitive to key indicators of biodiversity and ecosystem functioning could support the deeper integration of spaceborne remote sensing in ecological research, as well as the spatio-temporal monitoring of biodiversity and ecosystem functioning at high resolution.

6.5 Summary

Silvicultural management has the potential to alter forest structure towards an enhancement of structural complexity which can facilitate increased biodiversity and ecosystem multifunctionality. The implementation of experimental silvicultural treatments comprising aggregated (gap felling) and distributed treatments (selective removal of trees) leads to a diversification of light and temperature conditions. In addition, different deadwood structures ranging from an absence of deadwood to downed and standing deadwood lead to an increasing variety of habitat structures for deadwood-dependent species. The standardized experimental silvicultural treatments provide an unique opportunity to conduct comparative analysis of in-situ and spaceborne derived forest structural complexity indicators for monitoring the dynamics in forest structure.

Correlation analysis revealed that there are strong intra- and inter-platform correlations of forest structural complexity indicators which are sensitive to different forest structural attributes, e.g. canopy cover and openness, structural heterogeneity, as well as structural complexity. The identification of strong correlations of forest structural complexity indicators derived from MLS, TLS, Sentinel-1, Sentinel-2, and GEDI supports the integration of spaceborne indicators for large-scale analysis, thus bridging the local observations from in-situ remote sensing. Both in-situ and spaceborne remote sensing indicators demonstrated that small-scale openings in forests through gap felling can be monitored. Therefore, cost-effective and publicly available spaceborne time-series are specifically suited to characterize the temporal dynamics of forest structure. Furthermore, a sensitivity towards standing deadwood structures in aggregated treatments was found for forest structural complexity indicators derived from in-situ and spaceborne remote sensing. This finding highlights that spaceborne remote sensing indicators of forest structure hold a potential to delineate small-scale openings in forests with an absence of standing deadwood structures from openings with a presence of standing deadwood.

To summarize, monitoring forest structure dynamics in the context of silvicultural management is of great importance to foster future forest resilience through enhanced structural complexity. Novel management practices of different spatial tree felling arrangements, as well as deadwood generation can be monitored by both in-situ and spaceborne remote sensing. Specific spaceborne indicators (Sentinel-1 VH cv, Sentinel-2 NMDI cv, GEDI cover cv) were identified to upscale in-situ forest structural complexity indicators.

Chapter 7

Relationships of Forest Structure Indicators and Biodiversity Measurements

Investigating forest structure-biodiversity relationships is of high relevance to understand habitat structures providing ecological niches for different species, thus contributing to forest biodiversity and ecosystem functioning (Bohn and Huth, 2017; Heidrich et al., 2020). In the previous chapter 6, several spaceborne indicators of forest structural heterogeneity were identified as key indicators since they hold strong correlations to indicators derived from in-situ remote sensing (MLS, TLS). In the present chapter, the key spaceborne indicators are used to assess relationships to multi-variate biodiversity measurements. The analyses are contextualized to the experimental silvicultural treatments which were already under study in chapter 5 and chapter 6. Therefore, the enhancement of forest structural complexity through experimental silvicultural treatments characterized by spaceborne indicators, and its relationship to multiple biodiversity measurements is investigated. In comparison to previous regional analysis limited to the focus region of the BETA-FOR project (chapter 5, 6), the biodiversity data is available for various forest regions in Germany, thus supporting the identification of spaceborne-derived forest structure indicators serving as surrogates for forest biodiversity across regions.

The chapter on relationships of spaceborne forest structure indicators and in-situ biodiversity measurements is structured as follows: first, the data on spaceborne indicators of forest structure and biodiversity measurements is introduced (section 7.1). In the following, the methods to investigate relationships among forest structure and biodiversity measurements are presented (section 7.2). The results section (section 7.3), is sub-divided into the characterization of forest structure across regions and experimental silvicultural treatments through spaceborne data (section 7.3.1), as well as correlation analysis quantifying the relationships among forest structure indicators and biodiversity measurements (section 7.3.2).

In the discussion section (section 7.4), the potential of spaceborne indicators to asses forest structure-biodiversity relationships is elaborated (section 7.4.1), followed by a general discussion on identified relationships of forest structure and biodiversity in temperate forests (section 7.4.2). The chapter ends with a summary of the main findings (section 7.5).

7.1 Data

The analysis of forest structure-biodiversity relationships is based on spaceborne data characterizing forest structure characteristics, and in-situ sampling data of multiple biodiversity measurements. Thanks to the high spatio-temporal resolution of spaceborne data, all experimental silvicultural treatments of the BETA-FOR project across six regions (section 3.3) are assessed using multi-sensor spaceborne indicators on forest structural heterogeneity. The biodiversity data comprises taxonomic diversity measurements for bats, birds, gastropods, hoverflies, insects, moths, spiders, and trees which is available for three regions of the BETA-FOR project. In the following, the data characteristics of both spaceborne forest structure indicators, as well as biodiversity measurements is explained more in detail.

7.1.1 Spaceborne Indicators of Forest Structure

The considered spaceborne indicators of forest structure build up on previous findings of chapter 4 (modeling of forest structure attributes derived from GEDI based on Sentinel-1 and Sentinel-2 temporal-spectral metrics), chapter 5 (identification of specific Sentinel-1 and Sentinel-2 metrics assessing the enhancement of forest structural complexity), and chapter 6 (comparative analysis of spaceborne indicators calculated in chapter 4 and chapter 5 to in-situ remote sensing indicators of forest structural complexity).

The spaceborne indicators of forest structure characterize structural heterogeneity quantified as cv per patch. Table 7.1 provides an overview of the calculated spaceborne indicators. Each indicator was calculated as mean of 2022 and 2023 which are the main years of biodiversity sampling in order to quantify average forest structure conditions of the two years. Satellite time-series of Sentinel-1 VH cv and Sentinel-2 NMDI cv were aggregated per season: winter (December to February), spring (March to May), summer (June to July), autumn (September to November). Since the attributes of forest structure derived from the combination of GEDI, Sentinel-1 and Sentinel-2 data are available as annual products characterizing summer conditions of forest structure, only average conditions of canopy height (rh95), total canopy cover (cover), and above-ground biomass density (agbd) for summer 2022 and 2023 were calculated. The spaceborne data is available for all 234 patches of the

BETA-FOR project (section 3.3), thus enabling an across-region assessment considering six forest regions in Germany.

Table 7.1: Overview of spaceborne indicators of forest structural heterogeneity.

Sensor name	Sensor type	Year	Structural indicators	Structural attributes
Sentinel-1	radar satellite	2022, 2023	VH coefficient of variation (cv)	heterogeneity of surface roughness and moisture
Sentinel-2	multispectral satellite	2022, 2023	NMDI (Normalized Multi-band Drought Index) cv	heterogeneity of photosynthetic activity with sensitivity to drought stress
GEDI, Sentinel-1, Sentinel-2	spaceborne Lidar, radar satellite, multispectral satellite	2022, 2023	rh95 (canopy height) cv, cover (total canopy cover) cv, agbd (above-ground biomass density) cv	heterogeneity of vertical and horizontal structure (rh95, agbd), cover and openness (cover)

7.1.2 In-situ Biodiversity Measurements

In-situ biodiversity measurements comprise a range of taxonomic diversity calculations for various taxa. For bats, birds, gastropods, hoverflies, insects, moths, spiders, and trees taxonomic diversity was calculated for different orders of q (Hill numbers: 0 = species richness, 1 = Shannon diversity, 2 = Simpson diversity). Species richness is sensitive to rare species since all species count equally, i.e. not considering their relative abundance. Shannon diversity quantifies the diversity of common species since it is based on abundances. The diversity of dominant species is calculated as Simpson diversity which "disproportionately favors individuals of abundant species" (Chao et al., 2023). The calculation of taxonomic diversity was conducted in accordance to Chao et al. (2023) using rarefaction to quantify sample coverage (an objective measure of sample completeness), and then standardizing the diversity to the same sample coverage for all communities by inter- or extrapolation (Hsieh et al., 2016).

The biodiversity data (Table 7.2, Figure 7.1) is for most taxa available for all patches of three regions (Bavarian forest, Passau, University forest) of the BETA-FOR project (n patches = 180, section 3.3). Only for bats (n = 5) and birds (n = 1), few patches are missing due to errors during sampling or preparation of samples. The biodiversity measurements were conducted between April and September for both 2022 and 2023 (except for the tree inventory) in order to sample all patches. Therefore, the analysis of biodiversity data is based on pooled samples of the respective years.

Table 7.2: Overview of biodiversity measurements. For each taxa the three orders (q) of taxonomic diversity were calculated: 0 = species richness, 1 = Shannon diversity, 2 = Simpson diversity. Abbreviation: DBH (Diameter at Breast Height). Selected data sets are shared via Zenodo, an open science data repository commissioned by the European Commission (European Organization For Nuclear Research and OpenAIRE, 2013).

Taxa	Year	Patches (n)	Sampling	Reference
Bats	2022, 2023	175	bat recorder	10.5281/zenodo.14766335
Birds	2022, 2023	179	sound recorder	-
Gastropods	2022, 2023	180	pitfall traps, leaf litter samples, deadwood samples	10.5281/zenodo.14989540
Hoverflies	2022, 2023	180	pan traps	-
Insects	2022, 2023	180	Malaise traps	-
Moths	2022, 2023	180	light trapping	10.5281/zenodo.14282140
Spiders	2022, 2023	180	pitfall traps	10.5281/zenodo.14766448
Trees	2016-2023	180	ground-based tree species identification (DBH >= 7 cm)	10.5281/zenodo.15102200

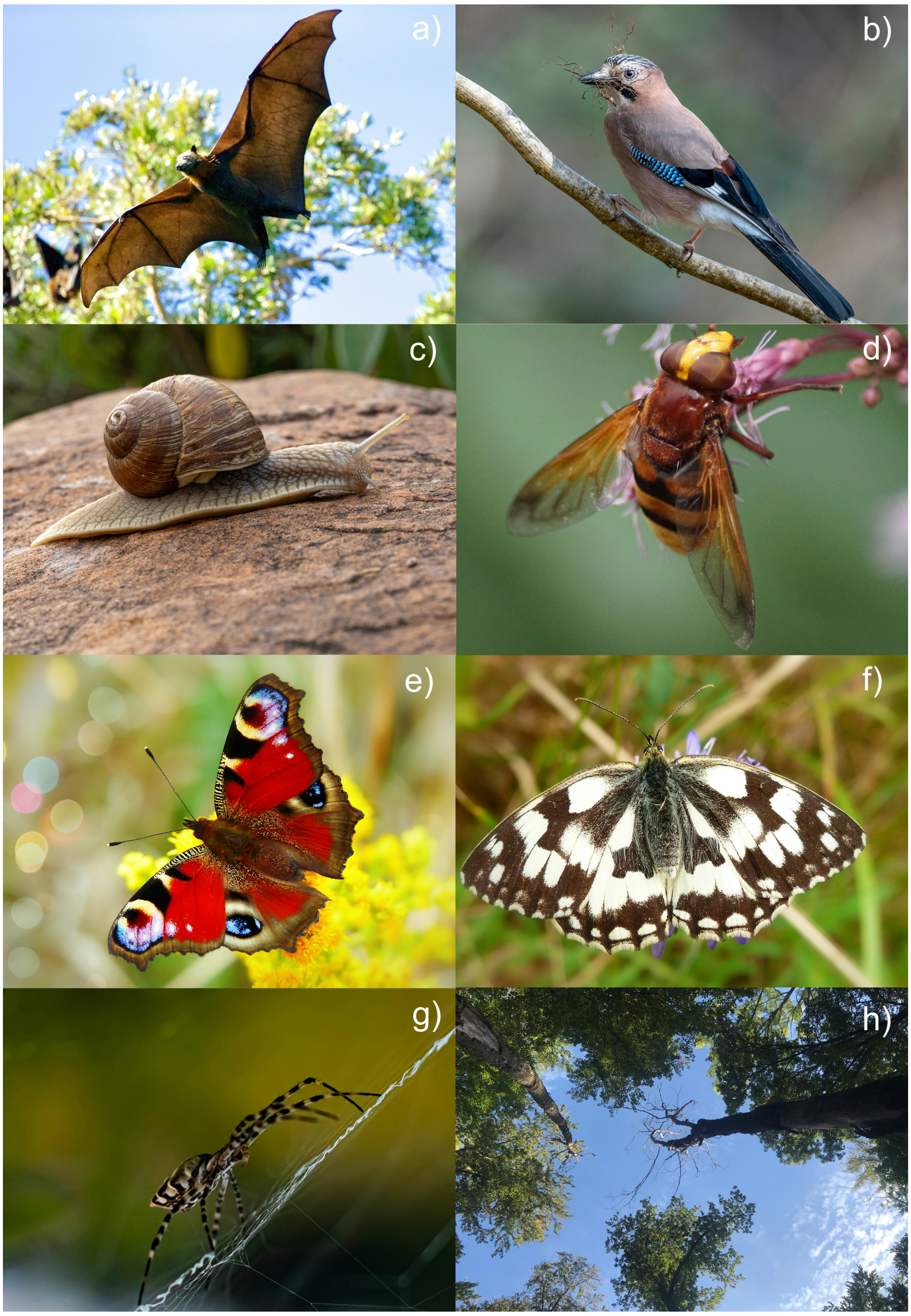

Figure 7.1: Exemplary photos of taxa (biodiversity measurements): bats (a), birds (b), gastropods (c), hoverflies (d), insects (e), moths (f), spiders (g), trees (h).

7.2 Methodological Approach

The following analyses aim to assess if forest structure indicators derived from multi-sensor spaceborne data can characterize the forest structural differences among experimental silvicultural treatments (aggregated and distributed cuttings) and control treatments (unaltered conditions) across multiple forest regions in Germany. In a second step, the spaceborne indicators of forest structure are linked to biodiversity measurements which are available for three regions. Therefore, correlations are investigated at the α-scale (diversity of local communities at patch-level, section 2.2) to better understand forest structure-biodiversity relationships, i.e. which biodiversity measurements are sensitive to the forest structural characteristics derived from spaceborne data.

7.2.1 Characterizing Forest Structure based on Spaceborne Indicators

The characterization of forest structure based on spaceborne indicators is making use of explorative statistics visualized as boxplots. Therefore, the forest structural conditions of control treatments from aggregated and distributed treatments are compared. For each region site of the BETA-FOR project (n = 11, section 3.3) the structural differences are shown in order to assess regional effects. The statistics are depicted for the spaceborne sensor which holds most strongest correlations to biodiversity measurements for a better understanding of the following analyses.

7.2.2 Assessing Relationships among Spaceborne Forest Structure Indicators and In-situ Biodiversity Measurements

Relationships among spaceborne forest structure indicators and in-situ biodiversity measurements are assessed using linear correlation analyses. First, absolute values of Pearson's correlation coefficient (|r|) are investigated per taxa stratified by "all regions" (Bavarian forest, Passau, University forest; n patches = 180), "Bavarian forest" (n patches = 72), and "University forest" (n patches = 90). Those analyses are carried out for each order of taxonomic diversity in order to assess regional effects for species richness, Shannon index, and Simpson index of taxonomic diversity separately. In the following, absolute values of Pearson's correlation coefficient (|r|) are analyzed as direct comparison of the different orders of taxonomic diversity based on data across all available regions. For each analysis, the spaceborne indicator of forest structure is shown holding the strongest correlation to the respective taxa and order of taxonomic diversity, thus serving as best predictor from the pool of calculated spaceborne indicators. All spaceborne indicators of forest structure characterize high structural heterogeneity as high values which is why the direction of correlations (positive and negative) serves as reference of increasing or decreasing taxonomic diversity.

7.3 Results

The results section is sub-divided into two sections according to the methodological analyses of section 7.2. First, the forest structure across all regions (n = 6) based on spaceborne indicators is characterized in order to assess the potential to consistently delineate the different treatment groups (control, distributed, aggregated) across multiple regions (section 7.3.1). In the following section, the relationships among spaceborne forest structure indicators and in-situ biodiversity measurements are analyzed using correlation statistics (section 7.3.2).

7.3.1 Forest Structure across Regions based on Spaceborne Indicators

In the following, the forest structure across all BETA-FOR regions based on spaceborne indicators is shown using Sentinel-2 time-series data. The forest structure indicators derived from Sentinel-2 were chosen because they hold most strong correlations to the biodiversity measurements. In addition, the Sentinel-2 time-series data is available for all four seasons whereas the modeled forest structure attributed derived from GEDI are only available for the summer period. Nevertheless, previous comparative analysis of spaceborne indicators have found moderate to strong correlations among Sentinel-2 to Sentinel-1 and modeled GEDI derived indicators (section 6.3.2). The following figures depict forest structural heterogeneity measured from Sentinel-2 data as NMDI cv per patch grouped by season (winter, spring, summer, autumn) in order to assess the dynamics of forest structural heterogeneity in the context of phenological changes.

Figure 7.2 shows the forest structural heterogeneity for averaged winter conditions of 2022 and 2023 across region sites. For all region sites, except Lübeck (L11), the forest structural heterogeneity was highest according to mean values for aggregated in comparison to control and distributed treatments. Overall, there are minor differences among control and distributed treatments with slightly higher forest structural heterogeneity for distributed treatments.

The forest structural heterogeneity for spring (Figure 7.3) holds lower maximum values and overall lower values for the different treatment groups in comparison to winter conditions. Nevertheless, control and aggregated treatments are clearly separated, the latter characterized by increased forest structural heterogeneity. The region sites of the University forest and Passau present higher forest structural heterogeneity quantified as mean ($>= 0.07$) per region sites compared to the aggregated treatments of other region sites (< 0.07).

The summer conditions of forest structural heterogeneity present little differences to spring conditions, except for the region sites of the Bavarian forest (Figure 7.4). There is a strong increase in forest structural heterogeneity for distributed and aggregated treatments. Based on summer observations of Sentinel-2 NMDI cv there is a clear separation of control to distributed treatments, as well as of distributed to aggregated treatments with control treatments holding lowest forest structural heterogeneity and aggregated treatments pre-

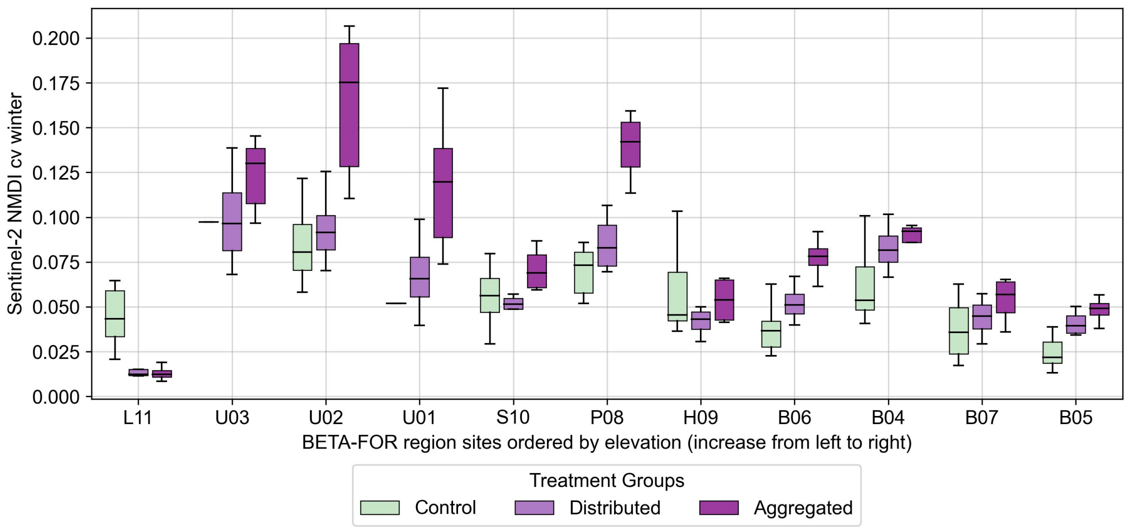

Figure 7.2: Sentinel-2 NMDI coefficient of variation (cv) of winter averaged for 2022 and 2023 across BETA-FOR region sites. The first letter of the BETA-FOR region sites serves as reference to the region: L (Lübeck), U (University forest), S (Saarland), P (Passau), H (Hunsrück), B (Bavarian forest). Please find more information about the BETA-FOR regions in section 3.3.

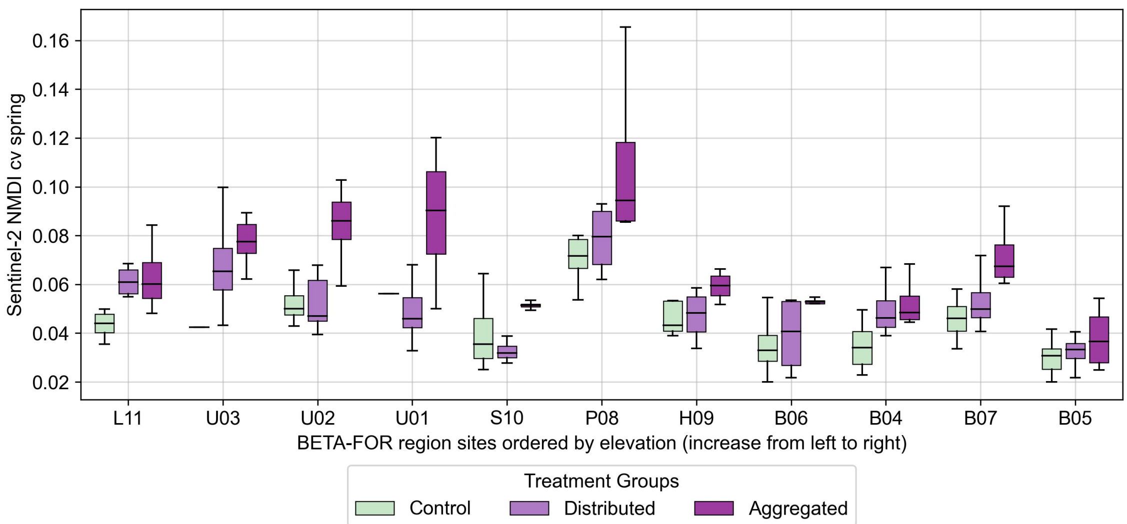

Figure 7.3: Sentinel-2 NMDI coefficient of variation (cv) of spring averaged for 2022 and 2023 across BETA-FOR region sites. The first letter of the BETA-FOR region sites serves as reference to the region: L (Lübeck), U (University forest), S (Saarland), P (Passau), H (Hunsrück), B (Bavarian forest). Please find more information about the BETA-FOR regions in section 3.3.

senting highest forest structural heterogeneity in the Bavarian forest. For the other regions, control and distributed treatments cannot be clearly delineated, only aggregated treatments are characterized by highest forest structural heterogeneity. Overall, summer conditions of forest structural heterogeneity hold the lowest maximum values across regions for the four seasons, i.e. not exceeding 0.13.

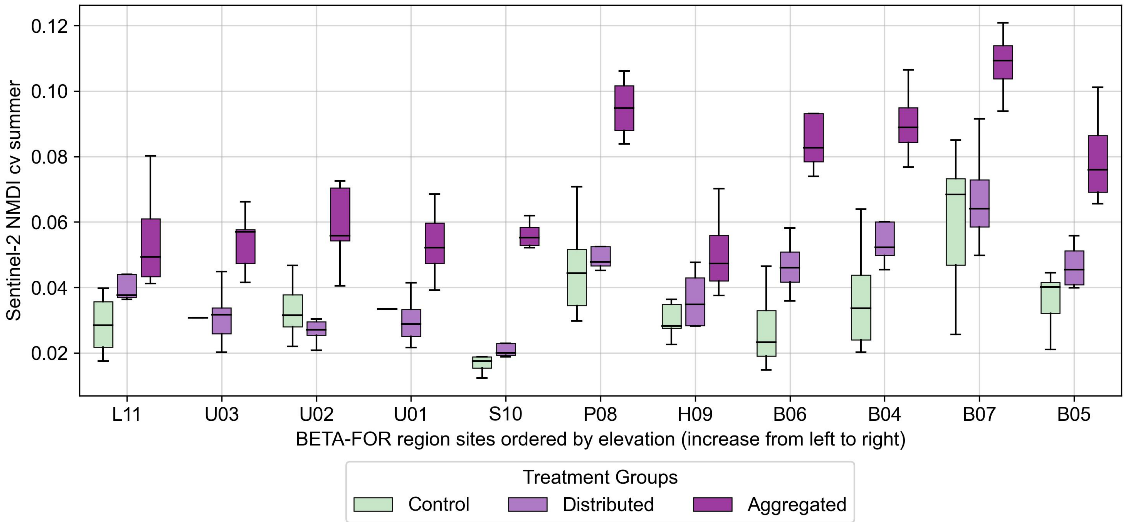

Figure 7.4: Sentinel-2 NMDI coefficient of variation (cv) of summer averaged for 2022 and 2023 across BETA-FOR region sites. The first letter of the BETA-FOR region sites serves as reference to the region: L (Lübeck), U (University forest), S (Saarland), P (Passau), H (Hunsrück), B (Bavarian forest). Please find more information about the BETA-FOR regions in section 3.3.

The forest structural heterogeneity of autumn conditions shows the most clear separation of the three treatment groups across region sites based on Sentinel-2 NMDI cv data (Figure 7.5). In comparison to summer conditions, there are strong increases in forest structural heterogeneity for aggregated treatments of the University forest. In addition, maximum values assessing the gain in forest structural heterogeneity from summer to autumn conditions are greater than 0.175. Compared to winter conditions, the differences among treatment groups are more distinct based on autumn data.

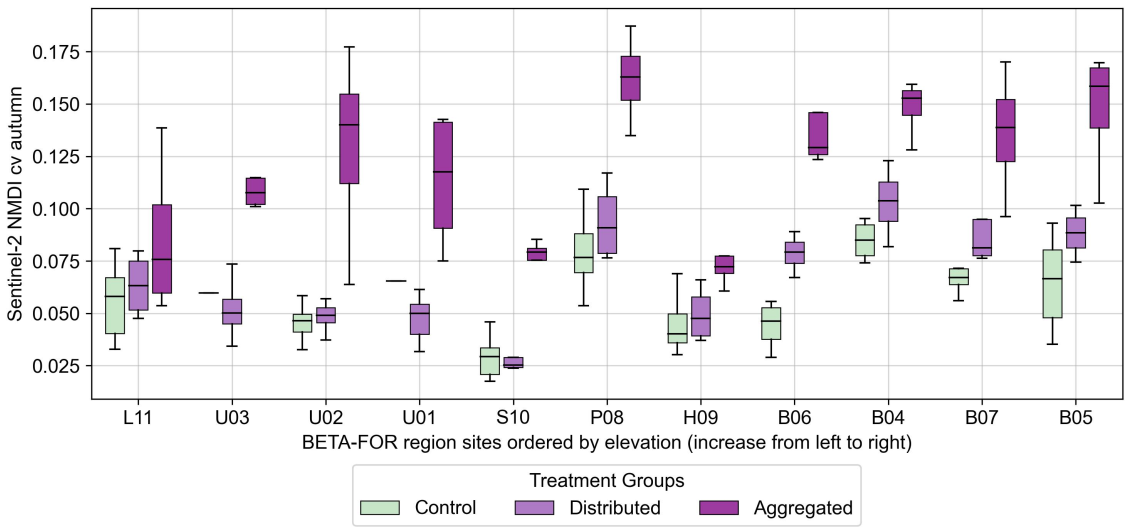

Figure 7.5: Sentinel-2 NMDI coefficient of variation (cv) of autumn averaged for 2022 and 2023 across BETA-FOR region sites. The first letter of the BETA-FOR region sites serves as reference to the region: L (Lübeck), U (University forest), S (Saarland), P (Passau), H (Hunsrück), B (Bavarian forest). Please find more information about the BETA-FOR regions in section 3.3.

7.3.2 Relationships among Spaceborne Forest Structure Indicators and In-situ Biodiversity Measurements

The correlation analysis to assess relationships among spaceborne forest structure indicators and in-situ biodiversity measurements was on the one hand conducted separately per order of taxonomic diversity and by distinguishing among relationships among all regions and the two focus regions of the BETA-FOR project (Bavarian forest, University forest). On the other hand, the findings are summarized as relationships among all considered regions (biodiversity measurements are available for the Bavarian forest, Passau, University forest) stratified by the three orders of taxonomic diversity. Therefore, spaceborne indicators of forest structure are identified which hold strongest correlations to the three orders of taxonomic diversity per taxa.

Figure 7.6 depicts the correlation analysis of spaceborne indicators of forest structural heterogeneity to species richness (q = 0, sensitivity to rare species) of different taxa. Strongest correlations across all regions are present for gastropods and insects reaching absolute correlations values of greater than 0.5. The species richness of hoverflies and tree species across all regions amounts to absolute correlations values of more than 0.4. Lowest absolute correlation values across all regions are found for bats, birds, and spiders. For most taxa, the regional differences in correlation to the average across all regions amount to less than 0.1. Only for tree species richness, there are stronger regional effects. Overall, Sentinel-2 NMDI cv observations hold most of the strongest identified correlations per taxa. For the two most strongest relationships which were identified across all regions (gastropods, insects), it is the Sentinel-2 NMDI cv winter indicator that reaches highest correlations. All aforementioned relationships are positive, i.e. the increase in forest structural heterogeneity quantified by spaceborne indicators is aligned with a gain in taxonomic diversity (species richness).

In general, the correlation analysis of spaceborne indicators and Shannon diversity quantifying the taxonomic diversity of common species (Figure 7.7) shows a similar result for most taxa as found for species richness (Figure 7.6). Across all regions, gastropods reach the highest absolute correlation value ($|r| = 0.53$ with Sentinel-2 NMDI cv winter), followed by birds ($|r| = 0.52$ with Sentinel-2 NMDI cv winter). Strong regional effects are found for insects since an absolute correlation coefficient value greater than 0.65 (with Sentinel-2 NMDI cv autumn) was found for the Bavarian forest. For hoverflies and insects the absolute correlation values amount to greater than 0.4 across all regions. Overall, the strongest correlations among all taxa across all regions were present for birds, gastropods, hoverflies, and insects with the direction of correlation being always positive. Therefore, the increase of forest structural heterogeneity measured by spaceborne indicators is related to an enhancement of taxonomic diversity of aforementioned taxa.

The correlation analysis of dominant species (Simpson diversity) of various taxa to spaceborne indicators of forest structure reveals that regional differences increased for the taxa reaching highest absolute correlations values across all regions: for hoverflies (with GEDI cover cv summer) and insects (with Sentinel-2 NMDI cv autumn) values of greater than 0.55 are reached for the Bavarian forest in comparison to values around 0.4 across all regions. For gastropods, the highest absolute correlation value is present across all regions (with Sentinel-2 NMDI cv winter). Similar to the findings of species richness (Figure 7.6) and Shannon diversity (Figure 7.7), also for Simpson diversity, the strongest identified correlations are positive.

Previous correlation analyses have identified birds, gastropods, hoverflies, and insects as being most sensitive to spaceborne indicators of forest structure. Nevertheless, regional effects, as well as differences in the correlations among the three orders of taxonomic diversity were found. Figure 7.9 summarizes the correlation statistics as an overview of correlations identified across all regions. Therefore, the general potential of spaceborne indicators of forest structure as surrogates for the taxonomic diversity of rare, common, and dominant species of various taxa is assessed. All correlations greater than 0.5 are positive: species richness of birds with Sentinel-2 NMDI cv winter, all three orders of taxonomic diversity of gastropods with Sentinel-2 NMDI cv winter, and species richness of insects with

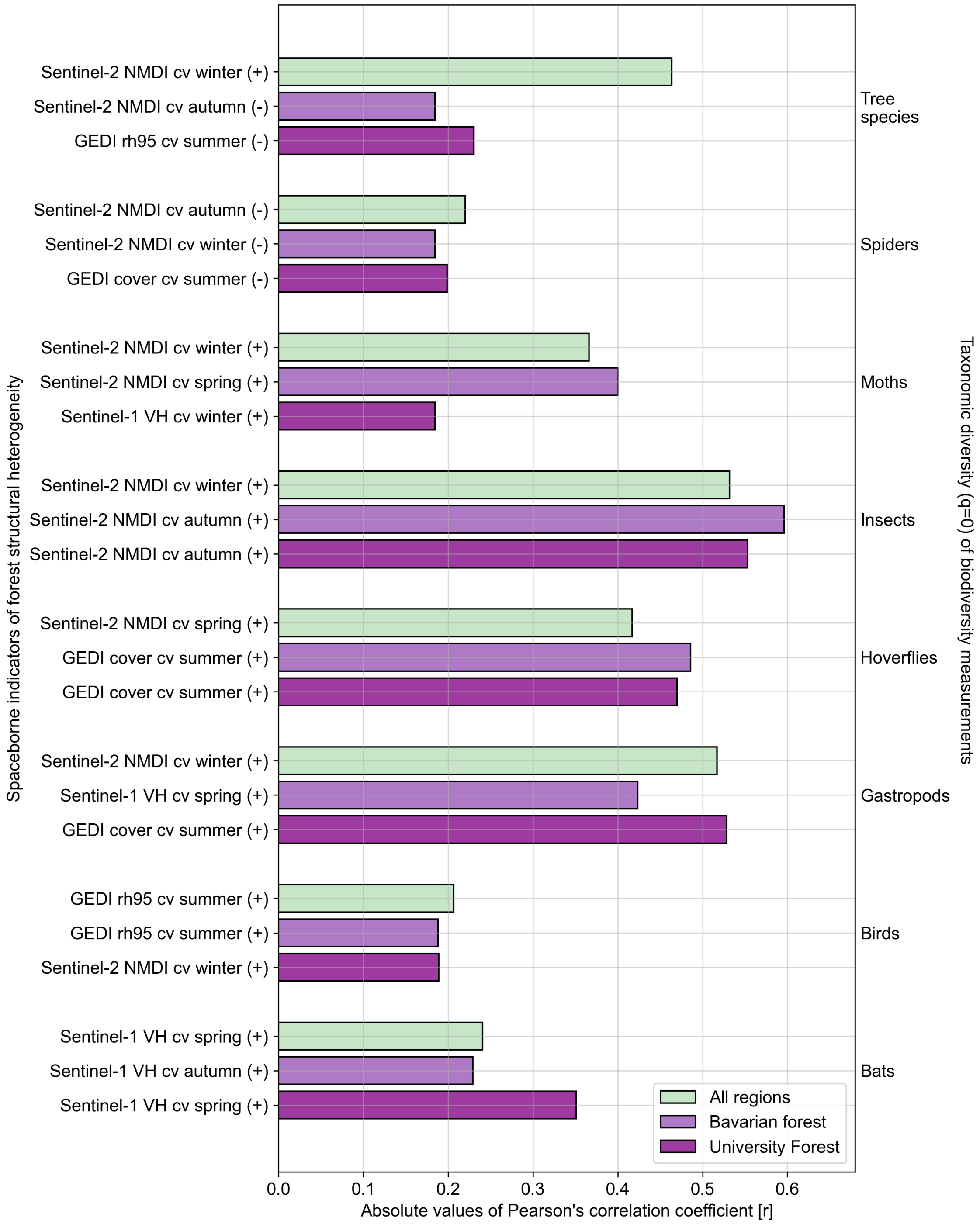

Figure 7.6: Correlation analysis of spaceborne indicators of forest structure with highest absolute correlation values to biodiversity measurements (q = 0, species richness). The heterogeneity of spaceborne indicators was calculated as patch-level coefficient of variation (cv). The direction of correlations, i.e. positive (+) and negative (-), are depicted for each spaceborne indicator on the y-axis.

Sentinel-2 NMDI cv winter. Strongest differences among the different orders of taxonomic diversity were found for birds since species richness amounts to about 0.2 in comparison to Shannon and Simpson diversity reaching values greater than 0.47. The diversity of tree

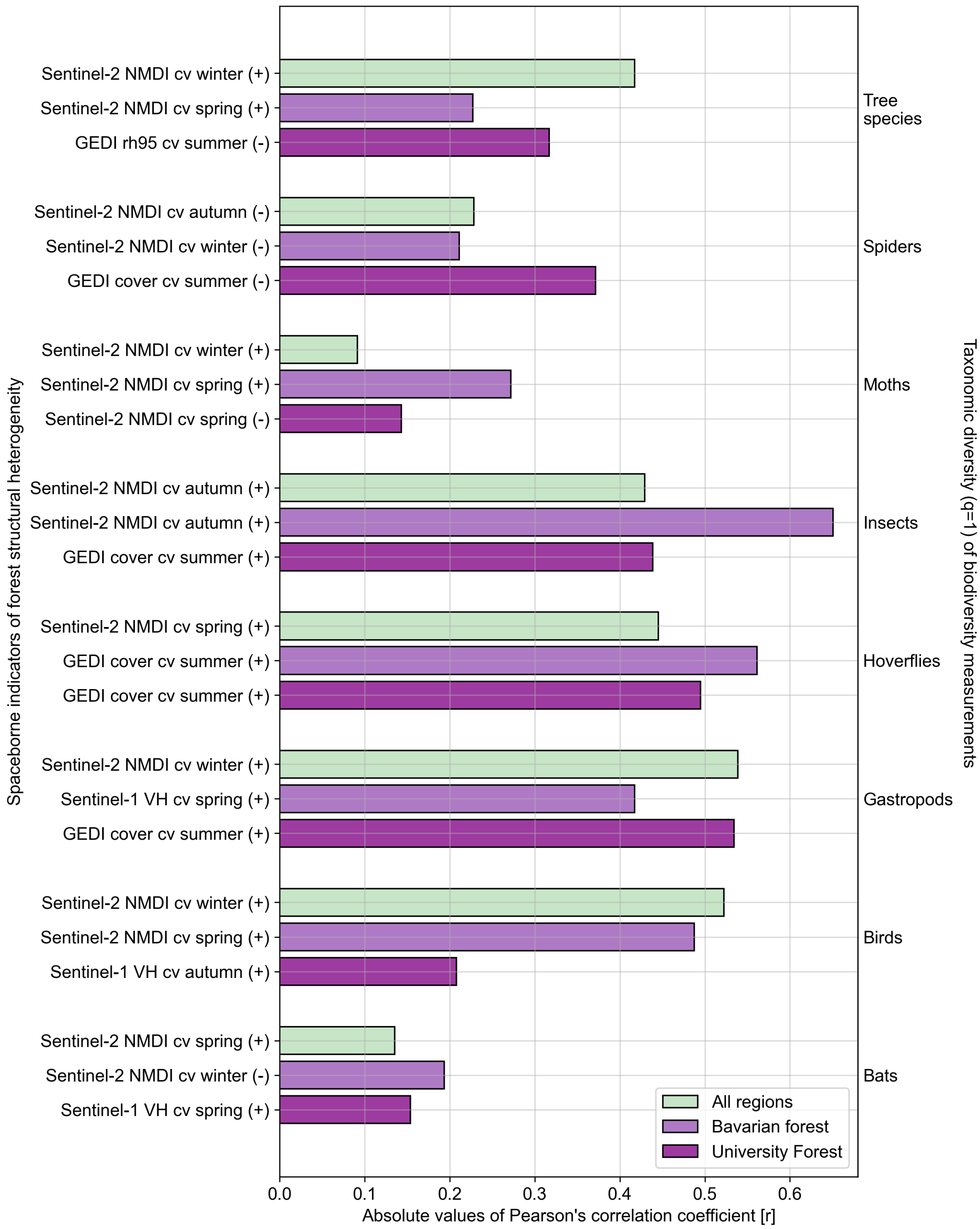

Figure 7.7: Correlation analysis of spaceborne indicators of forest structure with highest absolute correlation values to biodiversity measurements (q = 1, Shannon diversity). The heterogeneity of spaceborne indicators was calculated as patch-level coefficient of variation (cv). The direction of correlations, i.e. positive (+) and negative (-), are depicted for each spaceborne indicator on the y-axis.

species is most strongly related to Sentinel-2 NMDI cv winter since correlations for all orders of taxonomic diversity are around 0.4. Lowest correlations were identified for bats, moths, and spiders: independent of the order of taxonomic diversity, absolute correlation values are lower than 0.4.

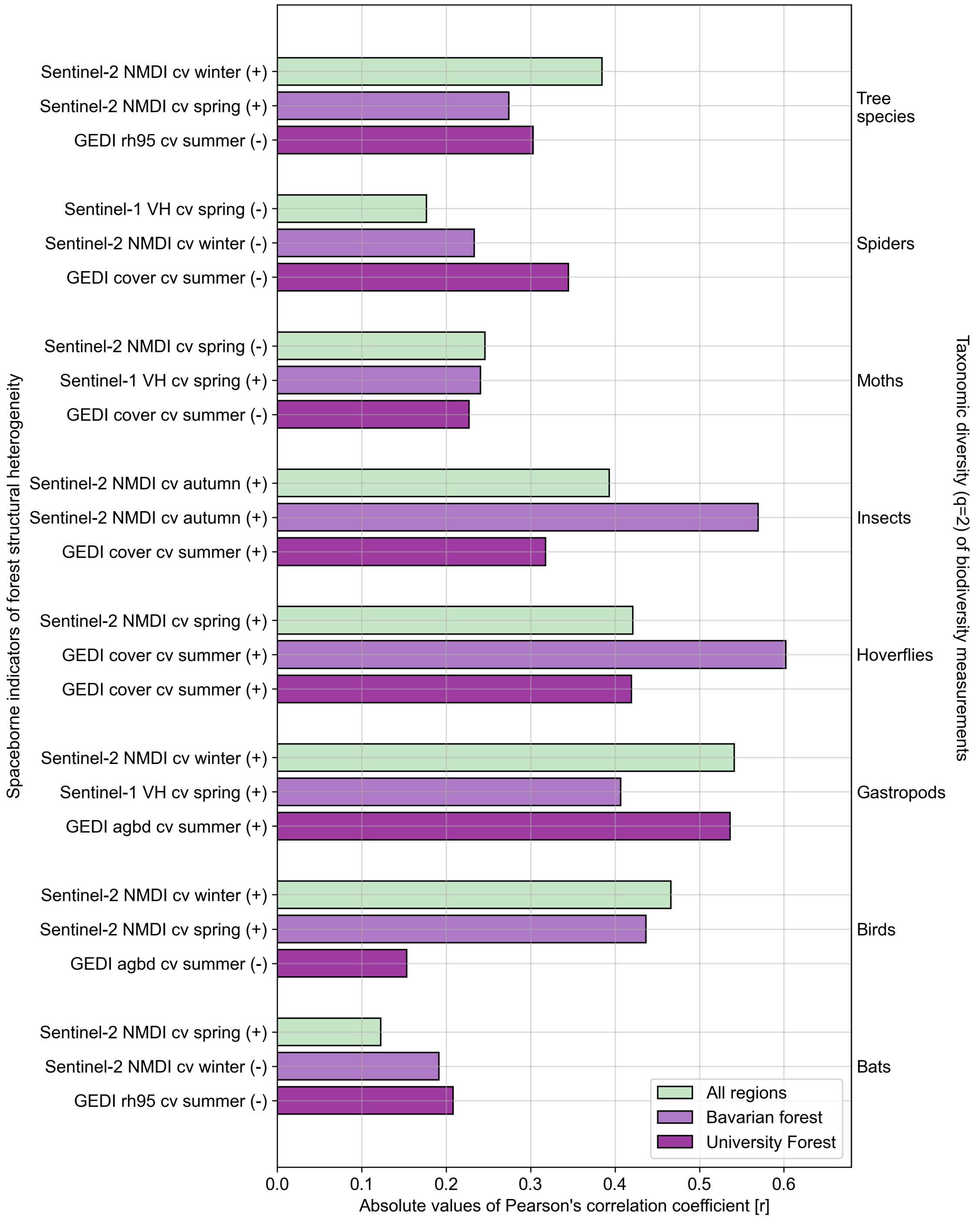

Figure 7.8: Correlation analysis of spaceborne indicators of forest structure with highest absolute correlation values to biodiversity measurements (q = 2, Simpson diversity). The heterogeneity of spaceborne indicators was calculated as patch-level coefficient of variation (cv). The direction of correlations, i.e. positive (+) and negative (-), are depicted for each spaceborne indicator on the y-axis.

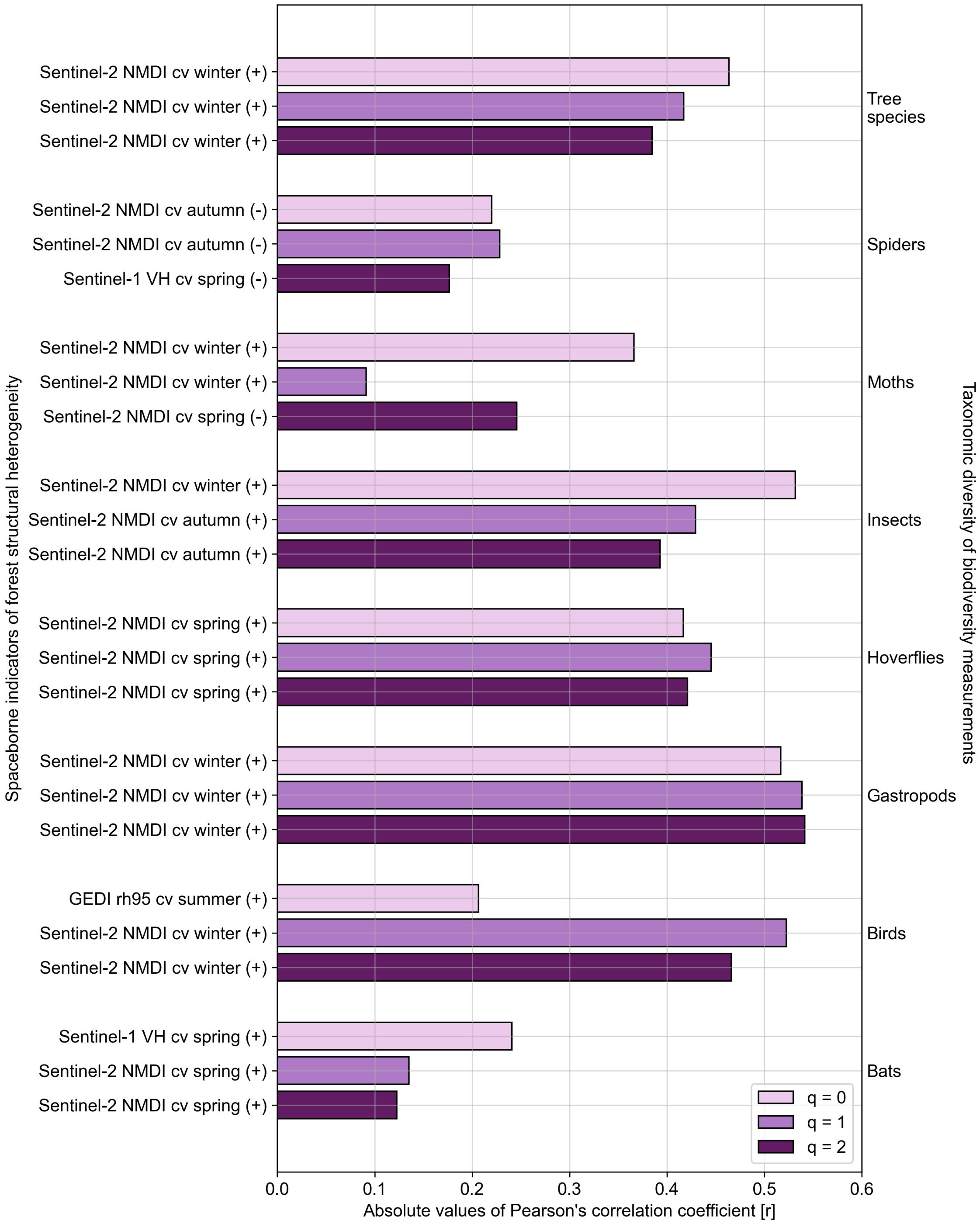

Figure 7.9: Correlation analysis of spaceborne indicators of forest structure with highest absolute correlation values to biodiversity measurements. Biodiversity measurements are characterized for different orders of q (taxonomic diversity): 0 = species richness (sensitive to rare species), 1 = Shannon diversity (sensitive to common species), 2 = Simpson diversity (dominant species). The heterogeneity of spaceborne indicators was calculated as patch-level coefficient of variation (cv). The direction of correlations, i.e. positive (+) and negative (-), are depicted for each spaceborne indicator on the y-axis.

7.4 Discussion

The discussion section aims to elaborate on the forest structure-biodiversity relationships which were assessed in the present study on the basis of spaceborne indicators of forest structure and in-situ biodiversity measurements (section 7.4.1). In the following, forest structure-biodiversity relationships which were identified across temperate forests are discussed in the context of forest management practices.

7.4.1 Assessing Forest Structure-Biodiversity Relationships Using Spaceborne Indicators

Characterizing forest structure is relevant for the assessment of forest habitats, thus being related to forest biodiversity according to identified structure-biodiversity relationships (Storch et al., 2023; Uhl et al., 2024; Zeller et al., 2023). The potential to measure forest structure at national (chapter 4) to local level (chapter 5, 6) using spaceborne data has been investigated in previous chapters. The comparative analyses of spaceborne and in-situ remote sensing indicators of forest structural complexity (chapter 6) have demonstrated the application of spaceborne indicators of forest structure as surrogates of indicators derived from close-range sensing techniques (MLS, TLS). Moderate to strong correlations were found among in-situ and spaceborne indicators. In addition, the indicators of forest structural heterogeneity based on spaceborne sensors hold moderate to strong correlations among each other as well (section 6.3.2). In the present study, the differences in forest structure among control, distributed, and aggregated treatments were in most cases characterized accurately by e.g. Sentinel-2 indicators (section 7.3.1). Therefore, the increase in forest structural heterogeneity from control to distributed and aggregated treatments was confirmed by spaceborne indicators across-regions (n = 6, e.g. Figure 7.5).

Forest structure-biodiversity relationships using spaceborne data (indicators of structural heterogeneity) and taxonomic diversity (various biodiversity measurements) were hypothesized since experimental silvicultural treatments have led to an enhancement of structural complexity. The potential of spaceborne indicators to characterize the differences in forest structure of control, distributed, and aggregated treatments was confirmed. Therefore, the increase in forest structural heterogeneity (quantified by spaceborne indicators) might promote multi-taxa diversity due to the implementation of experimental silvicultural treatments. Overall, biodiversity measurements are expected to be sensitive to the enhancement of forest structural complexity because of the diversification of light conditions and deadwood creation (habitat heterogeneity hypothesis, Cramer and Willig (2005); Mueller et al. (2022a,b)).

Strongest correlations (|r| > 0.4) across-regions were identified for common and dominant species of birds, rare and common tree species, as well as rare, common, and dominant species of gastropods, hoverflies, and insects. Regional effects were strongest among common birds species of the Bavarian forest and the University forest. Similarly, increased correlations among common insects and forest structure indicators were found for the Bavarian forest in comparison to the University forest. Dominant species of hoverflies and insects hold distinct regional differences among the Bavarian forest and the University forest, with the first holding higher correlations to spaceborne forest structure heterogeneity indicators.

Seasonal information on forest structure from Sentinel-2 NMDI cv, i.e. the heterogeneity of photosynthetic activity, was found to best most informative for the assessment of forest biodiversity since stronger correlations (|r| > 0.4) compared to the other indicators of forest structure were achieved for multiple taxa: rare and common birds (winter observations), rare, common and dominant gastropods (winter observations), rare, common, and dominant hoverflies (spring observations), rare and common insects (winter and autumn observations), as well as rare and common tree species (winter observations). In comparison to previous studies on forest biodiversity modeling solely integrating remote sensing data from a single sensor (e.g. Drag et al. (2023); Heidrich et al. (2020, 2023); Müller et al. (2018); Parisi et al. (2023)), the present study provides novel insights on the different potentials of spaceborne sensors for biodiversity monitoring through the integration of spaceborne Lidar (GEDI), as well as satellite radar (Sentinel-1) and multispectral (Sentinel-2). Multispectral time-series information of Sentinel-2 was identified as best predictor for multiple taxa (birds, gastropods, hoverflies, insects, and tree species) suggesting that information on the heterogeneity of photosynthetic activity is more relevant for the characterization of forest habitats of aforementioned species than the heterogeneity of surface structure (Sentinel-1) or vertical and horizontal structural information (modeled GEDI). This finding is aligned with the study of Parisi et al. (2023) identifying relationships among Sentinel-2 time-series indicators and the taxonomic diversity of beetles, birds and lichens in Italian beech forests. Previous studies on the prediction of multi-taxa diversity (e.g. Bae et al. (2019); Drag et al. (2023); Heidrich et al. (2020, 2023); Müller et al. (2018)) demonstrated the potential of airborne Lidar data. Since in the present study, modeled attributes of forest structure from spaceborne Lidar data of GEDI did not reach as high correlations as satellite multispectral indicators, there might be a scale dependency because spaceborne Lidar data captures structural characteristics as an aggregation of a 25 m footprint. In contrast, airborne Lidar derived indicators of forest structure hold e.g. 1 m spatial resolution (Drag et al., 2023), thus capturing more precise measurements (Morsdorf et al., 2018). In addition, modeling uncertainty from the derivation of forest structural attributes as continuous data might influence the characterization of small-scale structural heterogeneity (Kacic et al., 2023). Bae et al.

(2019) revealed that satellite radar indicators (ordination of several time-series metrics) of forest structure can reach similar accuracies when modeling multi-taxa diversity in German mixed forests compared to airborne Lidar. Although Sentinel-1 VH cv holds moderate to strong correlations ($|r| >= 0.5$) to the other spaceborne indicators (section 6.3.2), the correlation analyses of forest structure-biodiversity relationships of the present study indicate a higher performance of Sentinel-2 over Sentinel-1 indicators.

7.4.2 Forest Structure-Biodiversity Relationships in Temperate Forests: The Influence of Management

Forest management alters structural conditions in many different ways, depending on the area of tree removal (e.g. small-scale interventions compared to salvage logging of forest landscapes), the spatial arrangement of cuttings (e.g. distributed or aggregated cuttings), as well as the frequency of silvicultural practices (e.g. multi-annual in comparison to multi-decadal interventions). Aforementioned silvicultural practices strongly influence the development of tree age structures: Mohr et al. (2024) revealed that uneven-aged forests in comparison to even-aged forests hold more than 30 % lower disturbances rates in combination with reduced frequency (about 36 % lower), and maximum disturbance patch sizes (about 16 % lower). Therefore, uneven-aged forests have an increased potential to better cope with expected future increase of natural forest disturbances (Altman et al., 2024). Nevertheless, the relationships of forest disturbance rates, frequency, and intensity to forest structure of past observations might be modified by future climate change conditions. In addition, forest management not only influences the age-structure of forests, but also the understory functional structure: specifically intensive silvicultural practices (e.g. clearcutting, coppice with standards) cause a decline in functional diversity, as well as a gain in functional redundancy. As a conclusive statement, the authors stress that different silvicultural regimes (e.g. unmanaged, selection cutting, shelterwood) need to be developed at the landscape-scale in order to address the multifaceted aspects of forest biodiversity which can be promoted through specific management techniques (Chianucci et al., 2024). Dieler et al. (2017) noted that forest stand management has negative impacts on the amount of deadwood, the availability of ecological niches, as well as diversity of tree sizes (vertical and horizontal structure).

The review by Zeller et al. (2023) provides a comprehensive overview on the relationships of forest structure and forest biodiversity (species richness of different taxa) for temperate forests: The authors found small-scale canopy openings in combination with structural characteristics often present in primary forests as key structural characteristics that promote different species groups (e.g. arthropods, lichens, bryophytes, birds, fungi, and vascular plants). The following structural attributes hold most positive correlations to species richness of different species groups: "gaps - light", "deadwood - diversity", "tree species richness", "stand age", "tree species - oak", "share of old growth", and "diameter - big old trees". Most positive effects of "gaps - light" were identified for arthropods, lichens, and vascular plants. The diversity of deadwood is most highly correlated to the species richness of both arthropods and fungi. Tree species richness has most pronounced influences (positive) on bryophytes and birds. The stand age is very important for lichens, whereas the "share of old growth", as well as the "diameter - big old trees" is closely related to both lichens and birds. Storch et al. (2023) found that forest structure attributes are best predictors for species richness of aves, formicidae, and vascular plants, thus being aligned with findings by Zeller et al. (2023). The present study identified relationships for species richness ($q = 0$) of gastropods, hoverflies, insects, and tree species in the context of increased forest structural heterogeneity which is predominantly driven by aggregated treatments ("gaps - light", e.g. Figure 7.5). In contrast to the studies by Storch et al. (2023) and Zeller et al. (2023), the present analyses did not confirm a linkage of improved bird species richness and increasing forest structural heterogeneity. A relationship ($r > 0.4$) was only identified for common ($q = 1$), as well as dominant bird species ($q = 2$). This finding highlights the need to characterize taxonomic diversity of species groups not only as species richness ($q = 0$), which was the data basis for Storch et al. (2023) and Zeller et al. (2023), but also consider higher orders of taxonomic diversity, as investigated by the present study. Therefore, effects of forest structure on rare, common, and dominant species can be disentangled.

The present study was conducted in the context of an integrative concept for biodiversity and functionality (section 3.3): a patch-network of experimental silvicultural treatments was established across multiple regions of German broad-leaf dominated forests in order to enhance forest structural complexity. Aggregated and distributed cuttings in combination with different deadwood structures aim to diversify light and temperature conditions in the air and on the ground, as well as a provision of habitats for light- and deadwood-dependent species. Furthermore, specifically aggregated treatments can support increased diversity in future age-structures of forests (Mueller et al., 2022a,b). Therefore, this concept has the potential to promote forest biodiversity and multifunctionality through structural changes, thus proposing additional pathways to recent popular approaches (e.g. manipulation of tree species composition).

7.5 Summary

Experimental silvicultural treatments have the potential to diversify light conditions and generate additional deadwood structures in order to enhance forest structural complexity. Aggregated and distributed treatments, i.e. different arrangements of cuttings, have led to more heterogeneous forest structures in the study regions of the present study (section 3.3). The controlled experimental design provides the opportunity to study the relationship of forest structure and forest biodiversity. More precisely, spaceborne indicators of forest structure were calculated to assess correlations to multi-taxa diversity. The analysis of forest structure-biodiversity relationships synthesizes the findings presented in previous chapters: development of a novel modeling framework to derive multi-annual forest structure products for Germany (chapter 4), implementation of a new methodological approach using satellite time-series analyses to identify metrics best assessing forest structure changes through silvicultural management (chapter 5), and comparative analysis of spaceborne and in-situ remote sensing indicators of forest structural complexity for an improved understanding of cross-platform and -sensor characteristics (chapter 6).

Satellite time-series demonstrate that differences among control (unaltered forest structure), distributed (selective thinning), and aggregated treatments (gap felling) can be assessed across the six study regions in Germany (section 7.3.1). Therefore, the assessment of forest structural heterogeneity, which is lowest in control treatments and further increases from distributed to aggregated treatments, can be quantified using spaceborne indicators of forest structure, thus confirming the experimental treatment design. In addition to satellite time-series metrics best assessing the changes in forest structure (chapter 5) through the implementation of experimental silvicultural treatments (Sentinel-1 VH cv, Sentinel-2 NMDI cv), heterogeneity of modeled canopy height (GEDI rh95 cv), total canopy cover (GEDI cover cv), and above-ground biomass (GEDI agbd cv) data was considered (chapter 4). In-situ biodiversity measurements are available for three regions (n patches = 180) which were integrated for correlation analyses to the spaceborne indicators in order to quantify forest structure-biodiversity relationships in the context of experimental silvicultural treatments. Taxonomic diversity for rare, common, and dominant species was calculated for bats, birds, gastropods, hoverflies, insects, moths, spiders, and tree species. Linear relationships across the three regions were identified for multiple taxa using Pearson's correlation coefficients (r) reaching values greater than 0.4 for several taxa: birds, gastropods, hoverflies, insects, and tree species (section 7.3.2). Although regional effects exist, e.g. higher taxonomic diversity of common and dominant birds in the Bavarian forest compared to the University forest, forest structure-biodiversity relationships for gastropods, hoverflies, insects, and tree species hold across regions and across the three orders of taxonomic diversity (rare, common, dominant species).

The identified relationships of forest structure quantified by spaceborne data and in-situ biodiversity measurements of multi-taxa diversity are aligned with previous studies (e.g. Storch et al. (2023) and Zeller et al. (2023)) highlighting the linkages among forest structure and species richness of aves, birds, and vascular plants. The integration of three orders of taxonomic diversity data in the present study constitutes a novelty in comparison to previous studies solely integrating species richness (sensitive to rare species) as a measure of forest biodiversity. Furthermore, the cross-correlation of forest biodiversity data to multi-sensor spaceborne indicators of forest structure is another benefit of the present analysis, since sensor-dependent influences on forest structure-biodiversity relationships are assessed. Overall, the integration of time-series satellite data in combination with modeled attributes of forest structure derived from spaceborne Lidar demonstrates the potential of spaceborne data for forest structure and biodiversity monitoring. To conclude, the quantification of forest structure and relationships to multi-taxa diversity is an important task to support integrative forest management approaches aiming to improve forest biodiversity, and multifunctionality, thus benefiting future forest resilience.

Chapter 8

Synthesis and Outlook

This final chapter aims to synthesize the main findings on multi-sensor remote sensing of forest biodiversity. First, a summary and conclusive findings are provided by answering the overarching research questions of this dissertation (section 8.1). In the following, an outlook on future research directions of forest structure and forest biodiversity monitoring using spaceborne remote sensing data is given (section 8.2).

8.1 Summary and Conclusive Findings

Forest cover makes up about one third of the Earth's land surface and creates habitats for numerous animals and plants, but also provides ecosystem functions generating ecosystem services for human well-being. In Europe, the natural dominant forest type is a deciduous broad-leaved forest which is typical for temperate forests, e.g. dominated by European beech. Ecosystem functions of forests, such as carbon storage, habitat heterogeneity, or water filtration are depending on the structural characteristics of forests. In Germany, as well as in many other central European countries, silvicultural management since more than three centuries has altered the structure of natural forests, e.g. through timber harvest and plantations. As a result, forests are nowadays characterized by homogeneous structures, i.e. few tree species, age-class structures, and deadwood scarcity. The structural homogenization has multiple consequences: changing and degrading ecosystem services (e.g. carbon sequestration, temperature buffering), loss of forest biodiversity (reduction of habitat availability and heterogeneity), as well as increasing susceptibility towards disturbances (e.g. droughts, heatwaves) (section 1.1.1). Up-to-date continuous information on forest structure conditions and the influence of management practices are key requirements for the transformation of homogeneous to heterogeneous forest structures in order to support future forest resilience (section 1.1.3).

Continuous and multi-annual data on different forest structure attributes was not yet available, which is why one major objective of this dissertation was the development of a novel workflow using complementary spaceborne data to generate the first consistent and high spatial resolution products of forest canopy height, total canopy cover, and above-ground biomass density from 2017 to 2023 for Germany (chapter 4). In addition, assessing the potential of radar and multispectral satellite time-series to identify the enhancement of forest structural complexity through experimental silvicultural treatments was another objective of this dissertation (chapter 5). Furthermore, spaceborne indicators best characterizing the enhancement of forest structural complexity were correlated with in-situ remote sensing data to understand cross-platform and -sensor influences (chapter 6). Lastly, forest structure-biodiversity relationships were quantified to assess the potential of spaceborne indicators of forest structure as surrogates of taxonomic diversity of different species groups (chapter 7).

Overall, this dissertation aims to synthesize multi-sensor remote sensing data for forest structure and biodiversity characterization. The analyses were carried out in the context of an integrative approach of forest management through the implementation of experimental silvicultural treatments across multiple forest regions dominated by European beech in Germany: distributed and aggregated cuttings are means to enhance the structural complexity through diversification of light conditions, as well as the generation of different deadwood structures mimicking old-growth structures and potentially accelerating their evolution. Therefore, aforementioned objectives assess the potential of novel forest management practices to create more heterogeneous forests benefiting forest biodiversity.

To understand the current research status and identify research gaps of forest biodiversity monitoring with a focus on spaceborne remote sensing analysis, a systematic literature review was conducted. Overall, an improved understanding is needed on the quality and relevance of different methods to assess forest biodiversity. In addition, quantitative analyses on the integration of different remote sensing data characteristics, methodological concepts, and biodiversity aspects support the identification of best suited foci in terms of data, methods, and topics for enhanced monitoring of forest biodiversity. The research questions contextualized to this initial objective were as follows:

Research Questions - Objective 1:

1. How extensively has forest biodiversity monitoring based on remotely sensed spectral diversity been researched, and what are recent thematic and spatial foci?
2. What are typical data characteristics (sensors, temporal resolutions, spectral indices), methodological concepts, and biodiversity aspects (scales, environmental foci)?
3. Which research limitations and gaps are identified, and how can they potentially be investigated using spaceborne remote sensing data?

To answer those research questions, a systematic literature review was carried out comprising 109 studies (please find details in chapter 2). The reviewed studies were published between 2002 and 2022 holding a focus on forest biodiversity monitoring based on remotely sensed spectral diversity from spaceborne sensors. The review assesses information of study areas, methodological concepts, data characteristics, as well as thematic foci for all reviewed studies, thus providing structured information for the ongoing discussion on the validity of the SVH.

Since the initial publications on forest biodiversity monitoring using remotely sensed spectral diversity (as a surrogate of habitat heterogeneity being linked to species diversity) in 2002, an increasing number of studies were published until 2022. Most studies were published since 2016 with a growing share of inter-disciplinary studies: studies focusing on environmental sciences and remote sensing since 2016 amount to 22 studies (only 14 studies before 2016). There is a strong spatial foci on the United States and India. At the continental-scale most research was carried out for forests in Europe, followed by studies on Asian and North American forests (section 2.3).

Most reviewed studies conducted an analysis of multispectral data (about 70 % of all studies) to characterize spectral diversity based on mono-temporal observations. As a consequence, there is often a focus on a single sensor being sensitive to specific vegetation characteristics. Less than 17 % of the reviewed studies consider data other than optical imagery (multispectral and hyperspectral data). The integration of time-series data did not play a major role for studies before 2016, but since 2016 the number of time-series approaches increased in relevance (n = 13). In addition, the characterization of forest biodiversity has a strong focus on the alpha-diversity level (n = 93), i.e. local communities. Overall, the data of remotely sensed spectral diversity was in most studies correlated to floristic diversity measurements (93 % of all reviewed studies), e.g. tree species diversity. Relationships to faunistic diversity or a combination of floristic and faunistic diversity analyses remain understudied (section 2.3.1, section 2.3.2).

The systematic literature review highlights the importance of further inter-disciplinary research since forest structure-biodiversity relationships are influenced by spatio-temporal characteristics of remote sensing, as well as in-situ biodiversity data. The integration of multi-sensor remote sensing data holds a great future potential to better characterize different properties of vegetation, e.g. photosynthetic activity based on optical sensors, as well as structural properties using radar and Lidar data. Furthermore, decadal time-series data e.g. from Sentinel-1 and Sentinel-2 could further improve the understanding of inter- and intra-annual vegetation dynamics. In addition, the temporal stability of forest structure-biodiversity relationships can be explored using time-series data. Another informative data source from in-situ sampling would be faunistic diversity data in order to not only assess floristic diversity as a surrogate of forest biodiversity, but also faunistic patterns. As a consequence, the interplay of floristic and faunistic diversity could be further investigated, as well as the relationships to remote sensing data. To conclude, high spatio-temporal multi-sensor remote sensing data offers great benefits to move on from mono-temporal multispectral observations for a more multifaceted view on forest structure and biodiversity from a remote sensing perspective. Further gaps are the integration of both floristic and faunistic diversity data that does not only consider the local biodiversity scale (alpha-diversity).

The second objective of this dissertation was the development of a modeling framework to generate multi-annual forest structure products based on multi-sensor remote sensing data. Using high spatio-temporal data from Sentinel-1 and Sentinel-2, spaceborne Lidar samples derived from GEDI were modeled to obtain forest canopy height, total canopy cover, as well as above-ground biomass density data at 10 m spatial resolution for Germany. Therefore, the forest structure changes dynamics in the context of recent drought years could be quantified based on annual data from 2017 to 2023. The following research questions are linked to this objective:

Research Questions - Objective 2:

1. What is the potential of forest structure modeling using spaceborne data, and what are challenges to combine GEDI, Sentinel-1, and Sentinel-2 data?
2. How can a multi-annual modeling workflow be implemented to derive products on forest canopy height, total canopy cover, and above-ground biomass density?
3. What are spatio-temporal dynamics of forest structure in Germany, and how accurately are forest structure change dynamics assessed based on the multi-annual products?

The launch of the GEDI mission constitutes a major advance in forest structure research since the first full-waveform Lidar sensor was designed to acquire near-global sample measurements of forest structure. Since the sensor operates in the near-infrared, the sensor is specifically sensitive to vegetation structures. The combination of the GEDI sampling mission with high spatio-temporal data from satellite radar (Sentinel-1) and multispectral (Sentinel-2) holds a great potential to model different forest structure attributes based on continuous composites derived from the two satellite sensors (section 4.1). Multi-annual modeling products of forest structure can characterize pre- and post-disturbances structures. Therefore, the processing of multi-temporal and multi-sensor data requires cloud-storage and -processing for a time-efficient workflow implementation. Further challenges are the identification of linkages among structural properties derived from GEDI and canopy surface properties quantified by Sentinel-1 and Sentinel-2 data. In addition, the generation of multi-annual products for multiple attributes of forest structure needs to be developed through a flexible modeling workflow that can be used for several years and attributes of forest structure (section 4.4.2).

The multi-annual modeling workflow was implemented using machine-learning regression models. More specifically, per year and attribute of forest structure, a random forest regression model was trained using GEDI-derived attributes of forest structure as response and temporal-spectral metrics of Sentinel-1 and Sentinel-2 as predictors. Cloud-storage of all spaceborne data, as well as cloud-based processing facilitated the concatenation of multiple processing steps: data pre-processing, temporal-spectral metrics calculation, modeling set-up, model validation, and raster output generation at 10 m (section 4.2).

The derived products of forest structure, namely forest canopy height, total canopy cover, and above-ground biomass density, from 2017 to 2023 for Germany are the first consistent spaceborne-derived products of forest structure for Germany. Therefore, the novel forest structure data complements existing spaceborne data products for Germany, such as forest canopy cover loss (section 3.2.2). The dynamics of forest structure characterize changes in forest canopy height, total canopy cover, above-ground biomass for seven years, thus assessing pre- and post-disturbances structures in the context of consecutive drought years since 2018. The analysis of forest structure dynamics at the national-level served to identify hotspots of forest structure change which are dominating at larger-scale in central Germany (section 4.3.1). The regional analysis of forest structure change in the Harz and Thuringian forest demonstrated the high spatio-temporal characterization of forest structure loss based on 10 m spatial resolution data for seven years. Continuous forest cover with canopy height exceeding 25 m, total canopy cover reaching 80 %, as well as above-ground biomass density higher than 200 Mg/ha experienced major losses: for both the Harz and Thuringia forest, bi-temporal difference statistics from 2017 to 2023 amount to a reduction of 30 m in canopy height, 70 % in total canopy cover, and 200 Mg/ha for above-ground biomass density (section 4.3.2). The maps of forest structure differences highlight large-scale losses in forest structure, but also demonstrate the close proximity in some areas of major forest structure change and unchanged structures, thus emphasizing the high spatial detail due to 10 m spatial resolution. The results of model accuracy are in the range or higher than previous studies. Mean R^2 values across all years amount to 66.0 % for total canopy cover, 63.8 % for canopy height, and 57.4 % for above-ground biomass density. The cross-comparison to other published products of forest structure showed a general agreement (section 4.3.3), e.g. the RMSE value for canopy height models of 2019 amounts to 4.6 m.

As a third objective, multi-variate satellite time-series were calculated based on a comprehensive catalog of spectral indices in order to investigate to which extent radar (Sentinel-1) and multispectral data (Sentinel-2) can assess forest structure changes through experimental silvicultural treatments. Time-series change detection models were employed to identify for each sensor type the best indicators to characterize forest structural changes. The following research questions address this objective:

Research Questions - Objective 3:

1. Can the change in forest structure through small-scale experimental silvicultural treatments be characterized by satellite data using Bayesian time-series decomposition models?
2. To which extent can the implementation events of two groups of experimental silvicultural treatments, namely aggregated (gap felling) and distributed (selective thinning), be detected from Sentinel-1 and Sentinel-2 time-series data?
3. What are the best time-series characteristics (indices, spatial statistics, change point types) of Sentinel-1 and Sentinel-2 to assess the treatment implementation events?

The implementation of experimental silvicultural treatments was conducted as two spatial arrangements of cuttings, namely aggregated (gap felling) and distributed cuttings (selective removal), which have different influences on the light conditions. The gap creation of aggregated treatments has led to an opening of the canopy with a diameter of about 30 m, whereas the distributed removal of trees has led to smaller-scale openings in the canopy since single tree crowns were removed. In addition to the different arrangements of cuttings, various standardized deadwood structures were created to further diversify the habitat availability for species. For each patch (50 m x 50 m) of an experimental silvicultural treatment satellite time-series were calculated by aggregating for each time step the pixels as extreme, average, and heterogeneity statistics to characterize different structural properties (section 5.2.3). The calculation of spatial statistics was conducted for various spectral indices derived from a standardized catalog for both Sentinel-1 (n = 14) and Sentinel-2 (n = 129) (section 5.2.2). For each time-series metric (combination of spatial statistic and spectral index), a time-series decomposition model (BEAST) was calculated for which change points were assessed. Criteria for change points that represent the implementation event of the experimental silvicultural treatment are the following: change point date within the period of treatment implementation (November to December 2018), high change point probability (> 90 %), maximum change point probability of all change points among all assessed changed points of a specific time-series (section 5.2.4.2).

The assessment of change points showed that there is a great advantage to identify the implementation event of aggregated treatments in comparison to distributed treatments (section 5.3.3). There are differences among aggregated treatments which could be assessed by satellite time-series since treatments with habitat trees (tilted trees) could not be identified based on Sentinel-1 metrics, and only by few Sentinel-2 metrics. Other aggregated treatments could be well identified from both Sentinel-1 and Sentinel-2 time-series, no matter if standing deadwood structures are present or not.

Overall, best metrics for the identification of experimental silvicultural treatments are heterogeneity statistics (e.g. coefficient of variation) for Sentinel-1 VH and Sentinel-2 NMDI time-series. From all calculated indices a significant share of indices did not assess any change point that fulfilled the criteria of change points in the context of the implementation of experimental silvicultural treatments: 17 % for Sentinel-1 and 19 % for Sentinel-2. For both sensors, heterogeneity statistics were more informative than extreme or average statistics. Furthermore, most change points were detected in the trend component for both Sentinel-1 (about 95 %) and Sentinel-2 time-series (about 80 %). To sum up, the comparative analysis of Sentinel-1 and Sentinel-2 time-series for the identification of experimental silvicultural treatments demonstrated a general potential for both sensors to assess small-scale (50 m x 50 m) aggregated changes in forest structure. In addition, it is important to consider specific indices (e.g. Sentinel-1 VH, Sentinel-2 NMDI) since several popular indices showed a poor performance (e.g. Sentinel-2 NDVI).

The previous two objectives aimed to develop novel methodologies to calculate forest structure indicators, on the one hand based on a modeling workflow comprising GEDI, Sentinel-1, and Sentinel-2 data for continuous information on forest canopy height, total canopy cover, and above-ground biomass density for Germany from 2017 to 2023 at 10 m spatial resolution (chapter 4). On the other hand, a time-series change detection framework was implemented to calculate and assess Sentinel-1 and Sentinel-2 time-series metrics for the identification of experimental silvicultural treatments altering forest structure (chapter 5). In the context of the fourth objective of this dissertation, spaceborne data of modeled attributes of forest structure structure (second objective) and satellite time-series data from Sentinel-1 and Sentinel-2 (third objective) was integrated to correlate the spaceborne indicators of forest structure to in-situ remotely sensed indicators. In-situ remotely sensed indicators comprise data from MLS, as well as TLS, both characterizing a ground perspective on forest structure, in comparison to top-of-canopy measurements from spaceborne sensors. The analysis are embedded in the patch-network of experimental silvicultural treatments aiming to enhance forest structural complexity. Three specific research questions were defined for the fourth objective:

Research Questions - Objective 4:

1. Which spaceborne forest structure indicators hold highest correlations to in-situ remotely sensed indicators (MLS, TLS) characterizing forest structure conditions of experimental silvicultural treatments?
2. What is the potential of spaceborne and in-situ indicators to delineate aggregated, distributed and control treatments holding different conditions in forest structural complexity?
3. Can experimental silvicultural treatments with a presence of standing deadwood structures be differentiated from treatments with an absence of standing deadwood structures, and is there a different potential of only spaceborne indicators to combined spaceborne and in-situ indicators?

For spaceborne and in-situ indicators strong inter- and intra-platform correlations were identified (section 6.3.2). Although the indicators are summarized under the term "structural complexity", the indicators characterize different attributes of forest structure, e.g. canopy cover and openness (MLS canopy cover, TLS COI, modeled GEDI cover cv), structural complexity (MLS box dimension, TLS SSCI, TLS UCI), or structural heterogeneity (Sentinel-1 VH cv, Sentinel-2 NMDI cv, modeled GEDI canopy height cv, modeled GEDI total canopy cover cv, modeled GEDI above-ground biomass density cv) (section 6.1). Strongest correlations ($|r| >= 0.7$) were found for MLS indicators (box dimension, canopy cover) to TLS COI, Sentinel-1 VH cv, Sentinel-2 NMDI, and modeled GEDI total canopy cover cv.

Both spaceborne and in-situ indicators of forest structural complexity hold a great potential to differentiate among aggregated treatments (gap felling) and distributed (selective thinning) or control treatments (unaltered conditions). Neither spaceborne, nor in-situ indicators can delineate among distributed and control treatments. Based on bi-temporal spaceborne data (2019 and 2023), a temporal effect on forest structural complexity was assessed since spaceborne indicators of 2019 (first summer after the treatment implementations) more clearly characterize highest forest structural complexity for aggregated treatments in comparison to distributed and control treatments. In 2023 (fifth summer after the treatment implementation), several indicators (MLS box dimension, MLS canopy cover, TLS COI, modeled GEDI total canopy cover cv, and Sentinel-2 NMDI cv) still assesses structural differences among aggregated to distributed and control treatments, but differences are less pronounced compared to 2019 (section 6.3.3).

Based on unsupervised clustering analysis, the similarity of individual treatments was investigated based on spaceborne indicators only, and pooled spaceborne and in-situ indicators. Aggregated treatments with standing deadwood are different according to spaceborne, as well as combined spaceborne and in-situ remote sensing indicators, in comparison to aggregated treatments without standing deadwood. Furthermore, the similarity of aggregated treatments with and without standing deadwood structures changed from 2019 to 2023. In 2019, all aggregated treatments except the habitat tree treatments were grouped together due to high forest structural complexity. In contrast, the data from 2023 indicates that aggregated treatments without standing deadwood are characterized by highest structural complexity, but aggregated treatments with standing deadwood structures are more similar to distributed and control treatments (section 6.3.4). Overall, spaceborne and in-situ indicators of forest structural complexity are well aligned holding similar potentials to characterize forest structural complexity in the context of experimental silvicultural treatments.

The final objective of this dissertation was to quantify forest structure-biodiversity relationships in order to understand linkages among spaceborne indicators of forest structure and in-situ biodiversity measurements. Similar to the third and fourth objective, also the fifth objective is related to the patch-network of experimental silvicultural treatments across German broad-leaved forests (section 3.3). The research questions of the fifth objective are presented in the following:

Research Questions - Objective 5:

1. Can spaceborne forest structure indicators characterize the structural differences among experimental silvicultural treatments (control district vs. enhanced districts, i.e. aggregated and distributed treatments) of six regions?
2. Are in-situ biodiversity measurements sensitive to the enhancement of forest structural complexity (enhanced districts), thus showing high correlations to spaceborne forest structure indicators?

The comparative analyses of spaceborne forest structure indicators across all regions of the BETA-FOR project (n = 6 with 234 patches, Mueller et al. (2022a,b)) demonstrated the consistent assessment of the major increase in structural complexity through aggregated treatments. Control and distributed treatments cannot be differentiated based on spaceborne indicators independent of temporal filtering for all four seasons. There are seasonal influences on the differences in forest structural heterogeneity based on spaceborne indicators across aggregated to control and distributed treatments: for summer and autumn the differences are strongest (mean difference in Sentinel-2 NMDI cv for most regions in the range of 0.02 to 0.08) and decline from winter to spring (mean difference in Sentinel-2 NMDI cv for most regions in the range of 0.01 to 0.03). Therefore, the assessment for all four seasons was relevant to quantify the seasonal dynamics of forest structure. Furthermore, regional effects are apparent because forest structural heterogeneity of aggregated treatments is highest in regions with lower elevations (e.g. University forest) in winter and spring. In comparison, regions of higher elevations (e.g. Bavarian forest) present highest structural heterogeneity of aggregated treatments in summer. In autumn, differences among control and distributed treatments to aggregated treatments are most pronounced. In addition, forest structural heterogeneity of aggregated treatments of the University forest and Bavarian forest reach similar values (mean in Sentinel-2 NMDI cv greater than 0.11, section 7.3.1).

Some in-situ biodiversity measurements are sensitive to the forest structure conditions characterized by spaceborne indicators: highest correlations ($|r| > 0.4$) of spaceborne indicators were reached to taxonomic diversity of birds, gastropods, hoverflies, insects, and tree species. For each taxa, taxonomic diversity was calculated for different orders (rare, common, and dominant species). There are differences of the correlation strengths among spaceborne indicators of forest structure and in-situ biodiversity measurements: strongest relationships per taxa were found for dominant bird species ($r = 0.52$), dominant gastropod species ($r = 0.54$), common hoverfly species ($r = 0.43$), rare insect species ($r = 0.53$), and rare tree species ($r = 0.47$). From the pool of all spaceborne indicators of forest structure (Sentinel-1 VH cv, Sentinel-2 NMDI cv, modeled GEDI canopy height cv, modeled GEDI total canopy cover cv, modeled GEDI above-ground biomass density cv), most strong correlations were found for Sentinel-2 NMDI cv (section 7.3.2).

8.2 Outlook for Future Research

With a coverage of about a third of the German land surface, forests are a dominant ecosystem which is distributed across the complete national territory. Multiple centuries of forest management have shaped the structure of forests today. Plantation forestry management has led to a major share of mono-cultures dominated by spruce and pine trees. The increased susceptibility towards disturbances in particular of spruce plantations became apparent in the context of consecutive drought years since 2018. Unprecedented forest canopy cover loss from 2017 to 2024 highlights the need to monitor forest structure dynamics in the context of disturbances. The characterization of pre- and post-disturbance structures (e.g. delineation of stand replacing and non-stand replacing disturbances), and the general assessment of vertical and horizontal forest structure attributes is a critical task to guide forest management from homogeneous to more heterogeneous structures. Forest management promoting heterogeneity constitutes an integrative approach to enhance biodiversity and multifunctionality through different small-scale arrangements of cuttings and the generation of more diverse deadwood structures.

Future research on forest structure and biodiversity can explore forest structure-biodiversity relationships across space and time through a deeper integration of spaceborne remote sensing in ecology. Continuously expanding time-series of high spatio-temporal resolution satellite sensors, such as Sentinel-1 and Sentinel-2, are informative archives for multi-sensor and multi-temporal analyses at continuous spatial scale. With the planned mission extension of GEDI until 2031, more years of forest structure quantification from spaceborne Lidar are expected for sensor-fusion analysis (e.g. with satellite mapping mission data or close-range and airborne Lidar), if data remains publicly available. Further upcoming advancements in forest structure analysis have been prepared in the context of the first satellite swath-mapping Lidar instrument (Earth Dynamics Geodetic Explorer (EDGE)) by NASA as a follow-up mission of GEDI with a planned mission start in 2029: higher temporal resolution and more fine-scale characterization of forest structure (Maryland Today, 2024). The BIOMASS mission by ESA cannot acquire observations over Europe and North America due to defense restrictions, which is why the mission has a focus on tropical forest monitoring. Nevertheless, the BIOMASS mission constitutes the first spaceborne P-band mission, specifically designed for forest height and biomass quantification (Carreiras et al., 2017; Quegan et al., 2019). Overall, the increasing volume of spaceborne data archives are promising developments for the characterization of local to global forest structure conditions based on multi-sensor data. Furthermore, access and progress in parallel computing using cloud- and cluster-infrastructure facilitates the development of multi-sensor and multi-temporal research.

The development of a modeling workflow combining GEDI, Sentinel-1, and Sentinel-2 data for the generation of multi-annual forest structure products for Germany can be integrated for modeling upcoming years. In addition, the workflow can be configured to other study areas, e.g. to expand the product to the European scale. The second methodological framework which was developed in the context of this dissertation was the time-series change detection analysis of forest structure changes based on Sentinel-1 and Sentinel-2 time-series. This method can be applied to other study areas (e.g. different forest types), but also different time-series data (e.g. multi-decadal Landsat data). Furthermore, the integration of an univariate time-series decomposition model could be supplemented by multivariate models to combine multiple time-series metrics of different sensors to identify forest structure changes. The correlation analysis of spaceborne and in-situ indicators of forest structure has demonstrated the alignment of different indicators derived from various remote sensing platforms. Therefore, in-situ remote sensing indicators can be modeled based on spaceborne data to explore patterns in larger spatial coverage, and to assess the temporal dynamics in forest structure. The inter-disciplinary analysis of forest structure-biodiversity relationships has identified several linkages of spaceborne indicators and multiple species groups. Further analysis can investigate the temporal stability of found relationships and validate the relationships among different forest types. As as consequence, forest structure-biodiversity relationships can be quantified more holistically using multi-sensor and multi-temporal spaceborne data in combination with biodiversity estimates of floristic and faunistic diversity.

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