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Modeling European beech defoliation at a regional scale gradient in Germany from northern lowlands to central uplands using geo-ecological parameters, Sentinel-2 and National Forest Condition Survey data

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A B S T R A C T

Since 2018, severe droughts have affected a significant part of central Europe, causing premature leaf senescence in European beech (*Fagus sylvatica* L.). The correlation between the vitality of *Fagus sylvatica* L. and various geo-ecological and biological determinants (such as elevation, slope, aspect, tree age, and soil properties) concerning hydrological drought stress is still not well understood, especially when integrating multiple geographical datasets. In addition, the determination of crown condition by remote sensing and geo-ecological parameters is still under development; it would allow the assessment of an area-wide forest health status. Our analysis incorporated annual field data from the German National Forest Condition Survey (Waldzustandserhebung, WZE) as a response variable and employed geo-ecological parameters derived from a digital elevation model, soil properties and vegetation indices from a Sentinel-2 time series to explain and predict the crown defoliation of European beech throughout the drought-impacted period spanning 2016–2022 across the federal states Schleswig-Holstein, Lower Saxony, and Hesse of Germany. In a second step, the results of the modeling were used for mapping of crown defoliation in Hesse, Lower Saxony and Schleswig-Holstein. By employing Gradient Boosting Machines and Random Forest for regression analysis, the study uncovered the relationships between crown defoliation and the used predictors. Training was conducted on 80 % of the dataset, with the remaining 20 % serving as a test set for model validation. Regression findings based on static explanatory variable sets were improved by dynamic explanatory variables such as estimates of soil moisture, vegetation index metrics, and diameter at breast height. Furthermore, we identified key predictors for mapping crown defoliation of *Fagus sylvatica* L. and recommended using vegetation indices as additional predictors for future studies. The modeling results provided comparably accurate estimates compared to WZE estimates (R^2 of 0.794 and RMSE of 7.646 %) during testing. Topographic and static soil predictors were significant, with soil moisture being a particularly influential variable for model optimization. Based on the predicted crown defoliation, beech trees with low to moderate crown defoliation predominated in beech distribution areas across the examined federal states, while a small number of beech trees with high defoliation were identified mostly in South Lower Saxony and Hesse. The annual variations in the proportions of beech trees showing increasing and decreasing crown defoliation indicate that the condition of the crown temporarily deteriorated when soil moisture decreased, but beech trees recovered after prolonged periods of drought. Additionally, beech trees in the study region exposed to declining soil moisture may suffer from medium-term declines in vitality. The predicted crown defoliation data can be utilized for future climate-adaptive management practices in European beech forests.

1. Introduction

Climate conditions influence the structure and function of forest ecosystems, thereby playing an essential role in maintaining forest health (Jump et al., 2006; Allen et al., 2010; Dulamsuren et al., 2017; Hartmann et al., 2022). Severe droughts have affected extensive areas of

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central Europe since 2018, resulting in multiple forest damages, including insect infestation in coniferous forests and premature leaf senescence in deciduous broadleaf tree species (Hlásny et al., 2021; Obladen et al., 2021; Thonfeld et al., 2022; Schmied et al., 2023; Mathes et al., 2024). The European beech (*Fagus sylvatica* L.), a dominant species in Europe, has experienced a decline in vitality, resulting in dieback (Bosela et al., 2016; Braun et al., 2021; Arend et al., 2022; Neycken et al., 2022; Langer and Bußkamp, 2023). This species, characterized by its highly competitive ability, exhibits sensitivity to drought conditions. Consequently, it may face increasing threats from heatwaves and droughts induced by climate change within parts of its distribution range (Leuschner, 2020).

The distribution of *Fagus sylvatica* L. predominantly correlates with the temperate and warm temperate climatic zones of Europe. It extends geographically from southern Sweden through to southern Italy and from Spain eastwards to Greece (Peters, 2013; Rukh et al., 2023). With a share of 16 % of the stocked forest area, the European beech is the most common deciduous tree species in German forests, ranking third in distribution after the conifers spruce and pine (BMEL, 2023). Geographical factors such as relief, climate, or bedrock can significantly influence the growth and distribution of beech trees. These factors collectively contribute to variations in microclimates and soil conditions, shaping the ecological niche of European beech forests (Kolář et al., 2017; Dutcă et al., 2022; Weigel, et al., 2023). Soil properties play crucial roles in influencing the growth and development of *Fagus sylvatica* (Buhk et al., 2016). Beech trees generally prefer well-drained soils with a balanced texture. Soils with a balanced mixture of sand, silt, and clay are often ideal for tree growth (Coile, 1952; Greacen and Sands, 1980; Ampoorter et al., 2011; Soong et al., 2020). The optimal soil texture for the growth of beech trees is typically identified as silt soils. These soils maintain a balance between efficient drainage and the capacity to retain water, thereby providing ideal conditions for water availability to beech trees (Scharnweber et al., 2013).

The condition of beech forests in Germany has changed significantly in recent years. Many studies have revealed that soil water-related variables affect the vitality of European beech. For example, Weigel et al. (2023) have proven that hydrological drought stress influences the growth of European beech along a steep precipitation gradient in northern Germany. The study by Obladen et al. (2021) demonstrated significant beech dieback following hot droughts in 2018 and 2019. Beech trees generally require well-drained soils (such as silt soil) to prevent waterlogging (Packham et al., 2012), which can lead to root asphyxiation and diseases (Jung, 2009). Numerous studies have shown that droughts can cause trees to shed leaves prematurely, reducing their ability to photosynthesize, weakening their vitality, and directly impacting beech mortality rates (Archambeau et al., 2020; Obladen et al., 2021; Arend et al., 2022). Thus, soil water content plays an essential role in the health of forests. It is among others determined by soil properties, topographic variables such as elevation, aspect, and slope, as well as climatic conditions (Qiu et al., 2001; Clinton, 2003; Moeslund et al., 2013).

To quantitatively disclose the relationships between the vitality of European beech and various environmental conditions, measurable indicators of beech forest health are necessary. Previous studies have utilized crown defoliation as an indicator of beech vitality to explore its correlation with climatic factors (Seidling, 2007; Sousa-Silva et al., 2018; Ognjenović et al., 2022). For example, visibly sparse foliage associated with defoliation is considered an indicator of declining vitality in beech trees due to drought stress (Ognjenović et al., 2022). The German National Forest Condition Survey (Waldzustandserhebung, WZE) employs a comprehensive systematic terrestrial point-sampling design to monitor annual crown defoliation and additional parameters describing tree vitality. The regular sampling grid covers different geographical gradients, and the grid size is chosen so that the results are representative at the federal state level. However, it is not possible to make a differentiated statement about the vitality of individual forest stands. The WZE survey is conducted in accordance with the internationally harmonized manual of ICP Forests (Ferretti et al., 2020) and has been applied in a variety of studies (Aden et al., 2010; Knapp et al., 2024). The methodology for assessing forest condition involves visually examining individual trees on the ground to identify their health status or visible damage. The main evaluation metric is crown defoliation, measured by comparing needle or leaf loss in 5 % increments against a benchmark tree. The WZE plots are geolocated. Thus, they can be matched with geo-ecological parameters and satellite data to model area wide forest health status and reveal further forest system understanding.

Despite the availability of WZE data as measurable indicators and the increasing interest in monitoring beech forest health, current research is insufficient to support large-scale modeling of the vitality of *Fagus sylvatica*, revealing a notable gap that this study aims to fill. For example, previous studies either relied on field measurements or only explained the relationships between environmental factors and beech vitality derived from remote sensing data without area-wide mapping of crown condition in beech trees (Rohner et al., 2021; Ognjenović et al., 2022; Weigel, et al., 2023). However, utilizing multi-geographical data to monitor large-scale forest disturbances has become a critical methodology. The availability of data for ecological predictions, including satellite or aerial imagery and other remote sensing data, has significantly increased (Rammer and Seidl, 2019). Geographical data, such as digital elevation models and soil properties, are frequently used for ecological research modeling (Hörsch, 2003; Seidl et al., 2011; Balzter et al., 2015; Fang et al., 2016; de Sousa et al., 2020; Ågren et al., 2021). Numerous studies have employed satellite data to evaluate the health of forests (Wang et al., 2010; Lausch et al., 2016; Pause et al., 2016; Lausch et al., 2017; Massey et al., 2023; Grabska-Szwagrzyk and Tymińska-Czabańska, 2024). Vegetation indices (VIs) derived from multispectral remote sensing spectral bands offer continuous data on vegetation conditions across time and space. These indices are frequently utilized to monitor beech forests (Lukasova et al., 2014; Hlásny et al., 2015; Olano et al., 2021; West et al., 2022). For example, the short-wave infrared (SWIR) and red-edge bands of Sentinel-2 are closely associated with hydrological drought stress (Ghulam et al., 2007; Liu et al., 2021; Xu et al., 2024).

Regarding methodologies, machine learning (ML) regression algorithms such as Random Forest (RF) and Gradient Boosting Machines (GBM) have gained widespread popularity (Izquierdo-Verdiguier and Zurita-Milla, 2020; Singh et al., 2021; Abdul Gafoor et al., 2022; Li et al., 2024). ML is a powerful tool for understanding and predicting dynamics in ecological systems, surpassing traditional methods in flexibility, accuracy, and handling complex, high-dimensional datasets (Recknagel, 2001; Liu et al., 2018; Christin et al., 2019; Schratz et al., 2021; Ezzati et al., 2023).

There is a lack of studies integrating diverse datasets for explaining and mapping crown defoliation across large regions. This study aims to explain crown defoliation by employing data from the German National Forest Condition Survey (WZE) and to use the modeling results to map crown defoliation at the federal state level ranging from Northern Lowlands to Central Uplands of Germany and address the following research questions:

1. Can crown defoliation of *Fagus sylvatica* L. be explained by integrating field estimates from the WZE/ICP Forests design with multiple geo-ecological and Sentinel-2 data?
2. What are the most important predictors for accurately describing crown defoliation?
3. Can the resulting models be used to map crown defoliation?
4. Are there regional variations in beech crown condition and annual changes that can be derived from mapping results?
5. Is there a medium-term trend (2016–2022) for deterioration or recovery in crown condition visible through the modeling?

2. Material and methods

2.1. Study region

The study area includes three German federal states: Schleswig-Holstein, Lower Saxony, and Hesse (Fig. 1). The area spans 84,600 km^2, with 27 % covered by forests (Thünen Institute, 2014). The mean annual temperature ranges from 8.5 to 9.7 °C. The approximately 400 km-long precipitation gradient shows a decrease in mean annual precipitation (1948–2017) from nearly 850 mm in the oceanic Northwest to under 500 mm in the sub-continental Southeast (Weigel et al., 2023; Leuschner et al., 2023). The ecological niches of *Fagus sylvatica* span from the North German Lowlands to the low mountain ranges. The distribution of *Fagus sylvatica* aligns with the topography in the study area, with Lower Saxony and Hesse having more beech areas than Schleswig-Holstein. The WZE plots are evenly distributed across the beech-covered area (Fig. 1). According to the dominant tree species map of Germany (2017/2018) by Blickensdörfer et al. (2024), beech forests cover 31.39 %, 18.04 %, and 44.95 % of the forested area in Schleswig-Holstein, Lower Saxony, and Hesse, respectively.

2.2. National Forest Condition Survey data (WZE)

The WZE crown defoliation data for *Fagus sylvatica* L. from 2016–2022 were provided by the Northwest German Forest Research Institute (NW-FVA) and used as response variables. The fieldwork was conducted annually in July and August using the WZE approach (Ferretti et al., 2020). The WZE approach is a systematic method for terrestrial observation, where data on the crown condition of the main tree species is collected and assessed annually in a standardized manner across Germany. There are 1150 WZE cluster plots in the study region. Each cluster plot consists of four survey points located 25 m from the plot center in each cardinal direction (Fig. 2).

At each survey point six trees are selected (Fig. 2) and crown defoliation is visually assessed for all (up to six) trees on a scale from 0 % (healthy) to 100 % (dead) in 5 % increments. To exclude mixed-species plots, we only selected WZE plots in pure beech stands based on the dominant tree species map by Blickensdörfer et al. (2024) and further verified the tree species on each plot through visual aerial image interpretation. The use of orthophotos enabled the visual exclusion of survey points on which coniferous trees, such as Norway spruce (*Picea abies* L.), were visible. In total, 504 pure beech survey points from 1150 WZE cluster plots were selected as reference data (Fig. 1). Next, we calculated the average crown defoliation per survey point for each year. This value was used as the response variable for modeling.

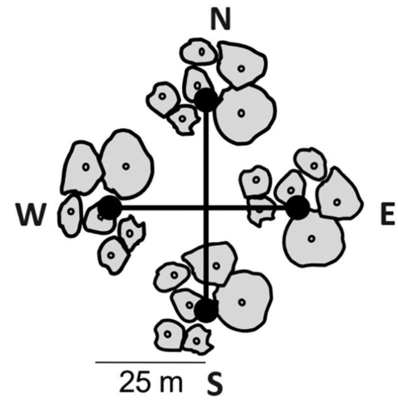

Fig. 2. Schematic representation of the cross-cluster plot design of the National Forest Condition Survey (WZE) (Ferretti et al., 2020).

2.3. Topographic factors, soil properties, and Sentinel-2 data

For demonstrating the relationships between crown defoliation and environmental factors, we utilized constant predictors including topographic variables (elevation, slope, aspect) and soil profile information, and dynamic predictors such as soil moisture and remotely sensed vegetation indices (VIs), along with diameter at breast height (DBH) for regressions (Table 1). The topographic variables were obtained from the European Digital Elevation Model (EU-DEM) with a 25-meter spatial resolution, available through the Copernicus Land Monitoring Service (https://land.copernicus.eu/). Soil profile information was sourced from SoilGrids, a global digital soil mapping system (Poggio et al., 2021). Soil moisture data for the entire soil depth were provided by the Helmholtz Centre for Environmental Research upon request (Zink et al.,

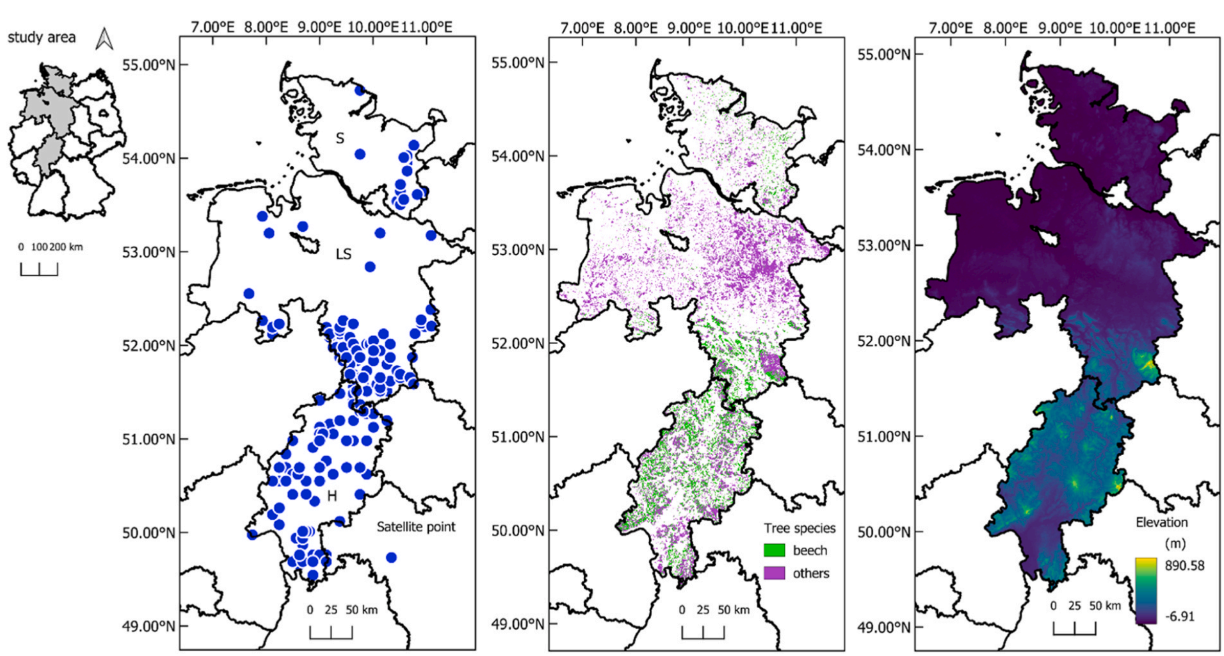

Fig. 1. Overview of the selected WZE survey plots with beech in the study region (left), tree species distribution (middle), and elevation (right) in the federal states of Schleswig-Holstein (S), Lower Saxony (LS), and Hesse (H).

Table 1
Explanatory variables in machine learning models. *The ratio of silt to sand was used (See 2.4).

Variable (unit)	Spatial resolution (m)	Temporal resolution	Source
Topographic			
Elevation (m)	25	constant	EU-DEM (https://land.copernicus.eu/)
Slope (°)			
Aspect			
Soil profile information			
Bulk density of the fine earth fraction (cg/cm^3)	250	constant	SoilGrids (https://www.isric.org/explore/soilgrids)
Cation exchange capacity of the soil (mmol(c)/kg)			
Volumetric fraction of coarse fragments (> 2 mm) (cm3/dm3 (vol‰))			
Proportion of clay particles (< 0.002 mm) in the fine earth fraction (g/kg)			
Total soil nitrogen content (cg/kg)			
Soil pH (pHx10)			
Ratio of 'proportion of silt particles (≥ 0.002 mm and ≤ 0.05 mm) and sand particles (> 0.05 mm) in the fine earth fraction'*			
Soil organic carbon content in the fine earth fraction (dg/kg)			
Organic carbon density (hg/m^3)			
Organic carbon stocks (t/ha)			
Soil moisture			
Sums of Soil Moisture Index from the previous year between January and December (SMI_PA)	1300	dynamic	German Drought Monitor (https://www.ufz.de/index.php?en=37937)
Sums of Soil Moisture Index from the current year between January and August (SMI_CA)			
Remote sensing (S2 Vegetation Indices)			
Peak of Normalized Difference Red Edge index (NDRE)	20	dynamic	
Peak of Normalized Difference Moisture Index (NDMI)			
Peak of Normalized Burn Ratio (NBR)			
Peak of Distance Red and SWIR (DRS)			
Peak of Moisture Stress Index (MSI)			
Tree parameter			
Diameter at breast height (DBH) (cm)	-	dynamic	WZE

2016). Soil moisture data were collected through single-profile measurements from spatially distributed sensor networks, including 10 cosmic-ray neutron stations and lysimeters at 40 sites in Germany (Boeing et al., 2022). Additionally, we included the following VIs from Sentinel-2 images as predictors: Normalized Difference Red Edge index (NDRE), Normalized Difference Moisture Index (NDMI), Normalized Burn Ratio (NBR), Distance Red and SWIR (DRS), and Moisture Stress Index (MSI) (Table A1). The DBH information was obtained from the WZE database, and any missing data were filled in using nearby DBH values. DBH is the only explanatory variable measured at the WZE survey point level, while topographic and soil predictors, along with VIs, cover the entire study area. DBH was therefore only used for comparing models but not utilized to map crown defoliation of European beech.

We calculated the sums of the Soil Moisture Index from the previous year between January and December (SMI_PA: previous annual SMI) and the current year between January and August (SMI_CA: current annual SMI) as metrics for training our models (Table 1). For example, the average crown defoliation of a WZE survey point in 2018 was explained by its soil moisture metrics from January to December 2017 (SMI_PA) and January to August 2018 (SMI_CA). The selection of SMI_PA helps determine whether there is a time delay in beech trees' response to drought stress.

Sentinel-2 data were acquired and preprocessed to obtain VI time series, using the Framework for Operational Radiometric Correction for Environmental monitoring (FORCE, Frantz, 2019). The preprocessing involved topographic normalization using the Shuttle Radar Topography Mission (SRTM) digital elevation model from the United States Geological Survey (USGS), as well as radiometric and atmospheric corrections. Additionally, clouds and cloud shadows were removed using the threshold-based delineation with the Fmask algorithm as implemented by FORCE (Frantz et al., 2018). We resampled all Sentinel-2 bands to 20 m using the nearest neighbor method to capture the spectral reflectance of beech trees (Fig. 2). Co-registration was performed to correct pixel displacement issues, which can be as high as 11 m within individual Sentinel-2 frames, as noted by the European Space Agency (2020). This displacement can add noise to the time series data. After preprocessing, Analysis Ready Data (ARD) at Level-2 are generated to support the computation of Vegetation Indices (VIs) in the Time Series Analysis (TSA) module. For each VI we extracted its maximum value observed in the time from July to August per year as a phenological metric using non-interpolated VI values. These values were utilized to model and explain crown defoliation, e.g. peak NBR values from 2019 were utilized to explain and predict the average crown defoliation in 2019.

2.4. Modeling approach

We employed two machine learning (ML) algorithms, Random Forest (RF) and Gradient Boosting Machines (GBM), to investigate the relationship between crown defoliation and environmental factors and evaluate algorithm performances. The RF constructs multiple decision trees during training and averages their predictions for regression tasks, thereby improving predictive accuracy and reducing overfitting compared to a single decision tree (Ali et al., 2012). Each decision tree in a Random Forest is trained on a bootstrapped sample, which is a random subset of the training data selected with replacement. This ensures that each tree learns from a slightly different dataset, increasing the diversity among the trees and, thus, the robustness of the model. Overall, RF offers multiple benefits, notably reducing overfitting, evaluating feature importance, and demonstrating superior generalizability and robustness (Segal, 2004; Jaiswal and Samikannu, 2017). GBM can achieve high prediction accuracy by combining multiple weak learners, typically decision trees, into a strong learner through an iterative process (Ridgeway, 2007; Touzani et al., 2018). Although GBM can overfit if not properly tuned, they offer parameters (such as the number of trees, tree depth, and learning rate) that can be adjusted to prevent overfitting. Proper tuning via cross-validation can significantly enhance the robustness and generalization to unseen data (Vulova et al., 2020).

There are two steps for regressions. We defined five sets of predictor variables and compared their performance when explaining crown defoliation (Table 2). Then, we used the predictor set that achieved the best evaluation metrics (R^2 and RMSE) to train a new model without reducing the sample size for mapping crown defoliation. When incorporating DBH into regressions and comparing its influence on crown defoliation with other explanatory variables, the sample size was reduced, since DBH is available on the survey point level only and not for the whole beech forest area. Hence, without using DBH for mapping,

Table 2
The applied model types with various predictor sets for modeling crown defoliation. *Only one VI was used each time.

Model	Predictor sets
M_geostat	Elevation, Slope, Aspect, Soil profile information
M_geo	Elevation, Slope, Aspect, Soil profile information, SMI_PA and SMI_CA
M_geobio	Elevation, Slope, Aspect, Soil profile information, SMI_PA and SMI_CA, DBH
M_geors*	Elevation, Slope, Aspect, Soil profile information, SMI_PA and SMI_CA, Peak of VI (NDRE, NDMI, NBR, DRS, MSI)
M_geobiors*	Elevation, Slope, Aspect, Soil profile information, SMI_PA and SMI_CA, DBH, Peak of VI (NDRE, NDMI, NBR, DRS, MSI)

more samples were retained to train models for mapping. In other words, DBH was excluded as it was not based on beech pixels and was not available for each study year. The ML model used for mapping was unable to predict crown defoliation when the predictors contained NA values. DBH should be available at an area-wide level from 2016 to 2022; once this data is obtained, the model will be able to produce values for crown defoliation and subsequently map it. Ultimately, DBH was not measured annually for the entire beech area during the actual fieldwork.

When comparing predictor sets, the five model types are incremental. The original resolutions of explanatory variables remained unchanged at this stage. The M_geostat model considers all constant environmental parameters (elevation, slope, aspect, and constant soil properties) to explore their influence on crown defoliation. The M_geo model adds the dynamic soil moisture data into the M_geostat model, the M_geobio incorporates DBH in the M_geo model and thus shows a relation to beech vitality, while the M_geors additionally integrates individual remote sensing VI based on the M_geo, demonstrating the relationship between remotely sensed data and beech crown condition. The M_geobiors combines all available predictors and is therefore considered a reference for the comparison of the other models.

Due to the strong correlation between VIs calculated using similar spectral bands (Fig. A1), we used only one VI each time to train a remote sensing related model (Table 2). It is important to identify which VI and bands are highly correlated with the crown condition of beech trees. Additionally, we observed a strong correlation ($r = -0.88$) between the proportion of sand particles (> 0.05 mm) and silt particles (≥ 0.002 mm and ≤ 0.05 mm) in the fine earth fraction, as determined by Spearman's correlation coefficients. Considering that sand and silt together with clay are the three main particles in soil structure, we did not arbitrarily remove any of them. To compromise on multicollinearity (Alin, 2010), we used the ratio of 'proportion of silt particles (≥ 0.002 mm and ≤ 0.05 mm) and sand particles (> 0.05 mm) in the fine earth fraction' ('silt/sand'), as a new metric for regressions. Overall, there are no other explanatory variables correlated with each other using Spearman's correlation coefficients with high correlation coefficient more than 0.75. Importantly, compared to traditional statistical models (Kärvemo et al., 2023), RF and GBM are more robust in handling multicollinearity (Garg and Tai, 2013; Derraz et al., 2023), offering an advantage for our study.

For mapping crown defoliation, all raster layers were resampled to 20 m to facilitate the raster data processing, in accordance with the spatial resolution of Sentinel-2 data. By excluding DBH, more samples were used at this stage to train a model than at the stage of developing the predictor sets, since DBH was only available at a point level and not for each beech pixel. Even though we found that including more samples increases the correlation between 'Organic carbon stocks' and 'Soil organic carbon content in the fine earth fraction' after resampling ($r = 0.86$), we did not remove them for mapping. The primary goal at this stage is area-wide mapping with a 20-meter resolution. Furthermore, the medium-term changes in crown defoliation from 2016 and 2022 were estimated by the predicted results for each year using a linear regression approach.

2.5. Training and testing sets

Overall, 80 % of the explanatory variables were used to train the RF and GBM regression models and 20 % were used to test the performance of the models, which was evaluated using RMSE and R^2. Ten-fold cross-validation was used to train the GBM and RF models (Ali et al., 2012). Besides, hyperparameters were used for fine-tuning. In terms of GBM, the depth of trees (interaction.depth) was tuned from 1 to n-2 (n refers to the number of explanatory variables in a model) with increments of 2. The number of trees (n.trees) was tuned from 100 to 1000 with increments of 50. Three values of the learning rate (shrinkage) were evaluated during tuning (0.01, 0.05, and 0.1). The minimum observations in terminal nodes (n.minobsinnode) were tuned using three values (6, 8, and 10) (Kuhn and Johnson, 2013; Vulova et al., 2020).

The sample sizes for the ten defined classes of crown defoliation vary depending on the number of samples per class (Table 3). Due to the limited sample size of each 5 %, we defined each 10 % as a class offering an overview of sample distributions. The sample size (in total 1297) in Table 3 is applicable for comparing the five model types applied, whereas the model for mapping crown defoliation contains 2793 samples (Table A2).

All procedures were conducted using QGIS, FORCE, and the statistical computing language R (RStudio Team, 2021). The R package 'caret' was utilized for training ML models, and 'terra' and 'raster' were employed for processing raster layers and mapping crown defoliation. Medium-term changes in crown defoliation were aggregated using zonal statistics in QGIS and displayed as hexagons for improved visualization.

3. Results

3.1. Model performance displayed by predictor sets

RF and GBM showed strong relationships between crown defoliation and the selected explanatory variables. RF almost outperformed GBM in all models, showing similar performance overall (Table 4). With regard to the remote sensing models, the best results were achieved using the NBR. The evaluation metrics for model type M_geors using other VIs are presented in Table A3.

In our study, using only static variables to explain crown defoliation has led to substantial accuracy, with the M_geostat showing a RMSE of 8.715 % and R^2 of 0.754 at testing for RF, and a RMSE of 8.858 % and R^2 of 0.746 at testing for GBM, respectively. When including the dynamic SMI metrics into regressions (M_geo), the RMSE at testing decreased and R^2 increased both using RF and GBM. When further incorporating DBH into regressions (M_geobio), the evaluation metrics were improved using GBM. However, the performance of the M_geobio was only slightly improved by DBH. This similarly occurred in the model M_geors including 'peak of NBR' based on the M_geo using both RF and GBM.

Table 3
The sample size per crown defoliation class for training and testing five models. A total of 1297 samples were used to compare five model types. 1039 samples were used for training the models, while the remaining 258 samples were used for testing the models for validation. The sample represents the average crown defoliation for beech trees at a WZE survey point.

Crown defoliation (%)	All	Training	Testing
0–10	227	179	48
>10–20	161	126	35
>20–30	290	238	52
>30–40	297	238	59
>40–50	185	146	39
>50–60	78	65	13
>60–70	40	32	8
>70–80	8	7	1
>80–90	2	0	2
>90–100	9	8	1
Total	1297	1039	258

Table 4
Evaluation metrics for testing all models. The best evaluation metrics are shown in bold. *Results are applicable for NBR.

Algorithm	Model	RMSE test (%)	R^2 test (-)
RF	M_geostat	8.715	0.754
	M_geo	7.784	0.807
	M_geobio	7.817	0.807
	M_geors*	**7.700**	**0.815**
	M_geobiors*	7.790	0.812
GBM	M_geostat	8.858	0.746
	M_geo	8.159	0.787
	M_geobio	7.884	0.799
	M_geors*	7.867	0.800
	M_geobiors*	7.745	0.806

Despite this, the M_geors of RF, using topographic, static, and dynamic soil properties and 'peak of NBR', achieved the lowest RMSE and highest R^2 at testing (RMSE = 7.700 %, R^2 = 0.815). When using all explanatory variables (M_geobiors), including DBH and NBR together in M_geo, evaluation metrics slightly improved during testing with GBM. This improvement, however, is not evident when using RF by M_geobiors.

Fig. 3 depicts the relative variable importance identified by model M_geors with the best evaluation metrics. The variable importance in M_geors provided the relative percentage scores for each predictor. However, variable importance for the same predictor sets differed greatly based on the ML algorithm employed (Fig. 3). As for M_geors using RF, topographic and soil properties were particularly influential, with 100 % importance for 'Cation exchange capacity of the soil'. However, remotely sensed 'Peak of NBR' and 'Ratio of proportion of silt particles ($\geq$ 0.002 mm and $\leq$ 0.05 mm) and sand particles (> 0.05 mm) in the fine earth fraction' contributed the largest relative percentages importance (100 % and 97.15 %, respectively) in GBM modeling, followed by 'Slope', 'Aspect', 'SMI_CA' and 'SMI_PA' with 65.87 %, 64.99 %, 64.78 % and 61.79 %, respectively. 'Peak of NBR' contributed 27.50 % importance and 'Proportion of clay particles (< 0.002 mm) in the fine earth fraction' and 'SMI_CA' were the least influential predictors (both less than 1 %) using RF.

3.2. Predicted crown defoliation and variations among federal states

3.2.1. Validation of the model used for mapping

The model applied for mapping achieved high accuracy (R^2 = 0.794 and RMSE = 7.646 %) when validated by WZE observations of crown defoliation (Table A4), with topographic and soil properties as the most influential factors (Table A5), confirming the robustness of RF when handling two highly correlated predictors 'Organic carbon stocks' and 'Soil organic carbon content in the fine earth fraction' (part 2.4).

We compared predicted and WZE observed crown defoliation for the entire study region and each federal state (Fig. 4). The testing data for validation covers crown defoliation ranging from 0 % to 100 %, showing a strong correlation between predicted and WZE observed crown defoliation. Higher crown defoliation was predominantly observed in Hesse and Lower Saxony. Beech trees in Schleswig-Holstein showed low to moderate crown damage condition (less than 70 %), but there is limited testing data available. When comparing predictions to WZE observations, high crown defoliation is often underpredicted.

3.2.2. Distribution of predicted crown defoliation across federal states

Crown defoliation maps were generated as raster layers for each year from 2016 to 2022 (Fig. 5; Fig. A2) and displayed the results for 2022 in the main text (Fig. 5). The largest part of the mapped area has crown defoliation values in the class 10–40 % for Hesse (90.22 % of the total beech area, 374,505.92 ha) and Lower Saxony (92.08 % of the total beech area, 191,354.12 ha), and 0–30 % for Schleswig-Holstein (94.46 % of the total beech area, 56,122.2 ha). Beech areas with high crown defoliation (>70 %, referring to the last three classes in Fig. 5) did not constitute the majority, but were identified in different sizes, such as 742 ha, 111.36 ha, and 0.04 ha in Hesse, Lower Saxony, and Schleswig-Holstein, respectively (Table A6).

3.3. Annual change detection and medium-term trends in predicted crown defoliation across federal states

We calculated changes in the proportions of beech trees with increasing and decreasing crown defoliation over consecutive years (Fig. 6). Considering that the model predicted continuous crown defoliation and the comparison between predictions and reference data indicated an underestimation (Fig. 4), a 2 % threshold was applied to assess the actual changes in the predicted results. This threshold was implemented to mitigate the issue of false negatives associated with the model (Radke et al., 2005; Kennedy et al., 2007).

Focusing on the period from 2016 to 2017, most of the beech area showed stable crown defoliation values. 36.65 %, 21.22 %, and 38.28 %

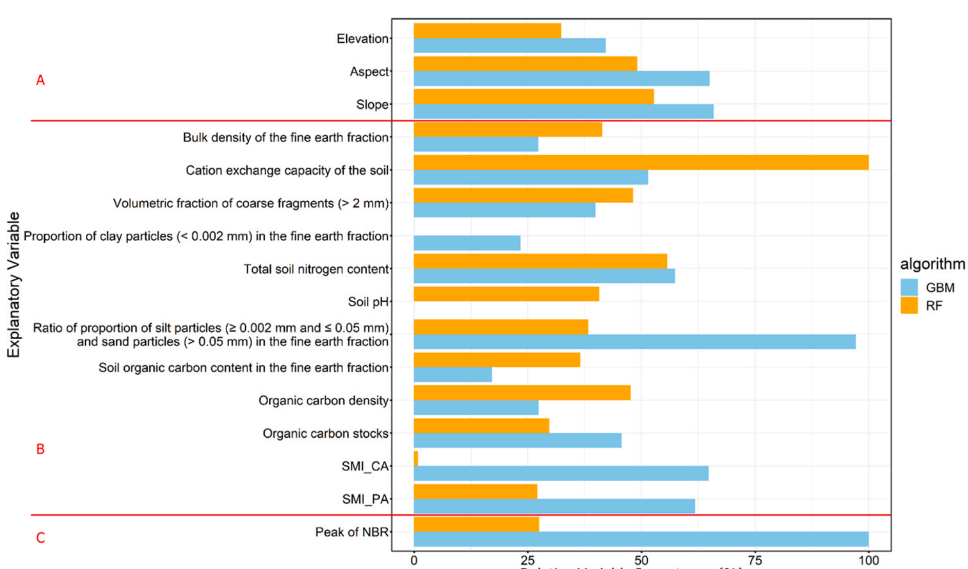

Fig. 3. Relative variable importance revealed by model M_geors. Red lines mark groups of A. topographic, B. soil properties, and C. remotely sensed variables, respectively.

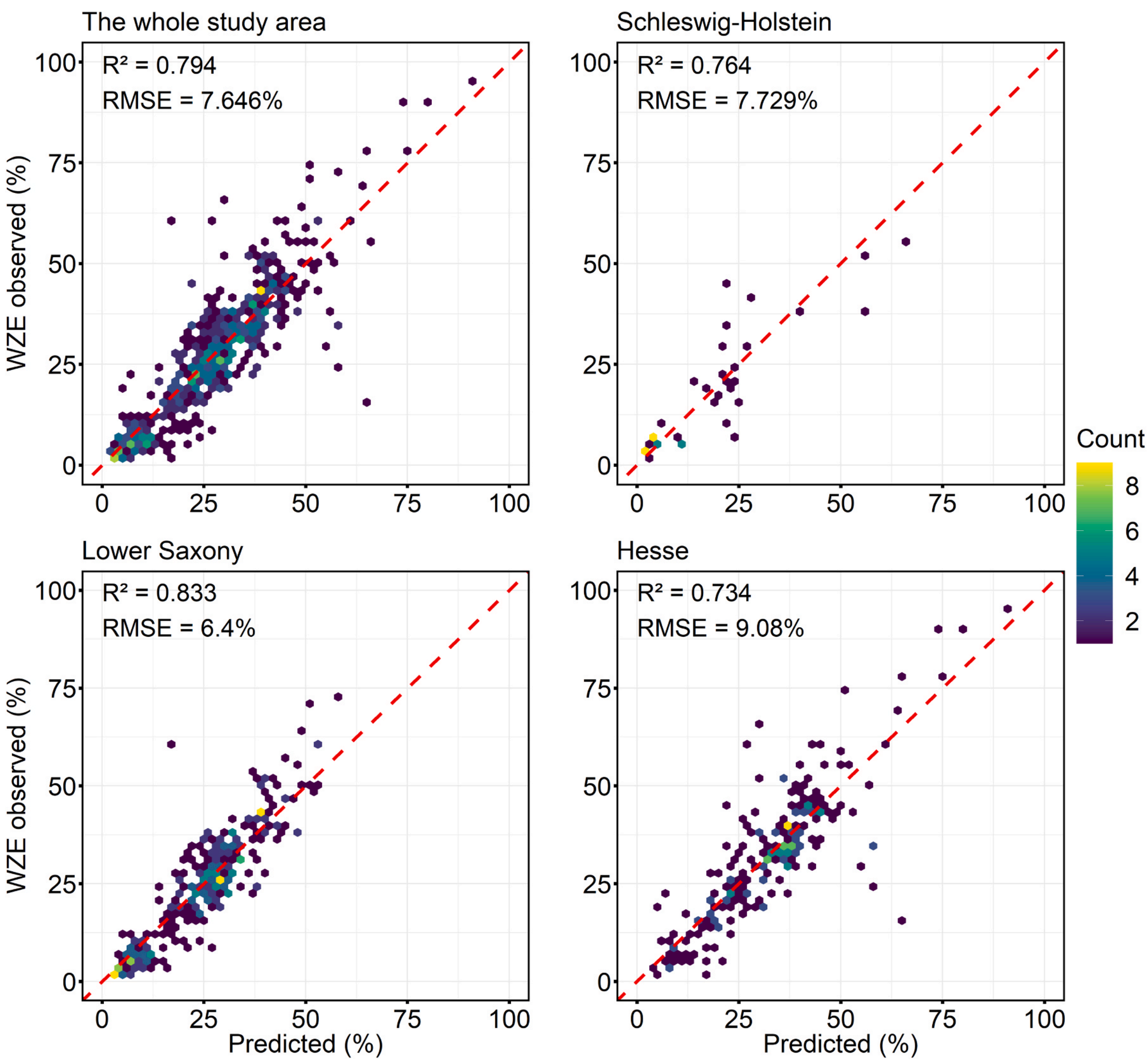

Fig. 4. Comparison between predicted and WZE observed crown defoliation from all years.

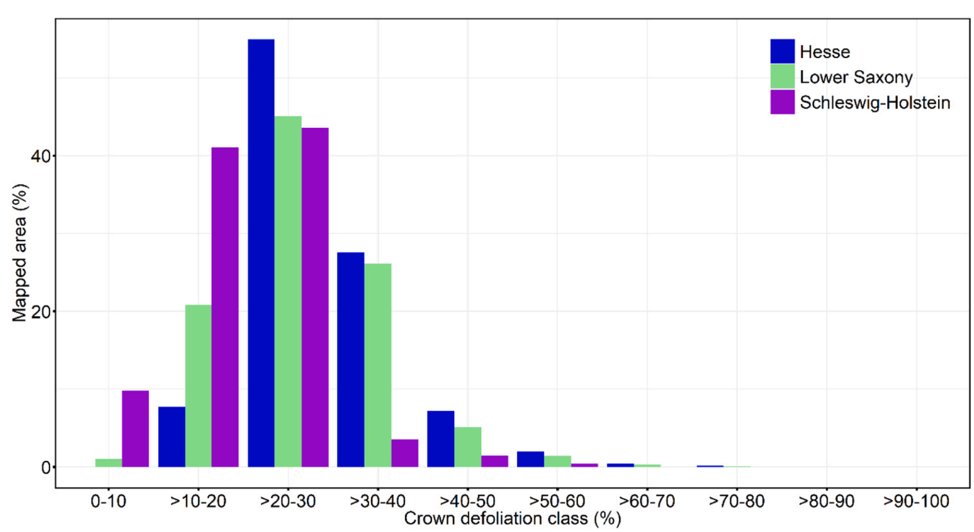

Fig. 5. Mapped area with *Fagus sylvatica* for all crown defoliation classes for all three federal states in the year 2022.

of the beech area in Schleswig-Holstein, Lower Saxony, and Hesse, respectively, exhibited a decrease in crown defoliation. These rates surpassed those of increasing defoliation in each respective federal state. A similar percentage of beech trees with decreasing crown defoliation (21.19 %) was identified from 2017 to 2018 in Lower Saxony, while no noticeable differences were observed for Schleswig-Holstein and Hesse

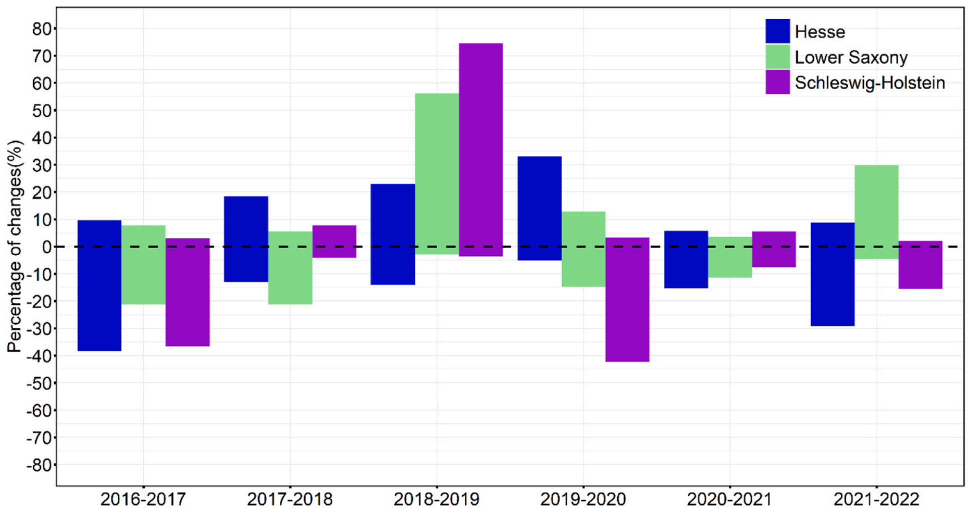

Fig. 6. Annual changes in the proportions of beech trees classified as 'increasing' (positive y-coordinates) and 'decreasing' (negative y-coordinates) in crown defoliation.

in terms of the percentages of beech trees showing increasing and decreasing crown defoliation. Noticeable changes occurred from 2018 to 2019, with 74.46 % of beech trees in Schleswig-Holstein and 56.12 % in Lower Saxony exhibiting increases in predicted crown defoliation. In contrast, this increase was not apparent in Hesse, with only 23 % of beech trees showing an increase in defoliation. Interestingly, from 2019 to 2020, more beech trees in Schleswig-Holstein exhibited a noticeable decrease in crown defoliation, up to 42.22 %, whereas in Hesse, a higher percentage of beech trees showed an increasing trend in defoliation (33.07 %) compared to those displaying a decreasing trend (5.18 %). No noticeable changes were observed in any federal states from 2020 to 2021. However, from 2021 to 2022, 29.83 % of beech trees in Lower Saxony showed an increasing trend in defoliation. In contrast, a higher percentage of beech trees in Schleswig-Holstein and Hesse exhibited decreasing crown defoliation compared to those showing increasing crown defoliation.

Medium-term trends from 2016 to 2022 were defined into 'increasing', 'stable' and 'decreasing'. Fig. 7(a) and (b) depict the spatial distribution of the medium-term trends in crown defoliation and the mapping results from 2022, respectively. According to the results, the 'stable' class was predominant, while the area from central to eastern Lower Saxony was identified with medium-term increasing crown defoliation. However, this area is not a primary distribution zone for *Fagus sylvatica* in the study region (Fig. 1). The area with increasing trends had low to moderate crown defoliation in 2022, as illustrated in Fig. 7(b). In addition, the medium-term decreasing trend in crown defoliation, which was observed in Lower Saxony, showed a much smaller area compared to other regions classified as 'increasing' and 'stable'.

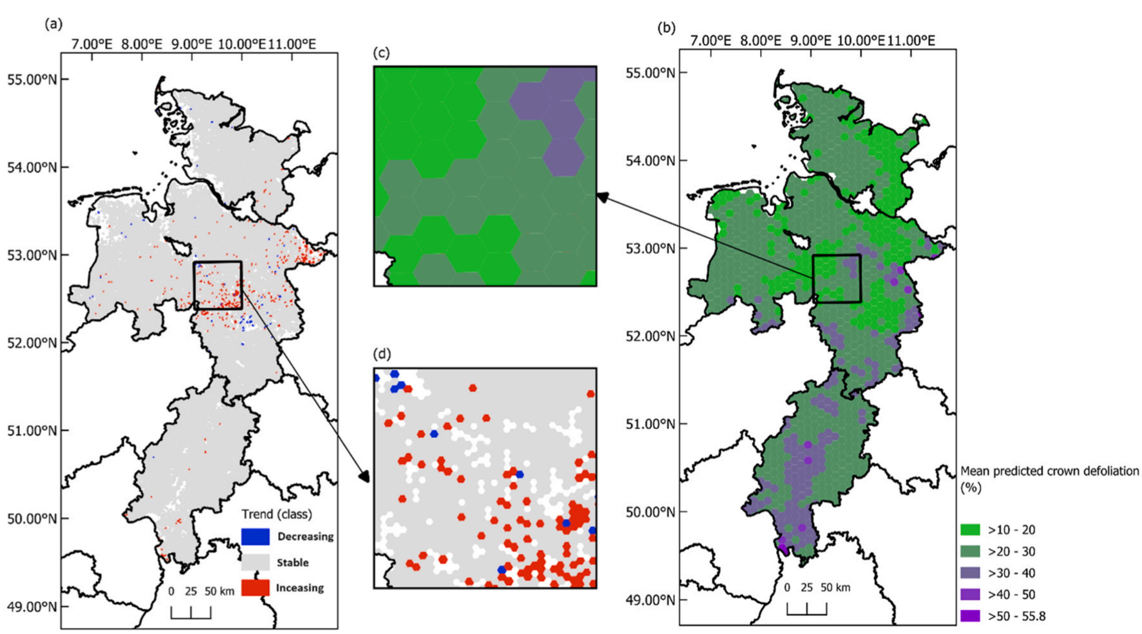

Fig. 7. (a) Medium-term trends in crown defoliation from 2016 to 2022 shown in 2 km-spacing (horizontal and vertical) hexagons; (b) mapped crown defoliation for 2022 in 10 km-spacing hexagons, where the mean predicted crown defoliation is calculated using all beech pixels with a 20 m resolution; (c) mean predicted crown defoliation for a zoomed area in 2022, and (d) the medium-term trend in crown defoliation for the same zoomed area.

4. Discussion

4.1. Important environmental factors describing crown defoliation

The Identification of environmental factors that describe crown conditions of *Fagus sylvatica* L. well is important in order to represent information for forest health - which has so far only been surveyed at sampling points - by means of regionalization approaches in the area. Successfully mapping crown condition will be beneficial for forest management. Results from machine learning regressions using various predictor sets demonstrate that relationships between crown defoliation and environmental factors can be found, whereby topographic and soil properties, DBH, and remotely sensed data are proven to be associated with crown defoliation. This aligns with the findings of Anderegg et al. (2015) that drought and climatic factors interact with biotic factors to influence defoliation in trees. In our study, the use of DBH did not significantly improve the model performance. Since it was not utilized for mapping, our discussion did not focus on a detailed examination of it.

Topographic and soil profile information played a crucial role in explaining crown defoliation and provided a solid foundation for model performance as these factors represent long-term environmental conditions. Although the integration of dynamic predictors, such as SMI and NBR only marginally improved model performance, this improvement highlights their importance in capturing short-term variability that static predictors alone do not account for. We assume that dynamic predictors, although they contribute minimally overall, are therefore a valuable addition to static predictors. Compared to previous studies (Leuschner et al., 2023; Weigel et al., 2023), we did not directly include climate data such as precipitation as explanatory variables. However, the SMI is a composite product with e.g. precipitation and temperature, and offers a unique advantage of combining soil and climate indicators, which has been discussed by Xu et al. (2024). Beech trees are susceptible to water deficits during the growing season. Studies have disclosed that soil water deficits affect the vitality of European beech and triggered tree mortality (Carsjens et al., 2014; Leuschner, 2020; Meyer et al., 2022; Schmied et al., 2023; Rukh et al., 2023). Soil moisture for the whole soil depth was therefore closely related to crown defoliation and improved the evaluation metrics in regressions. In addition, the soil moisture sums from preceding years were demonstrated to be associated with crown defoliation, indicating a lag effect between droughts and crown dieback. It has been widely discussed that beech trees not only experienced immediate physiological stress after droughts, but also exhibited pronounced symptoms of defoliation and crown decline in the subsequent year (Frei et al., 2022; Arend et al., 2022).

Remotely sensed data has demonstrated its ability to explain crown defoliation. However, it is important to note that the peak of a VI mainly reflects crown condition from a satellite perspective. Thus, it is linked to crown defoliation but does not represent a causal relationship. Our results demonstrate that utilizing NBR calculated using band 8 A and 12 achieved better performance in explaining crown defoliation than using other VIs (Table A3). Band 8 A is a band in the near-infrared (NIR) range, whereas band 12 represents the short-wave infrared (SWIR). As previously demonstrated by Ghulam et al. (2007) and Wang et al. (2018), near-infrared (NIR) and short-wave infrared (SWIR) bands are effective for assessing vegetation water content and are closely related to vegetation cover. The NBR was initially employed to assess the extent of burned areas but has since been utilized to detect a range of forest disturbances (König et al., 2023; Xu et al., 2024). The effectiveness of the NBR in identifying changes in vegetation health and structure makes it a valuable tool for monitoring not only fire impacts but also other disturbances such as disease, pest infestations, and deforestation. In our case, the crown condition of beech trees may be better reflected by band 8 A and 12 than by other visible bands (e. g., Band 4 and 5, as detailed in Tables A1 and A3). Despite NBR not playing a significant role in the RF model (Fig. 3; Table A5), it enhanced the model performance. NBR played a significant role in the model using GBM, contributing 100 % to its significance (Fig. 3), but the model shows a bit lower performance compared to RF. This may indicate that using remotely sensed VI as a side predictor makes the model more robust instead of considering it as a main predictor. RF considers multiple decision trees and averages the importance of predictors across many decisions. A predictor that is important in some trees may not be as significant in others. This averaging process smooths out the importance values, resulting in less pronounced differences among variable importances. In contrast, GBM calculates how much each predictor reduces the loss function at each split. If a predictor is very important during the early boosting phases, it can receive a heavy weight, thereby assigning it greater significance. In our study, NBR achieves 100 % variable importance from GBM but only 27.50 % from RF (Fig. 3), indicating that GBM assigned its entire weight to NBR. This is due to the emphasis on NBR's central role in minimizing errors during the initial iterations. Conversely, RF distributes importance more evenly across several features.

Uncertainties exist when using remotely sensed NBR peaks in regressions. According to our study design, a 20-meter resolution for pixels was adopted, for incorporating all six trees belonging to the same survey point (Fig. 2). There may still be positional inaccuracies between the six trees from a WZE survey point and a Sentinel-2 pixel. Mixed spectral signals may be generated due to other land classes. This issue may more likely influence the beech plots that suffer severe leaf losses, as the spectral signals of understory vegetation are mixed into the same pixels of pure beech plots. The understory vegetation may also result in the underestimation of crown defoliation in models (Fig. 4), whereby higher VI did not represent denser canopy of target beech trees but likely the detection of understory vegetation. To fully leverage the capabilities of WZE estimates in remote sensing applications, achieving a strong alignment between WZE and remotely sensed time-series data is critical. According to the WZE/ICP Forests plot design, six proximate trees were selected at each of four points located around a reference point. The morphology of these six trees is naturally often different. As a result, there may be a discrepancy between the crown defoliation acquired by terrestrial estimation and the VI metrics obtained from remote sensing data. In other words, the WZE/ICP Forests design is rather optimized for the precise and accurate statistical estimation of target crown defoliation but is not designed to be linked to satellite data. Similarly, this issue has been discussed by Blickensdörfer et al. (2024). Combining national, terrestrial survey and remote sensing data in forestry remains a challenge, as indirectly summarized by Fassnacht et al. (2024). Therefore, we recommend that VIs should be used more cautiously when deriving crown condition estimates from them.

4.2. Beech crown condition and annual developments for each federal state

Mapping crown defoliation provides area-related information to assess tree crown damage and compare regional differences, which is beneficial for forest management. The extensive mapping of crown defoliation in beech forests yields valuable insights, such as identifying beech plots with low to severe damage. This method - combining WZE/ICP Forests grid data with area-related geo-ecological and remote sensing data - offers a comprehensive overview for crown defoliation, enhancing our understanding of forest health and the consulting of forest managers. The mapping results indicate that most beech trees experienced low to moderate crown damage over the research years, with variations in the severity of damage observed across the three federal states from north to south. A greater number of healthy to minimally damaged beech trees were observed in Schleswig-Holstein, followed by Lower Saxony. In contrast, beech trees in Hesse clearly exhibited more moderate to severe damage (Fig. 5; Fig. 7(b); Fig. A2). These findings are in accordance with the WZE/ICP Forests grid data results.

Furthermore, detecting annual changes in the proportions of beech trees exhibiting increasing and decreasing trends in crown defoliation is essential for assessing beech health under the influence of dynamic predictors (soil moisture and vegetation index). Since we have discussed the important predictors in Section 4.1, we shift our focus to spatial patterns of dynamic predictors.

Our findings demonstrate that there are regional differences among the three federal states based on mapped crown defoliation. In Schleswig-Holstein, where beech trees exhibited a low-level damage, more beech trees with increasing crown defoliation were observed from 2018 to 2019. Beech trees there showed a greater capacity for recovery, as more trees with decreasing crown defoliation from 2019 to 2020 were identified compared to Lower Saxony and Hesse. This indicates a positive improvement in tree health. Healthy trees may appear more susceptible to drought stress, but they tend to recover faster (Haase and Hellwig, 2022). In Lower Saxony, where beech trees exhibited low to moderate crown damages, a high percentage of beech trees with increasing crown defoliation was also identified from 2018 to 2019, but no evident recovery was observed later. The rise in beech trees with increasing crown defoliation noted from 2021 to 2022 in Lower Saxony indicates a decline in tree vitality. Moreover, beech trees in Hesse with moderate to high crown defoliation experienced less changes compared to the other two federal states. In summary, the magnitude of annual changes appears to be linked to the damage level in crown condition.

In terms of uncertainties, limited samples of high crown defoliation (>60 %) can affect model performance, hindering the accurate prediction of high crown defoliation compared to low to moderate defoliation. Larger training samples benefit the prediction of low to moderate defoliation. There may be limitations in using a 2 % threshold to detect actual changes. Reducing the threshold to decrease false negatives can often lead to an increase in false positives. Consequently, the analysis might falsely identify changes in crown defoliation. To our knowledge, limited studies have mapped crown defoliation using the WZE design or discussed annual changes in beech trees. Thus, we recommend that future studies focus on the issue of threshold selection. Furthermore, the ML models utilized in this study are only capable of predicting area-wide crown defoliation for the current year and do not provide future forecasts. To accurately evaluate future crown defoliation, timely data on relevant predictors is essential for training new models that can map corresponding crown defoliation.

4.3. Medium-term trend in crown defoliation

Overall, no medium-term deterioration or recovery was observed in the mapped crown defoliation for European beech. Some beech plots in Lower Saxony exhibited signs of potentially deteriorating crown condition. This contradicts the WZE grid data showing a continuous deterioration of crown condition in Hesse during the observation period and a sudden deterioration in Lower Saxony. In Schleswig-Holstein WZE crown defoliation was only increased in 2019; this moderate reaction is probably due to the oceanic climate and moderate climate change to date in Schleswig-Holstein.

The stable medium-term trend observed in Hesse may be attributed to the moderate to high level of crown defoliation. Beech trees that are moderately to severely damaged may be not as susceptible to drought stress as healthy beech trees. However, this trend in Hesse could also be attributed to the model's underestimation of crown defoliation. In other words, the model may not accurately predict high crown defoliation (Fig. 4). Consequently, the actual medium-term trend for Hesse was not detected by the linear regression. This is because the mapped crown defoliation for each year appeared lower and thus depicted the beech forests as healthier than they actually were. While beech trees in Schleswig-Holstein experienced evident deterioration, they showed recovery later, as discussed above. This also indicates that the physiological responses of *Fagus sylvatica* L. to drought are complex. On the other hand, the soil moisture sums in Hesse and Schleswig-Holstein did not show a continuous decrease from 2016 to 2022, when compared to Lower Saxony. Still, a continuous decrease in soil moisture can result in the deterioration of beech crown condition. According to Leuschner et al. (2023), although beech mortality is currently lower in northern Germany, most of this region is expected to become unsuitable for beech growth within the next tree generation.

Furthermore, it is crucial to emphasize that in our study, crown defoliation was the sole indicator of the vitality of beech trees. However, research by van der Maaten et al. (2024) suggests that crown condition post-drought is a less reliable measure of tree vitality compared to ring width analysis. Additional indicators, such as insect infestations and the mortality rate, also reflect the health of beech forests (Meyer and Schmidt, 2011; Brück-Dyckhoff et al., 2019). Therefore, it is essential that modeling approaches take into account a broader range of physiological parameters to assess the vitality of beech trees comprehensively.

5. Conclusions

In this study we present a crown defoliation modeling approach for *Fagus sylvatica* L. on a federal state level by combining National Forest Condition Survey data (WZE) with a variety of geo-ecological variables and Sentinel-2 with high accuracy. Our findings have implications for evaluating the potential for mapping crown defoliation data using geo-ecological and remote sensing data, as we evaluated topographic and soil characteristics associated with crown condition and built machine learning models that map crown defoliation data. Topographic variables and static soil properties form the basis for explaining crown defoliation, while dynamic soil moisture and vegetation index (VI) metrics improve modeling accuracy. The comparison between predictions and WZE observations confirms the robustness of our models. Our study reveals the uncertainty in the positional accuracy of WZE data in relation to pixels derived from remotely sensed data. It highlights the challenges posed by mixed pixels, a topic that requires further optimization in subsequent studies.

The models show that most beech trees exhibited low to moderate crown condition in the study region. A higher number of trees with moderate to severe crown defoliation were observed in Hesse, followed by Lower Saxony and Schleswig-Holstein. Furthermore, healthy and minimally damaged beech trees were more susceptible to decreases in soil moisture but could recover faster than beech trees with moderate and high crown defoliation. Beech forests facing continuously decreasing soil moisture and drought stress may be experiencing medium-term deterioration in crown condition. Overall, our study not only demonstrates the interrelations among these variables but also utilizes environmental parameters to map crown defoliation across extensive areas, providing a valuable tool for evaluating beach health on a regional basis. This approach can serve as a stepping stone for using geo-ecological and remote sensing data to map the grid data of tree crown condition from the WZE survey. The WZE grid data can be evaluated at a national level, too. The grid width is chosen so that the results are representative for the respective federal state. However, only point-data are available in space and time. This means that area-wide information and forecasts on crown condition cannot be generated. The advantage of a modeling approach would therefore be the regionalization of the WZE grid data and the forecast of crown condition.

The model developed can be extended beyond the three federal states to the national level in Germany. It is also helpful to use the model to make statements for smaller biogeographical regions than the federal states. Various physiological variables related to tree functioning should be integrated and collectively utilized in future studies to improve the models. The aim is to develop a generalized model for the area-wide monitoring of European beech forests and other tree species based on the WZE grid data.

CRediT authorship contribution statement

Ulrike Talkner: Writing – review & editing, Investigation. **Philip**

Beckschäfer: Writing – review & editing, Investigation. **Birgit Kleinschmit:** Writing – review & editing, Supervision, Funding acquisition, Conceptualization. **Caroline Klinck:** Writing – review & editing, Investigation. **Michael Förster:** Writing – review & editing, Supervision, Conceptualization. **Chunyan Xu:** Writing – original draft, Visualization, Software, Methodology, Data curation, Conceptualization.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the author(s) used [Wordvice AI], [DeepL Write] and [ChatGPT] to correct English spelling and grammar errors and to adjust the order of sentences for coherence. After using this tool/service, the author(s) reviewed and edited the content as needed and take full responsibility for the content of the publication.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.foreco.2024.122383.

Data availability

The authors do not have permission to share data.

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