

Article

Estimating Forest Volume and Forest Volume Change Using Random Forests and Sentinel-2 Data

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Highlights

What are the main findings?

- Direct and indirect model-assisted approaches produced similar estimates of forest volume change, with the direct approach yielding smaller standard errors.
- Model-assisted estimators using remotely sensed auxiliary data substantially reduced standard errors.

What are the implications of the main findings?

- Integration of remotely sensed auxiliary data improves the precision of forest inventory-based estimates, particularly for change estimation.
- Finer spatial resolution (10 m) offered only a negligible gain over coarser (20 m) resolution, while requiring greater processing and analysis effort.

Abstract

Accurate and precise estimation of forest volume and its changes are fundamental for sustainable forest management, resource assessment, and long-term inventory monitoring. Multi-temporal remotely sensed data provide spatial auxiliary information that can substantially increase the precision of estimates of volume and volume change obtained from probability-based field samples. However, methodological differences between indirect and direct change estimation approaches may lead to differences in variance estimation and uncertainty propagation. This study, therefore, compares forest volume and forest volume change estimation under design-based inference by integrating probability-sampled National Forest Inventory (NFI) data with multi-temporal Sentinel-2 auxiliary variables at 10 m and 20 m spatial resolutions, using the random forest (RF) prediction algorithm and both indirect and direct estimation approaches. Forest volume means are estimated for two inventory years, 2013 and 2023. For the indirect approach, simple expansion and model-assisted regression estimators are formulated separately for each year, and change is estimated as the difference between time-specific estimates. For the direct approach, plot-level change is used as the response variable, and model-assisted regression estimators are constructed using changes in auxiliary variables, with residual-based variance estimators. Random forest models using Sentinel-2 auxiliary data explained approximately 51–62% of the variation in forest volume, with RMSE values ranging from about 79 to 97 m³/ha. The 10 m resolution data produced slightly more precise predictions than the 20 m data, though the gain was small relative to the greater processing effort required. Model-assisted estimators using both 10 m and 20 m Sentinel-2 data produced substantially smaller standard errors than simple expansion estimators, with relative efficiency



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analysis indicating an approximately fivefold gain in efficiency. The direct and indirect model-assisted approaches produced similar estimates of volume change, although the direct approach resulted in smaller standard errors. Overall, remotely sensed auxiliary data primarily improved the precision of forest volume change estimates but not the magnitude of the estimated change.

Keywords: forest volume; volume change; national forest inventory; Sentinel-2; random forests; design-based inference; model-assisted estimation; variance estimation

1. Introduction

Forests cover approximately 4.0 billion hectares globally, representing about 31% of the Earth's land area, and play a critical role in ecological stability, economic development, and biodiversity conservation [1]. They provide timber and non-timber resources [2,3], regulate hydrological cycles, and support millions of livelihoods [4]. Despite their importance, global forests continue to experience pressures from land-use change, natural disturbances, and varying management practices. Although deforestation rates have slowed in some regions, forest degradation and structural changes remain widespread, affecting forest composition, productivity, and resource availability [1,5].

Beyond forest area, forest volume and aboveground biomass are fundamental indicators of forest condition and productivity [6]. Changes in forest volume reflect growth, harvesting, disturbance, and regeneration processes and thereby provide more comprehensive information on forest dynamics than land area-based measures alone [7]. Accurate and precise estimation of forest volume and its temporal change is therefore essential for sustainable management and long-term monitoring of forest resources. National Forest Inventories (NFIs) provide statistically rigorous, probability-based estimates of forest attributes and remain the backbone of large-scale forest monitoring systems [6–8]. NFIs commonly use systematic or stratified sampling designs [9] in which field measurements are collected from permanent and/or temporary sample plots distributed across large geographic areas. Standardized protocols are used to measure variables such as tree diameter, tree height, and species composition, from which attributes including growing stock volume, biomass, and carbon are estimated. For some NFI population parameters, inventory sample sizes are too small to produce estimates with sufficient precision for operational applications, reporting, and decision-making [10,11]. To address this deficiency, remotely sensed data have been demonstrated to be an excellent source of auxiliary information [12,13].

Building on these developments, previous studies on volume change can be differentiated based on whether they employ direct [14], indirect [15], or combined approaches to change estimation [6,16,17]. The indirect approach, sometimes described as a two-step modelling approach, entails constructing separate models describing the relationship between the response variable and remotely sensed auxiliary variables for each of two time points, and subsequently estimating change as the difference between the estimates for those times [18]. In contrast, the direct approach involves constructing a single model of change by relating observed plot-level differences in the response variable to corresponding differences in the remotely sensed auxiliary variables between two dates [18]. A smaller group of studies has considered both direct and indirect approaches within the same framework to enable comparison of their performance [6,16,18–20]. For example, McRoberts et al. [18] conducted a statistically rigorous comparison of indirect and direct estimation of forest biomass change using forest inventory and airborne laser scanning (ALS) data. Using simple expansion as well as indirect and direct model-assisted estimators, they found

that ALS data improved precision for both approaches, while the indirect method yielded greater precision for the estimate of the study area mean than the traditional direct method. Similarly, Knapp et al. [20] considered three approaches for estimating biomass change, including the direct and indirect methods as well as a third approach, referred to as an enhanced direct approach which incorporates canopy texture information. Their results indicate that performance varied across approaches, with the indirect approach yielding smaller prediction errors than the direct approach, while the enhanced approach achieved comparable accuracy.

Advances in satellite remote sensing have created new opportunities to enhance forest inventory estimation through the integration of spatially exhaustive auxiliary information [21]. For instance, satellite data have been widely used to estimate key forest structural attributes such as canopy height [22,23], growing stock volume [24–26], and aboveground biomass [6,27,28], enabling spatially continuous assessments across large, forested areas. These developments have also prompted the application of additional prediction methods that support large-area estimation and improve the precision of forest attribute estimates [29–31]. In particular, model-assisted and model-based estimators have been successfully used to estimate biomass [10,29,32,33], volume [21,24], and forest change [6,28], using a range of approaches including linear regression models, nonlinear regression methods, and machine learning techniques such as random forest (RF), support vector regression, extreme gradient boosting, and convolutional neural networks [10,18,33,34]. Among these, RF has been one of the most widely used recent approaches [6,35–37] due to its ability to model complex nonlinear relationships and handle high-dimensional remotely sensed data. For example, Esteban et al. [6] applied RF with multi-sensor remotely sensed data to estimate forest volume, aboveground biomass, and their changes, demonstrating improved predictive performance and precision, while also addressing uncertainty in population estimates using bootstrapping methods.

In some studies, direct approaches led to more precise estimates [16,17]. For example, Cao et al. [17] reported that the direct approach reduced relative RMSE from 28.35% to 25.64% compared to the indirect approach, while Bollandsås et al. [16] found that direct approaches produced smaller prediction errors for biomass change estimation. In contrast, Knapp et al. [20] reported smaller RMSE for the indirect approach ($12.6 \text{ m}^3/\text{ha}$) compared to the direct approach ($18.7 \text{ m}^3/\text{ha}$). McRoberts et al. [18] also found that the indirect approach produced greater precision than the traditional direct approach, although modified direct formulations produced the greatest precision overall. This suggests that the relative performance of change estimation approaches is not consistent and may be influenced by differences in data, modelling strategies, and study conditions. However, systematic comparisons of these approaches within a consistent inferential framework, particularly across different spatial resolutions, remain limited.

Sentinel-2 multispectral imagery is widely used in forest remote sensing for forest structural variables such as aboveground biomass and growing stock volume because of its spatial resolution, frequent temporal coverage, and open access availability [38,39]. Spectral bands and vegetation indices derived from Sentinel-2 data are commonly used as auxiliary variables in regression and machine learning models linked with field inventory data [39–41]. However, it is important to note that forest structure is inferred rather than directly measured. Therefore, although Sentinel-2 provides useful auxiliary information for predicting forest variables, the knowledge of their usefulness for predicting forest volume change as a sole source of auxiliary variables remains relatively unknown and would benefit from additional research, particularly within design-based estimation frameworks where inference is based on probability sampling rather than model assumptions.

In this study, we employed three sets of statistical estimators including simple expansion estimators and both indirect and direct model-assisted regression estimators. The analysis focuses on comparing indirect and direct approaches to change estimation within the design-based inferential framework using multi-temporal Sentinel-2 data at 10 m and 20 m spatial resolutions over the period 2013–2023, with auxiliary relationships modelled using a RF algorithm. In the remote-sensing context, the indirect approach estimates change as the difference between time-specific mean estimates, whereas the direct approach models change explicitly using plot-level differences in both response and auxiliary variables. Accordingly, this study evaluates the performance of these approaches across spatial resolutions and examines the usefulness of Sentinel-2 data for supporting change estimation.

Therefore, the objectives of this study were fourfold: (1) to estimate forest growing stock volume and volume change using Sentinel-2 auxiliary variables within a design-based inferential framework, (2) to compare direct and indirect approaches for estimating forest volume change, (3) to evaluate the performance of model-assisted estimators in combination with the direct and indirect approaches relative to simple expansion estimators, and (4) to compare the relative advantages of 10 m and 20 m spatial resolutions.

2. Materials and Methods

2.1. Study Area

The selected study area is Estonia, located in northern Europe along the Baltic Sea coast. The country extends from 57°30'34"N to 59°49'12"N in latitude and from 21°45'49"E and 28°12'44"E in longitudes. It is bordered by the Baltic Sea to the west and the Gulf of Finland to the north (Figure 1). Approximately 53.6% of Estonia's total land area (45,339 km²) is covered by forests, amounting to about 23,308 km² [42].



Figure 1. Location of the study area in Northern Europe along the Baltic Sea and the Gulf of Finland (source: authors).

2.2. General Methodological Framework

This study integrates probability-sampled NFI data with multi-temporal Sentinel-2 auxiliary variables to estimate forest volume and forest volume change within a design-based inferential framework. NFI measurements from two inventory years, 2013 (t_1) and 2023 (t_2), were used to estimate population-level mean forest volume (m³/ha) and average annual change for the intervals $\Delta(t_1 t_2)$. The analysis was based on NFI sample plots with

repeated measurements for the two inventory years. These plots were selected using a systematic NFI cluster grid, with one plot selected from each cluster location, thereby ensuring spatial independence among observations [43].

Simple expansion and model-assisted regression estimators were implemented with both indirect and direct change estimation strategies. In the indirect approach, forest volume means were estimated separately for 2013 and 2023, and change was estimated as the difference between the corresponding time-specific mean estimates, with variance estimation explicitly incorporating covariances between repeated measurements. In the direct approach, plot-level mean annual volume change (MAAVC) was predicted from differences in repeated measurements and used to estimate forest volume change. Mean change per year for each interval was obtained by scaling MAAVC according to the length of the corresponding inventory interval. Model-assisted estimators were constructed from auxiliary variable differences $\Delta x_{t_i t_j} = x_{t_j} - x_{t_i}$, where x_t is an auxiliary variable derived from Sentinel-2 imagery at time t , with t_i and t_j denoting two inventory years used to define a change interval. RF models were used to calculate predictions using Sentinel-2 auxiliary variables for incorporation into the model-assisted estimators. Model development was conducted separately for each change interval $\Delta_{t_i t_j}$ using a 75% training and 25% testing split. The overall methodological workflow is illustrated in Figure 2.

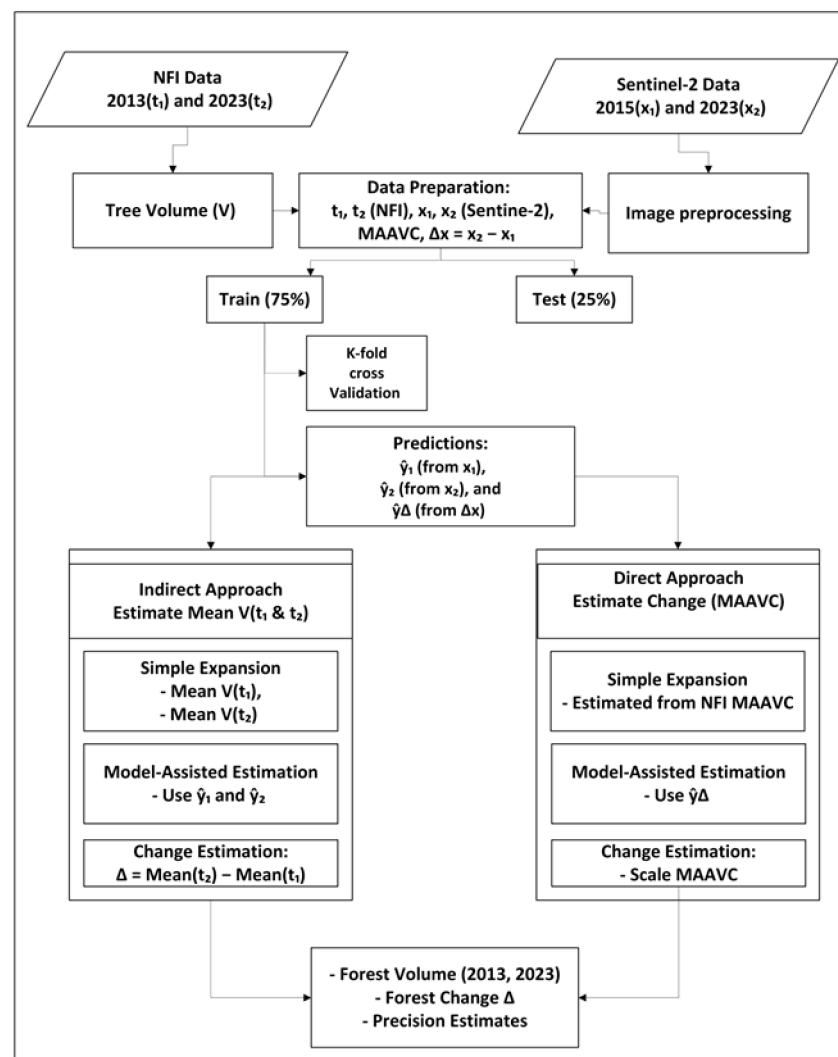


Figure 2. Schematic workflow comparing indirect and direct approaches for forest volume and change estimation.

2.3. Volume Estimation from the Estonian NFI Field Plots

Individual tree volume was predicted using a regional species-specific allometric model (Equation (1)) where uncertainty in the tree-level predictions was considered negligible relative to the uncertainty of the large area estimates.

$$V = (\beta_1 + \beta_2 \cdot h + \beta_3 \cdot f) \cdot \left(\frac{t}{t+5} \right)^{(\beta_4 + \beta_5 \cdot h)} + \varepsilon, \quad (1)$$

where V is the volume of a tree; β_1 – β_5 are species-specific parameters, whose estimates are obtained from unpublished local sources; h is tree height; t is tree age; and f indicates island (1) or mainland (0) conditions.

The field data were obtained from circular sample plots located using a systematic grid with radii of 10 m, corresponding to an area of approximately 315 m² [44]. Within each plot, trees with diameters at breast height (DBH) were measured at 1.3 m above ground level for all trees with DBH $\geq$ 5 cm in accordance with established inventory protocols to support subsequent DBH modelling and height estimation [45]. Tree height measurements were acquired using a hypsometer (Haglöf Sweden AB, Långsele, Sweden), which determines height based on ultrasonic signals and trigonometric calculations derived from distance and angle observations. Diameter at breast height was measured using a caliper (Haglöf Sweden AB, Långsele, Sweden) with an accuracy of ± 1.0 mm, following a consistent single-measurement procedure. The locations of the plot centres were determined using a Global Navigation Satellite System (GNSS) receiver (Trimble Inc., Westminster, CO, USA), with positional accuracy of up to 5 m, ensuring reliable alignment with satellite-derived data. Tree-level predictions obtained from Equation (1) were aggregated at the plot level to predict total sample plot volume, which was subsequently converted to a per-hectare basis (m³/ha).

2.4. Sentinel-2 Remotely Sensed Data

The Sentinel-2 mission, developed under the European Union's Copernicus program, provides multispectral imagery with fine spatial resolution. The mission includes Sentinel-2A (launched in 2015) and Sentinel-2B (launched in 2017), which together provide frequent image acquisitions [46]. The sensor records reflectance in 13 spectral bands covering the visible, near-infrared (NIR), and shortwave infrared (SWIR) regions, with spatial resolutions of 10 m, 20 m, and 60 m [47]. Because Sentinel-2 imagery was not available for 2013, data from 2015 were used as the closest temporal substitute for the earlier inventory measurements. The use of substitute imagery from an adjacent year is common when historical satellite data are unavailable [28,35,48]. The satellite images were obtained from the Copernicus Data Space platform <https://dataspace.copernicus.eu> (accessed on 2 December 2025), and bands 2–8, 8A, 11, and 12 were selected for analysis. The study area is covered by approximately 14 Sentinel-2 scenes, which were mosaicked into a single dataset. Atmospheric correction was performed using Sen2Cor (v2.09.00) within SNAP (v13), after which the bands were resampled to 10 m and 20 m to evaluate the influence of spatial resolution on model performance. Cloud and shadow masking were performed using the KappaMask processor (v2.4; KappaZeta Ltd., Tartu, Estonia) [49], and vegetation indices (VI) were calculated from the processed spectral bands. The characteristics of the derived variables are presented in Table 1.

2.5. Random Forest Prediction Models

RF, developed by Breiman [50], is an ensemble machine learning algorithm based on classification and regression trees (CART). RF models were implemented in R (v4.4.1) using the ranger package (v0.17.0) [51] to predict plot-level forest volume and volume change

using Sentinel-2-derived variables (Table 1). The data were split into training (75%) and testing (25%) sets, and model performance was evaluated using k-fold cross-validation. Model parameters were optimized using a grid search, with ntree ranging from 100 to 2000 (step 100) and mtry, minimum node size, and sampling fraction tuned. Models were developed for both spatial resolutions (10 m and 20 m) under the indirect and direct approaches. The indirect approach predicted volume separately for each inventory year and estimated mean change per unit area as the difference between estimated means. In contrast, the direct approach modelled plot-level mean annual average volume change (MAAVC), which was subsequently converted to volume change per unit area using the inventory time interval. RF predictions for all pixels in the study area were then incorporated into the model-assisted regression estimators to improve the precision of population estimates.

Table 1. Sentinel-2-derived variables and explanation *.

Variable	Notation	Description
Sentinel-2 band	Band 2 (B2)	Blue (458–523 nm)
	Band 3 (B3)	Green (543–578 nm)
	Band 4 (B4)	Red (650–680 nm)
	Band 5 (B5)	Red-edge 1 (698–713 nm)
	Band 6 (B6)	Red-edge 2 (733–748 nm)
	Band 7 (B7)	Red-edge 3 (773–793 nm)
	Band 8 (B8)	NIR 1 (785–899 nm)
	Band 8A (B8A)	NIR 2 (855–875 nm)
	Band 11 (B11)	SWIR 1 (1565–1655 nm)
Veg. indices	Band 12 (B12)	SWIR 2 (2100–2280 nm)
	NDVI	$(B8 - B4) / (B8 + B4)$
	ARVI	$(B8A - B4 - y \times (B4 - B2)) / (B8A + B4 - y \times (B4 - B2))$
	NDVIre705	$(B8 - B5) / (B8 + B5)$
	NDVIre740	$(B8 - B6) / (B8 + B6)$
	NDVIre783	$(B8 - B7) / (B8 + B7)$
	EVI	$2.5 \times ((B8 - B4) / (B8 + 6 \times B4 - 7.5 \times B2 + 1))$
	SAVI	$(B8 - B4) / (B8 + B4 + L) \times (1 + L)$
	chlre	$((B8) / (B5)) - 1$
	GNDVI	$(B8 - B3) / (B8 + B3)$
	MSAVI	$0.5 \times (2 \times B8 + 1 - \text{sqrt}((2 \times B8 + 1)^2 - 8 \times (B8 - B4)))$

* nm is the wavelength in nanometers, L is the soil brightness correction factor at 0.5 and y is 0.106.

2.6. Estimation of Population Means and Change

The dataset consisted of 280 plots arranged in clusters, within which one candidate plot was randomly selected per cluster and treated as an individual sampling unit [43]. This resulted in 104 sampling units for subsequent analyses. The selection was used to maintain spatial independence among observations and to allow the use of design-based estimators under the equal probability sampling assumption. Although the number of observations was reduced, the same sampling-unit definition was applied consistently across all estimators. Diagnostic analysis (Table A2) showed that the selected sample retained much of the GSV distributional structure, with similar variability and range coverage of approximately 75–78% across the two inventories years. Under this assumption, population means and changes were estimated using both simple expansion and model-assisted regression estimators under indirect and direct estimation approaches.

2.6.1. Indirect Estimation

With the indirect approach, population means were estimated separately for the two inventory years and mean average annual change per unit area was estimated as the

difference between the corresponding mean estimates. Variances of change estimates were estimated by incorporating the covariance between the estimates at the two inventory times.

Indirect Simple Expansion Estimator

The population mean was estimated using the simple expansion estimator [52,53]:

$$\hat{\mu} = \frac{1}{n} \sum_{i=1}^n y_i. \quad (2)$$

The variance of the estimate of the mean was estimated as:

$$\widehat{\text{Var}}(\hat{\mu}) = \frac{1}{n \cdot (n-1)} \sum_{i=1}^n (y_i - \hat{\mu})^2 = \frac{1}{n \cdot (n-1)} \left[\sum_{i=1}^n y_i^2 - \frac{1}{n} \left(\sum_{i=1}^n y_i \right)^2 \right]. \quad (3)$$

For indirect estimation of change, means and variances were first estimated for the two inventory times: $\hat{\mu}_1$, $\hat{\mu}_2$, $\widehat{\text{Var}}(\hat{\mu}_1)$ and $\widehat{\text{Var}}(\hat{\mu}_2)$.

Mean average annual change per unit area was then estimated as

$$\widehat{\Delta\mu} = \hat{\mu}_2 - \hat{\mu}_1 \quad (4)$$

with variance:

$$\widehat{\text{Var}}(\widehat{\Delta\mu}) = \widehat{\text{Var}}(\hat{\mu}_2) - 2 \cdot \widehat{\text{Cov}}(\hat{\mu}_1, \hat{\mu}_2) + \widehat{\text{Var}}(\hat{\mu}_1) \quad (5)$$

where the covariance term was estimated as:

$$\begin{aligned} \widehat{\text{Cov}}(\hat{\mu}_1, \hat{\mu}_2) &= \frac{1}{n \cdot (n-1)} \sum_{i=1}^n (y_{1i} - \hat{\mu}_1) \cdot (y_{2i} - \hat{\mu}_2) \\ &= \frac{1}{n \cdot (n-1)} \left[\sum_{i=1}^n y_{1i} \cdot y_{2i} - \frac{1}{n} \left(\sum_{i=1}^n y_{1i} \right) \cdot \left(\sum_{i=1}^n y_{2i} \right) \right] \end{aligned} \quad (6)$$

where n is the sample size and y_i is the observed value for the i -th sampling unit.

Indirect Model-Assisted Regression Estimator

The model-assisted regression estimator of the population mean is:

$$\hat{\mu} = \frac{1}{N} \sum_{i=1}^N \hat{y}_i + \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i) \quad (7)$$

where N is the total number of population units (pixels) for which predictions were calculated, $\hat{y}_i$ are RF predictions and residuals are defined as $\varepsilon_i = y_i - \hat{y}_i$.

The variance of the estimate of the mean was estimated from the residuals as

$$\begin{aligned} \widehat{\text{Var}}(\hat{\mu}) &= \frac{1}{n \cdot (n-1)} \sum_{i=1}^n (\varepsilon_i - \bar{\varepsilon})^2 \\ &= \frac{1}{n \cdot (n-1)} \left[\sum_{i=1}^n \varepsilon_i^2 - \frac{1}{n} \left(\sum_{i=1}^n \varepsilon_i \right)^2 \right] \end{aligned} \quad (8)$$

Relative efficiency (RE) was also used to assess the utility of the remotely sensed auxiliary data for time-specific mean estimation. Following McRoberts et al. [54], RE was calculated as the ratio of the estimated variance of the simple expansion estimator, $\widehat{\text{Var}}_{\text{exp}}(\hat{\mu})$, to the estimated variance of the model-assisted estimator, $\widehat{\text{Var}}_{\text{ma}}(\hat{\mu})$:

$$\text{RE} = \frac{\widehat{\text{Var}}_{\text{exp}}(\hat{\mu})}{\widehat{\text{Var}}_{\text{ma}}(\hat{\mu})} \quad (9)$$

Because variance is inversely proportional to sample size, RE can be interpreted as the factor by which the sample size for the simple expansion estimator would need to be increased to achieve the same variance as the model-assisted estimator.

For indirect estimation of change, mean estimates per unit area were calculated separately for each inventory year and mean average annual change per unit area was estimated as:

$$\widehat{\Delta\mu} = \widehat{\mu}_2 - \widehat{\mu}_1 \quad (10)$$

with variance estimated as

$$\widehat{\text{Var}}(\widehat{\Delta\mu}) = \widehat{\text{Var}}(\widehat{\mu}_2) - 2 \cdot \widehat{\text{Cov}}(\widehat{\mu}_1, \widehat{\mu}_2) + \widehat{\text{Var}}(\widehat{\mu}_1) \quad (11)$$

where the model-assisted covariance term was estimated using the following residuals:

$$\begin{aligned} \widehat{\text{Cov}}(\widehat{\mu}_1, \widehat{\mu}_2) &= \frac{1}{n \cdot (n-1)} \sum_{i=1}^n (\varepsilon_{1i} - \bar{\varepsilon}_1) \cdot (\varepsilon_{2i} - \bar{\varepsilon}_2) \\ &= \frac{1}{n \cdot (n-1)} \left[\sum_{i=1}^n \varepsilon_{1i} \cdot \varepsilon_{2i} - \frac{1}{n} \left(\sum_{i=1}^n \varepsilon_{1i} \right) \cdot \left(\sum_{i=1}^n \varepsilon_{2i} \right) \right] \end{aligned} \quad (12)$$

2.6.2. Direct Estimation

With the direct approach, change was estimated directly from plot-level MAAVC. The estimator was first applied to MAAVC, and mean change per year was then estimated by multiplying the estimated mean annual change by the time interval between the two inventory years.

Direct Simple Expansion Estimator

The simple expansion estimator for direct estimation is

$$\widehat{\Delta\mu} = \frac{1}{n} \sum_{i=1}^n \Delta y_i \quad (13)$$

with variance:

$$\widehat{\text{Var}}(\widehat{\Delta\mu}) = \frac{1}{n \cdot (n-1)} \sum_{i=1}^n (\Delta y_i - \widehat{\Delta\mu})^2 \quad (14)$$

where Δy_i represents plot-level MAAVC for the i -th sample unit. Mean average annual change per unit area was then estimated as:

$$\widehat{\Delta\mu} = \widehat{\mu}_\Delta (t_2 - t_1) \quad (15)$$

where $t_2 - t_1$ is the time interval between the two inventory years.

Direct Model-Assisted Regression Estimator

The model-assisted direct estimator is:

$$\widehat{\Delta\mu} = \frac{1}{N} \sum_{i=1}^N \widehat{\Delta y}_i + \frac{1}{n} \sum_{i=1}^n (\Delta y_i - \widehat{\Delta y}_i) \quad (16)$$

with variance:

$$\widehat{\text{Var}}(\widehat{\Delta\mu}) = \frac{1}{n \cdot (n-1)} \sum_{i=1}^n (\Delta \varepsilon_i - \overline{\Delta \varepsilon})^2 \quad (17)$$

where n is the number of sampled plots, N is the number of population units (pixels) for which auxiliary predictions were available, $\Delta \varepsilon_i = \Delta y_i - \widehat{\Delta y}_i$ and $\widehat{\Delta y}_i$ is the RF prediction of change for the i th sample unit.

3. Results

3.1. Statistical Models with Random Forests

Model performance differed slightly between the 10 m and 20 m spatial resolutions for both inventory periods (Figure 3). For the 2013 inventory period, R^2 at 20 m resolution (Figure 3c) was 1.8% greater than at 10 m resolution (Figure 3a), but RMSE at 10 m resolution was $5.45 \text{ m}^3/\text{ha}$ smaller, corresponding to a 6.5% reduction in prediction error. For the 2023 inventory period (Figure 3b,d), the 10 m model was slightly more accurate with R^2 2.6% greater and RMSE $13.14 \text{ m}^3/\text{ha}$ smaller, corresponding to a 13.6% reduction in prediction error compared with the 20 m model (Figure 3d). Overall, prediction errors were slightly smaller at 10 m resolution, but the differences between the two resolutions were small for both RMSE and R^2 .

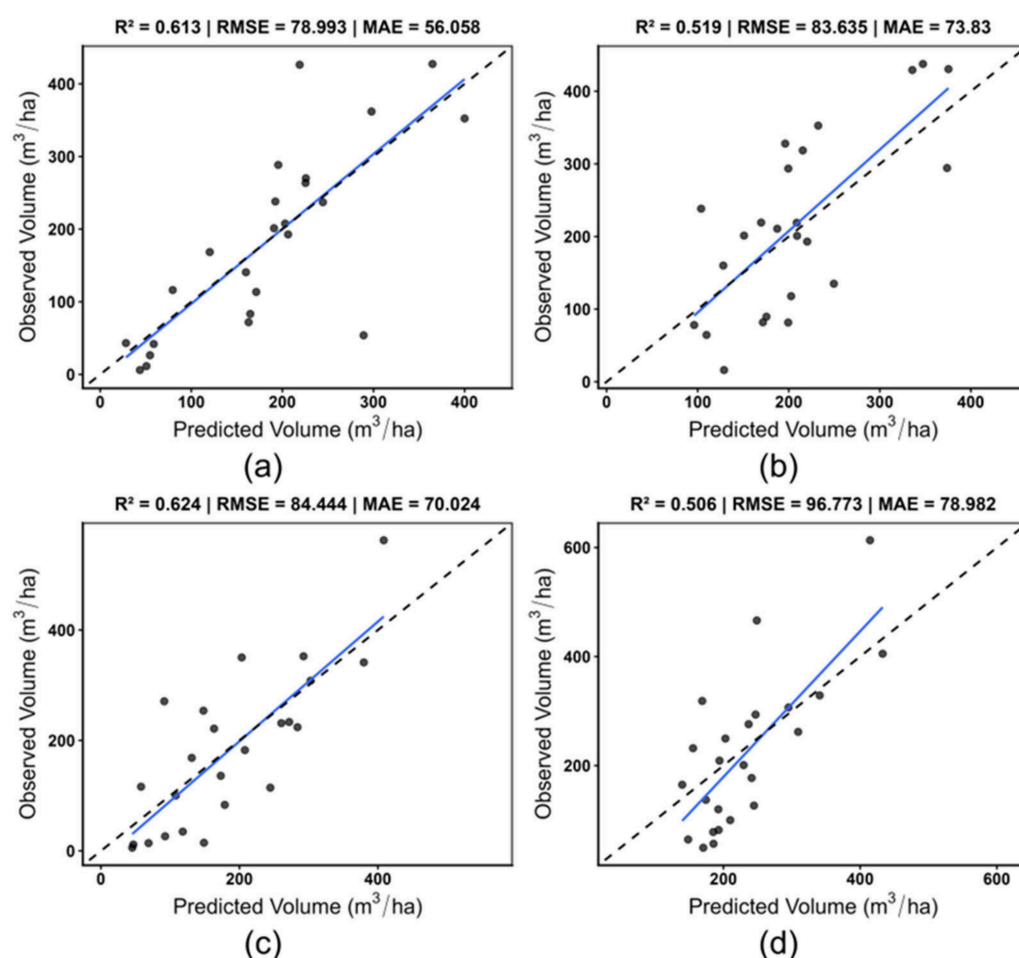


Figure 3. Observed versus predicted volume for the test data: (a) 2013 at 10 m resolution, (b) 2023 at 10 m resolution, (c) 2013 at 20 m resolution, and (d) 2023 at 20 m resolution. Grey dots represent individual sample plots, the dashed line indicates the 1:1 reference line, and the solid line represents the fitted regression.

3.2. Variable Importance

The variable importance rankings (Figure 4) showed that the models relied mainly on Band 5, near-infrared and red-edge bands (Band 8, Band 8A, Band 6), and VI (SAVI) for the 2013 models across spatial resolutions (Figure 4a,c), while the 2023 models relied mainly on VI (EVI, MSAVI, NDVIre705) together with Band 8, Band 7, Band 5, Band 12, and Band 3 across spatial resolutions (Figure 4b,d). Overall, the models were driven mainly by Band 5, Band 8, Band 8A, Band 6, Band 3, and vegetation indices (SAVI, EVI, MSAVI, NDVIre705), with additional contribution from Band 12 in the 20 m models.

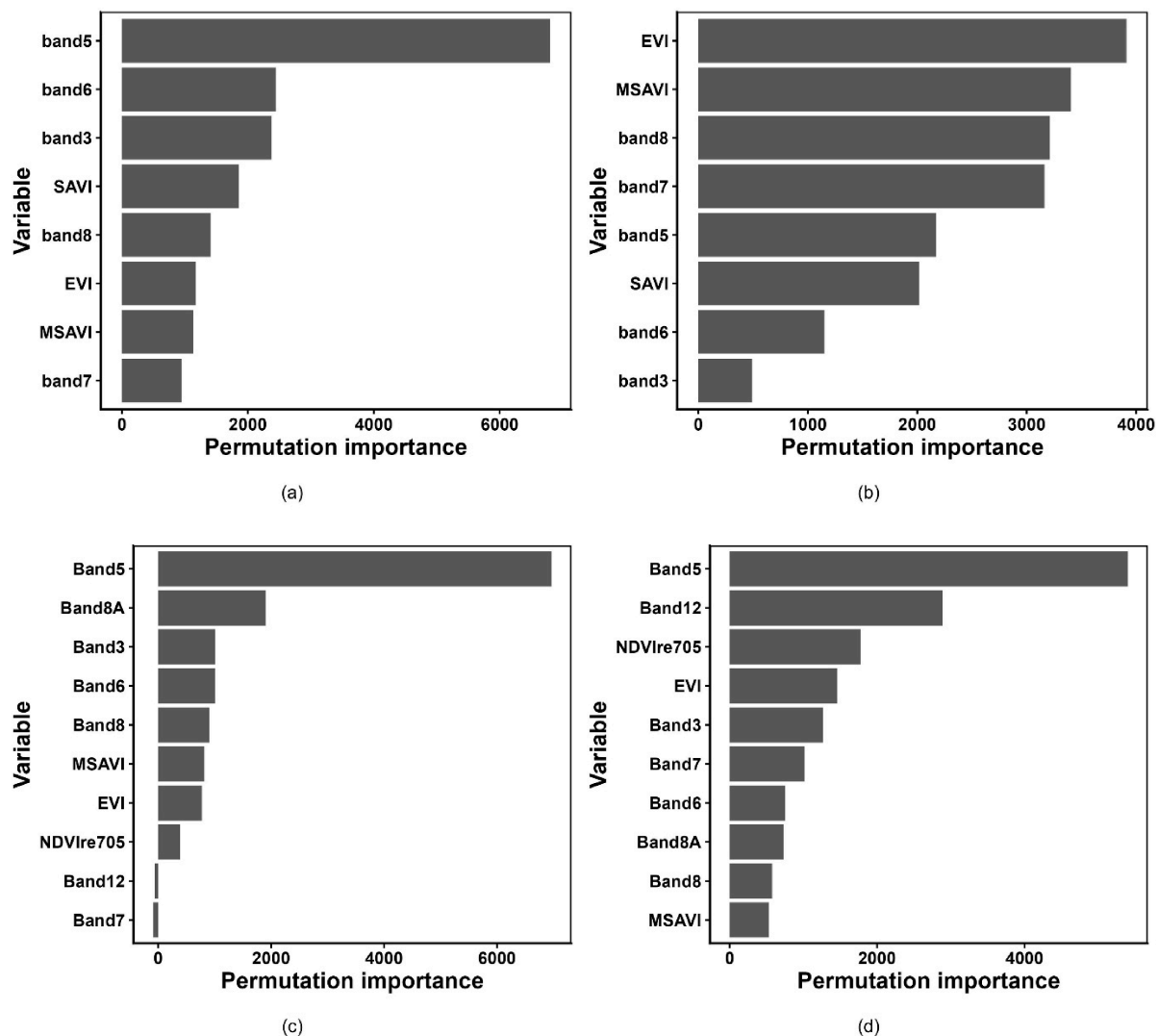


Figure 4. Variable importance ranking: (a) 2013 (10 m), (b) 2023 (10 m), (c) 2013 (20 m), and (d) 2023 (20 m).

3.3. Model Fit and Residual Analysis

Model fit was evaluated using observed versus predicted graphs and residuals graphs based on the full dataset (Figure 5). The observed versus predicted graphs showed generally moderate agreement between observed and predicted volumes, with points distributed around the 1:1 line, although some deviations were observed at both small and large prediction ranges. The residual graphs showed differences in the distributions of residuals between spatial resolutions and years. For 2013, the 10 m model showed residuals approximately symmetrically distributed around zero, whereas the 20 m model showed greater variability and slight systematic deviation. For 2023, differences in the distributions of residuals were observed for both spatial resolutions, although the 20 m model showed slightly less dispersion than the 10 m model.

3.4. Time-Specific Population Parameter Estimation

The simple expansion estimators produced mean volume estimates of 182.06 m³/ha with SE = 13.46 m³/ha for 2013 and 219.58 m³/ha with SE = 13.34 m³/ha for 2023. The model-assisted estimators yielded estimates that were similar to each other across both spatial resolutions, while differing from the simple expansion means, and with substantially smaller standard errors. For 2013, the model-assisted estimates were 181.52 m³/ha with

SE = 5.69 m³/ha for the 10 m resolution and 176.64 m³/ha with SE = 5.79 m³/ha for the 20 m resolution, while for 2023 the estimates were 208.11 m³/ha with SE = 6.17 m³/ha and 200.70 m³/ha with SE = 6.22 m³/ha for the 10 m and 20 m resolutions, respectively. The larger difference between the simple expansion and model-assisted estimates in 2023 is attributed to sample imbalance (Section 4.2). For both years, the estimates for the 10 m resolution were greater, but not significantly greater, than those for the 20 m resolution, and the standard errors were similar between resolutions. Overall, the results indicate an increase in mean volume between 2013 and 2023 (Table 2).

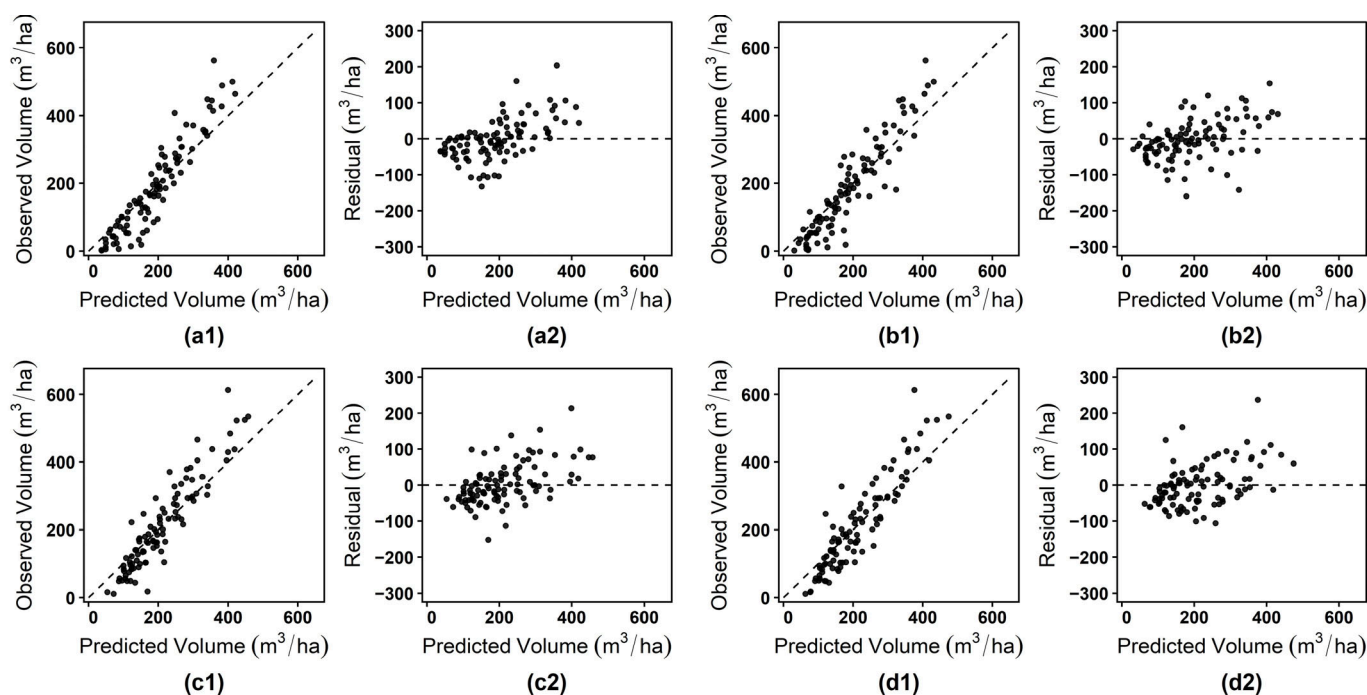


Figure 5. Observed versus predicted volume and residual graphs for the 2013 and 2023 inventory periods at 10 m and 20 m spatial resolutions. Panels (a1,a2) represent 2013 at 10 m resolution, (b1,b2) represent 2013 at 20 m resolution, (c1,c2) represent 2023 at 10 m, and (d1,d2) represent 2023 at 20 m resolution. Grey dots represent individual sample plots. In the observed versus predicted panels, the dashed line indicates the 1:1 reference line. In the residual panels, the dashed line indicates the zero reference line.

Table 2. Estimates of population mean volume for 2013 and 2023 using simple expansion (Sim-exp) and model-assisted (Mod-ast) estimators.

Year	Estimator	Resolution	Mean (m ³ /ha)	SE (m ³ /ha)	SE (%)	RE
2013	Sim-exp	—	182.06	13.46	7.39	1
2023	Sim-exp	—	219.58	13.34	6.07	1
2013	Mod-ast	10 m × 10 m	181.52	5.69	3.14	5.60
2023	Mod-ast	10 m × 10 m	208.11	6.17	2.97	4.68
2013	Mod-ast	20 m × 20 m	176.64	5.79	3.28	5.41
2023	Mod-ast	20 m × 20 m	200.70	6.22	3.10	4.60

The smaller SEs for the model-assisted estimators than for the simple expansion estimators reflect the usefulness of the additional information in the auxiliary Sentinel-2 data. Despite only moderate prediction accuracies at the plot-level (Section 3.1), at the population level the increases in precision achieved using both the 10 m and 20 m Sentinel-2 data were operationally significant. Specifically, for the 10 m and 20 m model-assisted

estimators, RE values ranged from 4.60 to 5.60, meaning that the Sentinel-2 data produced an approximately fivefold reduction in variance estimates relative to the simple expansion estimators. Operationally, this means that with the Sentinel-2 data, the sampling intensity and associated sampling costs could be reduced by a factor of approximately 5 with no loss in precision relative to the simple expansion estimates, certainly a substantial and meaningful result.

In all cases, the use of auxiliary variables in the model-assisted estimators substantially reduced the standard errors compared with the simple expansion estimators.

3.5. Estimates of Volume Change Between 2013 and 2023

The indirect and direct model-assisted estimators produced very similar mean average annual change per unit area estimates, differing by less than 1.0 m³/ha for both spatial resolutions (Table 3). However, the direct model-assisted estimator produced smaller standard errors than the indirect estimator, with reductions of approximately 19% for the 10 m resolution and 30% for the 20 m resolution, indicating greater precision for the direct approach. RE values for the model-assisted estimators were 2.48 and 2.21 for the indirect 10 m and 20 m estimates, respectively, and 3.84 and 4.57 for the corresponding direct estimates, indicating improved precision relative to the simple expansion estimator. In comparison, the simple expansion estimator produced the largest estimate of change (37.52 m³/ha), approximately 30–35% greater than the model-assisted estimates, although these differences were not statistically significantly different at the $\alpha = 0.05$ level. This result is attributed to sample imbalance (Section 4.2). Differences between estimates for the Sentinel-2 10 m and 20 m spatial resolutions were small, with the 10 m resolution producing change estimates approximately 2 m³/ha (about 8%) greater than the 20 m resolution. The simple expansion estimates are identical for the direct and indirect approaches because both are based on the same repeated plot observations.

Table 3. Estimates of volume change between 2013 and 2023 using simple expansion (Sim-exp) and model-assisted (Mod-ast) estimators using indirect and direct approaches.

Estimator	Resolution	Indirect Mean (m ³ /ha)	Indirect 95% CI	Indirect SE (m ³ /ha)	Indirect RE	Direct Mean (m ³ /ha)	Direct 95% CI	Direct SE (m ³ /ha)	Direct RE
Sim-exp	—	37.52 ^a	19.67–55.37	9.11	1	37.52 ^a	19.67–55.37	9.11	1
Mod-ast	10 m × 10 m	26.59 ^a	15.26–37.93	5.78	2.48	26.03 ^a	16.93–35.14	4.65	3.84
Mod-ast	20 m × 20 m	24.06 ^a	12.05–36.08	6.13	2.21	24.60 ^a	16.25–32.95	4.26	4.57

Note: means followed by the same letter within a column are not significantly different at the 0.05 significance level.

4. Discussion

Estimating forest volume and especially volume change using multispectral (MSI) remotely sensed data remains a challenging task [55] due to its inherent limitations [56]. However, MSI satellite information, in particular Sentinel-2 data, remains useful auxiliary information since it was launched in 2015 [56–58], although the relative performance of direct and indirect approaches for model-assisted estimation of forest volume change using multispectral satellite data has not been extensively evaluated. Therefore, this study examined volume and volume change estimation using direct and indirect approaches under simple expansion and model-assisted estimation with Sentinel-2 multispectral data at 10 m and 20 m spatial resolutions using RF algorithms.

4.1. Volume Estimation Using Sentinel-2 and RF

The random forest models explained 51–62% of the variation, with RMSE values of 79–97 m³/ha. These errors are fairly large relative to the mean, as expected for NFI

data, where plots span the full range of forest conditions from recently harvested to mature stands. The models therefore showed moderate predictive performance at the plot level. Nevertheless, at the population level, these moderate plot-level prediction accuracies corresponded to an approximately fivefold reduction in variance relative to simple expansion estimates, with important implications for sampling intensity and field-sampling costs. RF has been widely used for modelling relationships between forest variables and remotely sensed data [6] and has produced prediction accuracies sufficient to support forest inventory estimation [6,27,39,59,60]. Most importantly, the combination of multi-spectral Sentinel-2 data and RF algorithms has shown moderate prediction accuracies comparable to those reported in this study for forest structural variables such as volume and biomass [40,45,59]. Although optical satellites mainly capture horizontal forest information and often miss vertical structure information [61], recent developments such as multi-view stereopsis allow three-dimensional forest structure reconstruction from optical imagery [62,63]. However, these developments have not replaced MSI satellite data in forest inventory applications, especially Sentinel-2 auxiliary variables, which remain valuable due to their wide spatial coverage, frequent revisit time [56], and red-edge and near-infrared bands sensitive to vegetation structure [64]. Previous studies have also demonstrated the potential of Sentinel-2 data for predicting forest structural variables such as biomass and volume with comparable predictive performance [28,64–66], although model performance varies depending on the study area, predictor composition, and the variability of the reference inventory data. Yu et al. [64] evaluated Sentinel-2 and LiDAR data for larch growing stock volume (GSV) estimation in China and reported RMSE values of 59.69 m³/ha and 79.10 m³/ha under different validation conditions. Mirpulatov et al. [67] evaluated multiple machine learning models and combinations of Sentinel-2, vegetation indices, canopy height model, DEM, coordinate, and age variables for plot-level GSV estimation using remote-sensing data fusion, with the best-performing models reporting RMSE values of approximately 83–84 m³/ha. Zhou and Feng [25] reported RMSE values ranging from 13.743 to 19.257 m³/ha for Sentinel-2-based forest stock volume estimation; however, that study was based on datasets with substantially lower mean forest stock volume values of approximately 31 m³/ha, compared to the substantially larger mean GSV values in the present study.

4.2. Sample Imbalance and Model-Assisted Estimates

The relatively large differences observed between the simple expansion and model-assisted estimates for 2023 mean volume are attributed to sample imbalance, despite the probability sampling, with the result that the proportion of pixels in the population with small volume predictions was greater than the proportion of plots with small volume observations. For the predictor variables with the largest importance rankings, sample imbalance was assessed using the ratios of their means for the sample and their means for the population. Similar ratios were calculated for their standard deviations. The means of these ratios over the predictor variables were calculated for 2013 and 2023 (Table 4).

In the absence of sample imbalance, these ratios and their means over predictor variables should be approximately 1.0. The predictor-variable means deviated from 1.0 more in 2023 than in 2013, by a factor of approximately 5 to 10. This same pattern appears in the estimates: the simple expansion and model-assisted estimates agreed closely in 2013, where the ratios were near 1.0, but deviated in 2023, where the departure from 1.0 was larger. The correspondence between the degree of imbalance and the size of the estimator difference propagates from the 2023 estimates to the 2013-to-2023 change estimates, while the means of the ratios for the standard deviations were greater for 2023 than for 2013 by factors of 2 to 5. This smaller measure of sample imbalance for 2013 corresponds to

the smaller differences between the simple expansion and model-assisted estimates for 2013; simultaneously, this greater measure of sample imbalance for 2023 corresponds to the greater differences between the simple expansion estimates for 2023.

Table 4. Ratios of all-pixel means to sample-pixel means and all-pixel standard deviations to sample-pixel standard deviations for the 10 m and 20 m Sentinel-2 predictor variables.

10 m					20 m				
Variable	Mean		SD		Variable	Mean		SD	
	2013	2023	2013	2023		2013	2023	2013	2023
B6	0.989	1.028	0.987	1.014	B3	1.064	1.098	1.714	1.638
B7	0.979	1.021	0.929	0.995	B5	1.061	1.099	1.510	1.506
B3	1.064	1.098	1.642	1.685	B6	0.993	1.028	1.000	1.013
B5	1.053	1.101	1.464	1.673	B7	0.985	1.020	0.942	0.990
B8	0.978	1.023	0.949	1.003	B8	0.983	1.026	0.976	1.005
MSAVI	0.964	0.989	0.933	0.981	B8A	0.987	1.023	0.948	0.985
SAVI	0.976	0.992	0.943	1.002	B12	1.092	1.176	1.626	1.747
EVI	0.971	0.993	0.946	1.005	EVI	0.974	0.995	0.963	1.002
					MSAVI	0.968	0.991	0.949	0.978
					NDVIre705	0.974	0.968	1.134	1.075
Mean	0.997	1.031	1.099	1.170	Mean	1.008	1.042	1.176	1.194

The effects of this sample imbalance propagate from the 2023 estimates to the 2013-to-2023 change estimates. Because RF is a non-transparent, black-box technique, the exact effects of sample imbalance on its predictions cannot be fully determined [68,69].

4.3. Direct and Indirect Change Estimation

Change estimation uses 2015 Sentinel-2 imagery for the initial inventory in 2013 (Section 2.4), a mismatch in years between the auxiliary and field data. Such mismatches are common where imagery for the exact year of field measurement is unavailable [35,70–72] or too affected by cloud and shadow; systematic Sentinel-2 acquisition only began in 2015. This discrepancy might be expected to introduce bias into the change estimators. However, because the field observations form a systematic probability sample, the effects of the discrepancy are realized only in additional uncertainty, not in bias in the estimators. At plot level, the 2013 R^2 and RMSE values were comparable to those for 2023 (Figure 3). For the population estimates, Table 2 shows similar SEs for 2013 and 2023, and the RE values for the model-assisted estimators indicate reduced efficiency for 2023 relative to 2013. These results suggest that the temporal mismatch introduced no additional uncertainty and had no adverse consequences for the estimates.

The direct and indirect model-assisted estimators produced similar mean average annual change per unit area estimates, although the direct approach resulted in smaller standard errors, with reductions of approximately 19% at 10 m and 30% at 20 m (Table 3). This indicates that the main difference between the two approaches was not the estimated mean change, but the precision of the estimates. The indirect approach used separate year-specific models and estimated change by differencing the annual estimates, whereas the direct approach used a single model formulated for plot-level volume change [18]. Although the indirect approach incorporates covariance between annual estimates, the indirect estimators did not produce smaller standard errors than the direct estimators in the present study. Similar findings regarding precision differences between direct and indirect approaches have also been reported previously [18]. Recent comparisons of direct and indirect remote-sensing approaches have likewise shown that the relative

performance of the two approaches may vary depending on the estimation framework and implementation [19].

In addition to the smaller standard errors obtained with the direct approach, the method was also simpler to implement because it required only one change model and did not require external estimation of the covariances between estimates for the two dates, whereas the indirect approach required separate year-specific models together with differencing and covariance estimation between annual estimates. The model-assisted estimators produced substantially smaller standard errors than the simple expansion estimator, indicating that the additional information in the Sentinel-2 auxiliary data improved the precision of the volume change estimates. Similar results were reported by Næsset et al. [73], who found that the use of remotely sensed auxiliary data substantially improved the precision of biomass change estimates through model-assisted estimation. These results are consistent with McRoberts et al. [18], who showed that remotely sensed auxiliary data improve the precision of change estimates and that both indirect and direct model-assisted estimators can produce comparable precision depending on modelling performance. They also noted that although the direct approach is often preferred for change estimation, indirect methods may sometimes provide greater precision. Esteban et al. [6] showed that RF models with remotely sensed auxiliary data improved the precision of forest volume, biomass, and change estimates relative to design-based expansion estimators, and that the most appropriate approach depends on the available data and modelling framework.

4.4. Effects of Sentinel-2 Spatial Resolution on Model Performance

Our findings (Figure 3) indicate that the relative performance of the 10 m and 20 m Sentinel-2 predictor configurations varied between inventory years and evaluation metrics. In 2013, the 20 m configuration produced slightly greater R^2 by 0.011, whereas the 10 m configuration reduced RMSE by 5.45 m³/ha. In contrast, for the 2023 inventory period the 10 m configuration produced a slightly greater R^2 by 0.013 and a smaller RMSE by 13.13 m³/ha than the 20 m configuration. These differences suggest that the influence of spatial resolution on model performance at the plot level was not consistent across the two inventory periods, with the relative advantages varying between R^2 and RMSE. Although the field plots had a 10 m radius, predictor values were extracted from the pixels intersecting the plot coordinates for both spatial resolutions. The 20 m pixels therefore more closely matched the overall plot extent, whereas the 10 m pixels may have retained greater within-plot spatial variation, which may partly explain the small differences observed between the two predictor configurations. However, the differences between estimates obtained using data with the two spatial resolutions were relatively small, indicating that both resolutions produced broadly comparable model performance. Previous studies have also explored the influence of spatial resolution on remote-sensing mapping and modelling performance, including comparisons involving finer- and coarser-resolution products or predictor configurations [74–76]. Morell-Monzó et al. [75] reported that the inclusion of Sentinel-2 20 m bands together with 10 m bands did not improve classification accuracy relative to the 10 m configuration alone. In contrast, Du et al. [76] reported that a 10 m spatial-resolution product preserved more detailed spatial information and produced more accurate mapping results than the corresponding 20 m product. Therefore, the 20 m Sentinel-2 data may be used for operational applications where reduced processing and storage effort are priorities, without meaningful loss of model performance. These studies therefore indicate continued interest in evaluating the influence of spatial resolution on remote-sensing modelling and mapping performance.

4.5. Random Forests

RF constructs multiple regression trees using bootstrap samples of the training data, while a random subset of predictor variables is considered at each split. The final prediction is obtained by averaging predictions across the trees. In this study, this structure accommodated multiple Sentinel-2 bands and vegetation indices and was suitable for modelling nonlinear relationships between the auxiliary variables and forest volume.

In addition to prediction, RF provides information on the relative importance of predictor variables [77], which helps to identify the variables that contribute most to model performance. The variable importance results (Figure 4) showed that the models were mainly driven by near-infrared and red-edge bands together with vegetation indices such as SAVI, EVI, MSAVI, and NDVI_{re705}. These variables are known to be sensitive to vegetation structure, canopy density, and biomass, which explains their importance for volume estimation [25,70,74]. For example, Zhou and Feng [25] showed that Sentinel-2 red-edge bands were strongly related to forest stock volume and significantly improved model accuracy, with red-edge-derived variables contributing substantially to reducing prediction error.

However, fitting and tuning the RF models across inventory years and spatial resolutions was computationally intensive. In addition, because RF is a non-transparent, black-box technique, it did not permit a detailed analysis of the effects of sample imbalance on individual predictions or on the resulting model-assisted estimates [68,69].

4.6. Summary of Results, Recommendations, and Future Direction

Overall, the results provide an operational evaluation of direct and indirect model-assisted forest volume change estimation using Sentinel-2 auxiliary data under repeated Estonian NFI conditions, including comparisons between 10 m and 20 m spatial resolutions and improvements in precision relative to the simple expansion estimator. Based on the findings of this study, three recommendations are made. First, because the 10 m and 20 m Sentinel-2 resolutions produced comparable results with no statistically significant difference in the resulting estimates, the additional effort required to use 10 m imagery may not be justified for operational applications where reduced processing and storage demands are priorities. Second, because the relative performance of direct and indirect approaches may vary with the dataset and estimation framework, both approaches should be applied and compared where possible. Third, because RF required repeated model fitting, parameter tuning, and wall-to-wall prediction across inventory years, spatial resolutions, and estimation approaches, it had high computational demands. Therefore, alternative prediction techniques with fewer computational requirements may be considered in future large-area applications, while more transparent techniques may also be useful where detailed interpretation of sample-imbalance effects is required. Future work should apply the comparison to other National Forest Inventory datasets, evaluate stratified estimation where suitable stratification data are available, and further examine the effects of sample imbalance.

5. Conclusions

This study compares forest volume and volume change estimation using Sentinel-2 auxiliary data within a design-based inferential framework, applying indirect and direct model-assisted estimation approaches. Four main conclusions can be drawn. First, Sentinel-2 auxiliary data combined with random forest modelling can be used to estimate forest volume and volume change within a design-based framework. Second, the direct and indirect model-assisted approaches produced similar estimates of volume change, although the direct approach resulted in smaller standard errors. Third, despite only moderate plot-level prediction accuracies, the model-assisted estimators produced substantially

smaller standard errors than the simple expansion estimators, demonstrating the benefit of incorporating auxiliary information and indicating substantial potential savings in sampling intensity and field-sampling costs. Fourth, Sentinel-2 auxiliary data combined with random forest modelling can be used to estimate forest volume and volume change, with the 10 m and 20 m spatial resolutions producing comparable prediction accuracy and no statistically significant difference in the resulting estimates.

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Appendix A

Table A1. Species-specific coefficients used for growing stock volume estimation within the Estonian National Forest Inventory framework.

Species	$\hat{\beta}_1$	$\hat{\beta}_2$	$\hat{\beta}_3$	$\hat{\beta}_4$	$\hat{\beta}_5$
MA	−68.8362	26.5981	37.4629	20.1523	−0.3501
KU	−93.0840	24.7104	104.4000	19.1073	−0.3051
KS	−272.4000	29.6551	20.5290	14.9942	−0.2275
HB	−384.0000	34.6887	−23.9733	16.4334	−0.3142
LV	−76.8916	23.4961	−58.2197	12.0424	−0.1845
LM	−332.5000	33.7791	25.6576	12.8815	−0.2009
Others	−34.6320	23.8111	−43.1965	19.4465	−0.3402

Note: MA = Scots pine (*Pinus sylvestris*), KU = Norway spruce (*Picea abies*), KS = silver birch (*Betula pendula*), HB = downy birch (*Betula pubescens*), LV = grey alder (*Alnus glutinosa*), LM = black alder (*Alnus incana*), and Others = other tree species.

Table A2. Comparison of volume (m³/ha) distribution between full and subsample datasets.

Variable	Mean (Full Sample)	Mean (Subsample)	SD (Full Sample)	SD (Subsample)	Full Range	Subsample Range	Coverage Ratio
V (2013)	204.96	178.95	146.24	135.22	0.00–743.95	2.23–562.42	0.753
V (2023)	233.74	213.81	140.73	136.31	4.53–772.71	16.14–613.33	0.777

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