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Large Scale Forest Resource Mapping in Norway: An Assessment of SR16's Prediction Accuracy and Economic Viability

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Forest studies

Acknowledgements

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Abstract

Long-term forest management strategies depend on reliable and up-to-date forest resource information. At the property level, this information can be acquired through forest management inventories (FMI) that describe forest attributes at stand level to support decision-making. At a national level, information of forest attributes is collected by the Norwegian national forest inventory (NFI), which provides annual updates regarding regional or national forest statistics.

Large-scale forest prediction maps of forest attributes, such as SR16, have become available for large parts of the productive forest areas in Norway due to the increased availability of data from airborne laser scanning (ALS) campaigns. SR16 use ground reference values from the Norwegian NFI field sample plots as calibration data for prediction models. The use of NFI field data has its advantages, primarily for cost-saving reasons, but also the possibilities of regular updates of forest attributes as opposed to sporadic updates from NFIs.

This study aimed to assess the prediction accuracy of SR16 predictions for basal area (G), dominant height (Hdom), site index (SI), number of trees (N) and age (A) at plot level (250 m^2) against ground reference values. In a subsequent loss analysis, optimal silvicultural management strategies maximising the net present value (NPV) were simulated using ground reference values. In contrast, suboptimal silvicultural management strategies were simulated to maximise the NPV using the presumably erroneous SR16 predictions. Economic losses were defined as the reduction of the NPV using SR16 predictions instead of ground reference values. The data material comprises 552 field sample plots from three regional FMI inventories.

SR16 predictions resulted in prediction accuracies (MD%) of 9.7 % for G, 2.4 % for Hdom, 7.5 % for SI, 6.6 % for N and 2.3 % for A. The results indicate that SR16 provides accurate estimations at a regional level. However, results varied significantly when assessed locally for each inventory project. In the loss analysis, SI and A resulted in the most significant NPV losses, however, observed losses varied significantly between inventory projects. Prediction errors on the remaining variables did not significantly reduce the NPV. In its current form, SR16 cannot be considered a viable replacement for local FMIs, however through the development of new inventory procedures and new methods of predicting SI, it can play a greater role for decision-making in operational forest management in the future.

Sammendrag

Langsiktig og rasjonell forvaltning av skogressursene er avhengig av pålitelig og oppdatert ressursinformasjon. På eiendomsnivå kan denne informasjonen bli anskaffet gjennom skogbruksplantakster som beskriver skogforholdene på bestandsnivå og benyttes hovedsakelig av beslutningstakere for avgjørelser knyttet til skogforvaltning. På et nasjonalt nivå samles ressursinformasjon av Landsskogstakseringen som bidrar med årlige oppdateringer vedrørende regional eller nasjonal skogstatistikk.
Nasjonale skogressurskart, har gjennom introduksjonen av flybåren laser scanning (ALS) i skogbruksplanleggingen, blitt tilgjengelig for størsteparten av det produktive skogarealet i Norge. Slike skogressurskart, som SR16, benytter feltdata fra landsskogtakseringen som kalibreringsdata til prediksjonsmodeller. Dette har sine fordeler, først og fremst av kostnadsbesparende årsaker, men også på grunn av mulighetene for regelmessige oppdateringer sammenlignet med sporadiske oppdateringer av dagens skogbruksplaner.

Målet med denne studien var å vurdere nøyaktigheten av prediksjoner fra SR16 for grunnflate (G), dominerende trehøyde (Hdom), bonitet (SI), treantall (N) og alder (A) på prøveflatenivå ($250m^2$) sammenlignet med bakkemålte referanseverdier. I en påfølgende tapsanalyse ble optimal skjøtselsstrategi simulert som en maksimering av nettonåverdien for bakkemålte referanseverdier, mens nettonåverdien for «usikre» SR16 prediksjoner ble maksimert gjennom en simulert suboptimal skjøtselsstrategi. Økonomiske tap ble definert som en nedgang i nettonåverdi ved å benytte seg av SR16 prediksjoner. Datamaterialet brukt i denne studien bestod av 552 prøveflater fra tre regionale skogbruksplantakster.

SR16 prediksjoner resulterte i en prediksjonsnøyaktighet (MD%) på 9.7 % for G, 2.4 % for Hdom, 7.5 % for SI, 6.6 % for N and 2.3 % for A. Resultatene viser at SR16 gir på regionalt nivå gir presise prediksjoner, men resultatene varierer imidlertid mye når resultatene betraktes på et lokalt nivå. I tapsanalysen resulterte SI og A i de mest signifikante reduksjonene av nettonåverdi, men tapene varierte mye avhengig av takstprosjektene. Prediksjonsfeil hos øvrige variabler reduserte ikke nettonåverdien nevneverdig. SR16 kan i dagens utgave ikke betraktes som en fullverdig erstatning for skogbruksplaner, men kan gjennom utvikling av takstprosedyrer og nye metoder for estimering av SI, utgjøre en større rolle for operativ skogforvaltning i fremtiden.

Contents

1. Introduction

1.1 Background

The total land area of Norway consists of 385 207 km^2, of which 14 million hectares or 37% of the land are forested. Substantial roots and traditions linked to the right to own private property mean a significant share of the forested areas is under private ownership. Of a total of 125 000 forest properties, 77% have private ownership (SSB, 2022). The total harvested timber volume for industry purposes was 11.5 million m^3 in 2022, the largest harvested quantity ever recorded in Norway (SSB, 2022). Norway spruce (*Picea abies*), Scots pine (*Pinus sylvestris*) and European white birch (*Betula pendula* and *Betula pubescens*) are the most common species of tree in Norway.

All forest properties in Norway, with legal basis from the Forestry Act § 5 "Forest management inventory and forest management plan", are required to have a forest management inventory (FMI) which should include the following information at property level (Landbruksdirektoratet, 2022; Lovdata, 2022):

- Total area of distinctive types of land
- Productive forest areas allocated over development class and site index
- Standing volume allocated over species, site index and development class
- Annual increment
- Production potential

In addition, the FMI must contain information at stand level, such as, development class, age, annual increment, and areas with environmental importance to the landscape, recreation, heritage sites and biodiversity (Landbruksdirektoratet, 2022).

The FMI provides valuable information about the available forest resources but also represents a significant expense for the forest owner. Concurrently, Bergseng et al. (2018) report from 1978 to 2016 that the annual change in current prices for sawnwood of Norway spruce has developed at half the rate of the yearly change of the consumer price index. This has reduced the actual value of sawnwood of Norway spruce by 50% within the analysed period. As a result, the value of maintaining the forest as an essential source of income may have been reduced, and forest owners might be less willing to invest in FMIs. Therefore, the government created subsidies for FMIs designed to stimulate increased activity, increase demand, and to reduce the costs paid by forest owners.

The production of an FMI is a complex process characterised by the continual development of the design and intensity related to data collection. Technological developments have also increased the capability of delivering more precise stand estimations for FMIs. On the other hand, more precise estimations have come at the price of an increased cost of producing FMIs. Therefore, even after the application of subsidies, forest owners might struggle to see the advantages of having an updated FMI available for their property. Consequently, it might be desirable to examine what options decision-makers could have to reduce inventory costs while maintaining the same level of prediction errors.

1.2 Mapping of forest resources

The mapping of forest resources in Norway has traditionally been divided between the National Forest Inventory (NFI) and FMIs. Norway's NFI ensures nationwide forest data, whereas FMIs aim to provide local forest information to be used for decision-making by forest owners for current and future silvicultural treatments (Bergseng et al., 2015). However, the decisions concerning silvicultural treatments are often made at the stand level. Therefore, information is typically acquired through FMIs (Bollandsås et al., 2023).

Rahlf et al. (2021) describe that FMIs produced with complementary data from airborne laser scanning (ALS) share common steps, which are "(1) manual stand delineation, (2) stratification of the stands into strata based on, for example, tree-species, maturity-classes, (3) ALS data acquisition, (4) measurements of some hundred field sample plots distributed over the strata, (5) fitting of stratum specific linking models for timber volume and other response variables, and (6) estimation of stand-level parameters". ALS data are acquired for the area of interest, which might consist of several municipalities. After the acquisition, the ALS data are grouped into grid cells that serve as primary prediction units (Bollandsås et al., 2023). Field sample plots containing ground reference values are often distributed across the area according to a stratified sampling design (Næsset, 2014). Measurements at the plot level are necessary for providing relationships that can link relevant ALS metrics to specific linking models for ALS data across the area of interest. Subsequent prediction models for forest attributes are created and applied to grid cells before eventually being aggregated from cell predictions to stand-level estimates (Bollandsås et al., 2023; White et al., 2013).

The mapping of forest resources can also be done to sustain regional or national statistics as an NFI. An NFI aims to provide statistics for reporting and policy-making on a regional to national scale (Rahlf et al., 2021; Tomppo et al., 2010). Due to the vast amount of data required to provide NFI statistics, it requires ground reference values to be collected over several years. For example, the Norwegian NFI has a five-year rotation period. Therefore, each field sample plot used in the Norwegian NFI is subjected to measurements every fifth year to sustain annual updates to national forest statistics. However, the manual field sampled fraction of the data is comparably smaller for a NFI than a FMI (Rahlf et al., 2021)**.** The Norwegian NFI consists of a fixed 3×3 km grid of about 16 000 permanent field sample plots where manual field measurements are regularly conducted. These measurements represent a vast database of information previously utilised primarily at a regional or national scale for volume estimations, volume increment, carbon sequestration, etc.

Producing NFIs and FMIs has traditionally been viewed as separate activities. However, the increasing availability of ALS data from national campaigns has contributed to creating nationwide forest attribute maps such as SR16 (Rahlf et al., 2021). SR16 is a national forest resource map with raster-based predictions of forest attributes that covers large parts of the productive forest areas in Norway (Astrup et al., 2019; Bollandsås et al., 2022; Hauglin et al., 2021). Predictions are structured into cells of 16×16 m that can be used to estimate means and totals of forest attributes within a defined area of interest, for example, at stand level. SR16 combines ground reference values from permanent NFI field sample plots with the newest and most up-to-date ALS data available for the specific regions (Bollandsås et al., 2022).

There are several advantages and disadvantages for inventory systems using NFI field sample plots as ground reference values instead of FMI field sample plots. The main advantage of using the NFI plots as ground reference values is that the cost of measuring the plots is already covered by other budgets (Bollandsås et al., 2023). Field sample plots require staff to be physically in the field to conduct measurements and apply as a considerable cost in the production of an FMI. Costs regarding measurements at NFI field sample plots are paid by the Norwegian NFI, which means forest owners are not exposed to the related expenses. Secondly, data for NFI field sample plots are collected continuously, exemplified by the Norwegian five-year rotation period. Thirdly, intervals between FMI projects within the same geographic region have traditionally been 10 – 20 years. However, using NFI data for model linking and calibration enables wall-to-wall prediction maps of forest attributes to be updated frequently due to using the newest and most up-to-date ALS projects available.

The most critical challenge of using NFI field sample plots as calibration data for predictions comes from the relatively low sampling intensity compared to FMIs. Prediction models from NFIs are calibrated with field sample plots collected over a large spatial domain, typically over tens of thousands of square kilometres (Bollandsås et al., 2023). Creating general prediction models over vast areas with a comparably small total sampling intensity tends to generalise local forest conditions. A model calibrated for a large region might struggle to provide relationships between ground reference values and ALS metrics representative of smaller geographical areas (Nilsson et al., 2017). Bollandsås et al. (2023) describe that large regional models for forest attributes such as tree height, stem diameter and volume are challenging to provide a specific relation between ground reference values and ALS metrics representative for smaller areas, because these attributes vary relative to factors such as latitude, elevation, soil properties and other factors with distinct geographical patterns (Næsset, 2014).

Another challenge could be due to temporal differences regarding model calibration and predictions based on NFIs. The temporal differences might occur between ALS acquisitions and parts of the NFI field sample plot dataset (Bollandsås et al., 2023). For example, larger regions could be subject to field data acquisitions over several years, which have to be projected to a specific date (Bollandsås et al., 2023), whereas non-overlapping ALS acquisitions over several years might use different acquisition parameters and instruments that could affect the point cloud and the derived metrics (Nicholas R. Goodwin, 2006; Næsset, 2005; Næsset, 2009). Furthermore, as opposed to ground reference values, ALS data cannot be forecasted or backcasted, and therefore ground reference values and ALS data could reflect different forest conditions affecting models (Bollandsås et al., 2023; Hill et al., 2018). In addition, there could be temporal inconsistencies between ground reference values and ALS data within the same geographical area, representing forest stands that could be portrayed in different states. Ground reference values might be collected over plots that could have been subject to silvicultural treatments, whereas ALS data might have been collected before the treatments were applied. Therefore, detecting disturbances before analyses is essential because failure to detect even a small number of plots with disturbances could potentially inflate the model uncertainty (Bollandsås et al., 2023; Massey & Mandallaz, 2015).

Bollandsås et al. (2022; 2023) compared ground reference values against SR16 predictions across a broad range of forest conditions in Norway. The studies concluded that SR16 predictions did not produce suitable results to replace more accurate predictions from an area-based FMI. However, SR16 predictions were suitable only in areas with forest conditions that did not deviate much from the average forest conditions in the regions. These areas resulted in predictions that were not prone to large systematic prediction errors (Bollandsås et al., 2022; Bollandsås et al., 2023)

Adapting regional or nationwide prediction maps of forest attributes into strategic forest planning represents a significant potential for cost savings, but also the risk of significant prediction errors (Bollandsås et al., 2023). Additional empirical research is needed to assess the accountability of prediction maps across a broad range of differences in local forest conditions (Bollandsås et al., 2023).

1.3 Loss analysis

Hamilton (1978) suggested that a loss analysis can be used to develop a link between errors in data and economic costs. The application of forest inventories in the context of long-term decision-making is a delicate balance between the consideration of the intensity of the inventory work, inventory costs and NPV losses (figure 1). For example, precise stand estimates can be achieved at the expense of large inventory costs, bringing total costs to an unsustainable level, and vice versa.

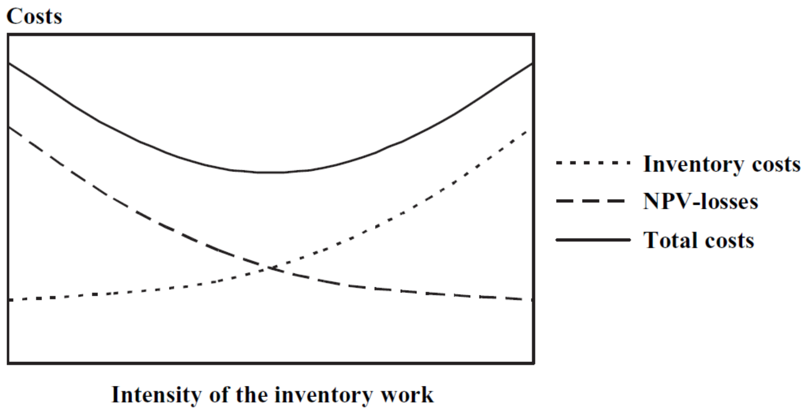

Figure 1: (Eid, 2022). Costs of obtaining forest resource information can occur in several different ways, for example the correlation between erroneous data and NPV-losses, or the correlation between expensive inventory costs and precise stand estimates. *Personal communication, Beslutning – verdien av informasjon. Ås: NMBU*

Loss analyses focuses only on the economic losses caused by an erroneous dataset by excluding the addition of inventory costs in the analysis. Economic losses are defined as a reduction in net present value (NPV) because of future incorrect decisions regarding silvicultural treatments over a specified period. Loss analyses require two contrasting datasets. One dataset is regarded as the “true” dataset, using “correct” values, which in turn maximises the net present value, whereas the “false” dataset uses an alternative source of data with a certain error level. Loss analyses can also be applied by comparing ground reference values from FMI field sample plots against SR16 predictions. Ground reference values are, in these cases regarded as the “true” dataset aiming to maximise the NPV through a simulation of optimal silvicultural treatments over a specified period of time. On the other hand, SR16 predictions are data obtained from an alternative data source with an expected error level resulting in suboptimal silvicultural treatments and reduced NPV.

Loss analyses have been applied in other studies, such as Eid (2000), which evaluated forest inventories' design and intensity. On the other hand, Bollandsås et al. (2022) applied a loss analysis to analyse the economic implications of using an NFI-based inventory method compared against ground reference values and predictions from an area-based FMI.

1.4 Research objectives

This study aimed to assess the prediction accuracy and economic viability of using predictions from the nationwide prediction map of forest attributes SR16. Ground reference values from FMI field sample plots were compared against SR16 predictions to determine the prediction accuracy of basal area (G), dominant height (Hdom), site index (SI), number of trees/ha (N) and age (A) across a dataset consisting of 552 field sample plots from 3 regional FMI project in south-eastern Norway.

The cost of adopting SR16 predictions into strategic forest planning was evaluated using a loss analysis that simulated optimal silvicultural management strategies with ground reference values and suboptimal silvicultural management strategies with SR16 predictions. The economic costs of using SR16 predictions will be evaluated through eventual losses of NPV.

The results could reveal if the national forest resource map SR16 can be adopted into strategic forest planning.

2. Material and method

2.1 Study area

Field sample plots data obtained from the property of Mathiesen Eidsvold Værk are regarded as project one in this study (coloured green in figure 2). The data were located in the municipalities of Hurdal (60°25'N, 11°4'E, 200 – 600 metres above the sea), Eidsvoll (60°20'N, 11°15'E, 120 – 700 metres above the sea), Nannestad (60°14'N, 10°57'E, 130 – 717 metres above the sea), Ullensaker (60°08'N, 11°10'E, 130 – 350 metres above the sea) and Nes (60°07'N, 11°29'E, 100 – 500 metres above the sea) in Viken county, and Gran (60°°26'N, 10°29'E, 130 – 810 metres above the sea) and Østre Toten (60°36'N, 10°54'E, 120 – 840 metres above the sea) located in Innlandet county.

Field sample plot data for project two (coloured yellow in figure 2) were obtained from the municipalities of Sigdal (60°03'N, 9°36'E 100 – 1450 metres above the sea) and Flesberg (59°50'N, 9°28'E, 150 – 1240 metres above the sea). Field sample plot data for the third project (coloured red in figure 2) were collected from Modum (59°57'N, 9°58' E, 10 – 750 metres above the sea), Lier (59°52'N, 10°12'E, 0 – 610 metres above the sea) and Asker (59°42'N, 10°30'E, 0 – 460 metres above the sea). All municipalities for projects two and three were located in the county of Viken, and the data from these projects were a part of the data material used in the studies by Bollandsås et al. (2022; 2023)

The dominant species of trees in the project areas are Norway spruce, Scots pine and European white birch.

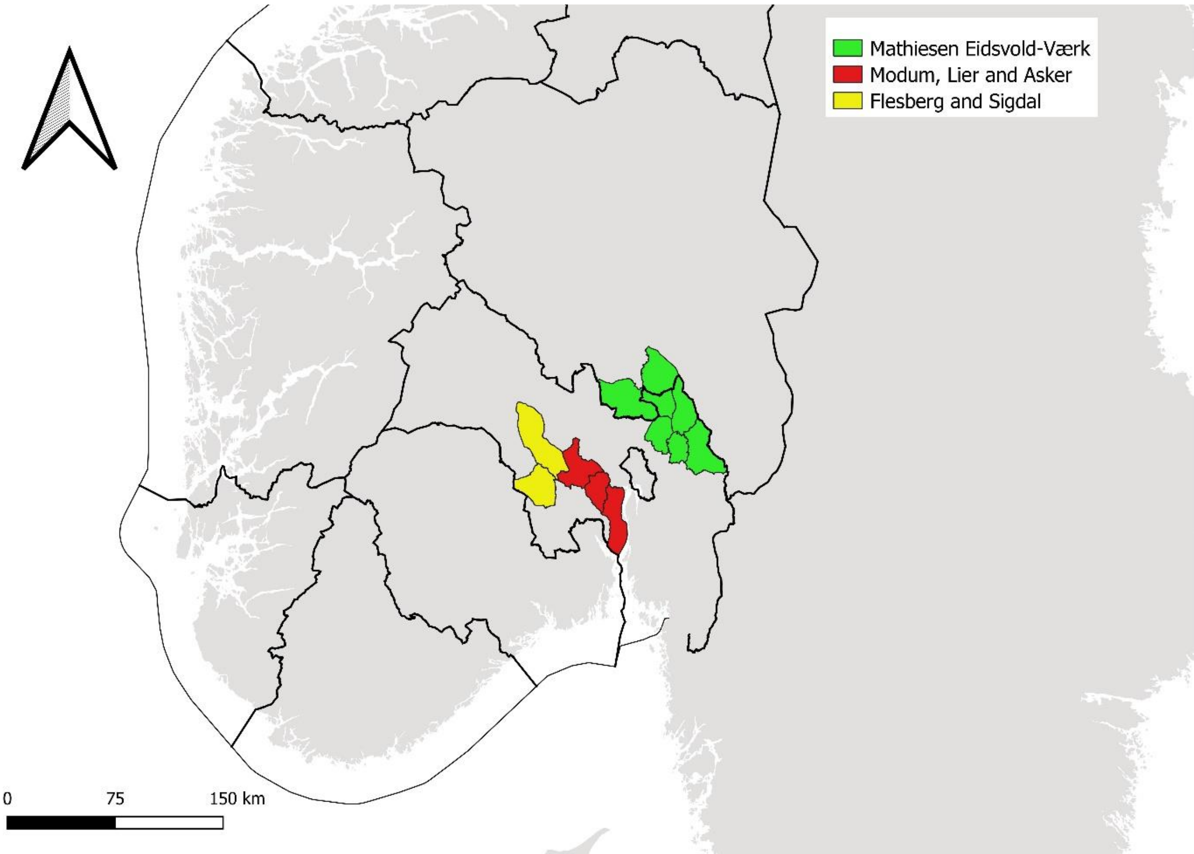

Figure 2: Forest inventory projects included in the study. Green areas are designated to project one, yellow for project two and red for project three.

2.2 Data material

The ground reference values were obtained during measurements of field sample plots which occurred during three regional ALS-assisted FMI campaigns, whereas SR16 data were extracted as additional information specifically for studies:

1. Project one consists of 116 field sample plots for ground reference values and SR16 predictions. The field sample plots are located on the private property of Mathiesen Eidsvold-Værk.
2. Project two consists of 267 field sample plots for ground reference values and SR16 predictions.
3. Project three consists of 169 field sample plots for ground reference values and SR16 predictions.

Ground reference values regarding project one refer to a private initiative by the large forest estate, Mathiesen Eidsvold-Værk. The estate required an updated source of forest information for strategic planning due to outdated information from their previous FMI conducted in 2007. Therefore, the new FMI, with accompanying ground reference values, was acquired in 2021, whereas SR16 predictions were acquired in 2020 (table 1).

The ground reference values from project two (Sigdal-Flesberg) and three (Modum, Lier and Asker) relate to the same regional ALS campaign undertaken by Viken Skog ASA. Ground reference values were acquired in 2019, whereas SR16 predictions were acquired in 2020 (table 1).

Table 1: The year of acquisition of ground reference values and SR16 predictions for each project.

Project id.		**Reference**	**SR16**
1	**Mathiesen Eidsvold-Værk**	2021	2020
2	**Sigdal and Flesberg**	2019	2020
3	**Modum, Asker and Lier**	2019	2020

The dataset consists of 552 field sample plots with ground reference values, supported by accompanying SR16 predictions.

2.2.1 Ground reference data

Measurements undertaken at field sample plots follow the intention of a project's descriptive goals. FMIs are produced to assist decision-making at stand level. However, undertaking a total measurement of all variables of interest on all trees at plot level could significantly increase inventory costs.

The ground reference values contain information regarding site basal area (G), dominant height (Hdom), site index (SI), number of trees (N) and age (A) from field sample plots the size of 250 m^2.

To ease the task of measuring tree heights, the term "selection trees" was introduced. Selection trees mean that a specific selection of trees within a field sample plot applies for more extensive measurements, including height. However, it should be selected objectively to avoid systematic errors because of a subjective selection process (Fitje, 1984). For example, systematic errors can be avoided by measuring the height once every fourth tree. Fitje (1984) developed models to predict tree heights using the diameter at breast height (dbh) as input due to the strong correlation between dbh and tree height. However, the correlation between dbh and tree height can vary depending on the site index and density of trees/ha.

Similarly to Bollandsås et al. (2023), the procedure of the height measurement protocols means sample trees were selected with a probability proportional to the stand basal area using a relascope aiming for 10 sample trees per plot. Then, tree heights were measured using a Vertex hypsometer and the dominant height was calculated based on the plot registrations.

Site index describes the potential forest growth based on the dominant height at 40 years age at breast height (H_{40} in Norway). Site index at the plot level is calculated by using a correlation between the average age at breast height and the average height of the two largest trees at the field sample plot using tables from Tveite (1977). For calculations at hectare level, the 100 largest trees/ha is instead used.

The basal area (G, m^2/ha) was calculated as the sum of the basal area measured from individual trees during relascope aiming and scaled to m^2/ha. Next, tree species was determined. The diameter at breast height (dbh, cm) was measured for all trees equal to or larger than 10 cm at breast height. Each tree over the diameter limit was recorded to determine the total number of trees (N/ha). Finally, measurements were concluded with measurements of stand age (A, yr).

Based on age and site index, forest stands are classified into development classes. Development class is defined as a national system of maturity classification (Anon, 1987). The classification includes classes 1 to 5, which describe the maturity of clear-felled stands towards harvest, 5 being the most mature class defined as ready for harvest. Development classes classify the stages in which silvicultural treatments are valid, such as young growth thinning, thinning and final harvest. Therefore, it is necessary to provide information on basal area, mean height, and volume to manage these treatments properly. This study only included plots in development classes 3 to 5.

All ground reference values used in this study were collected through FMIs produced by the forest owner association Viken Skog ASA. As a result, field instructions remained identical for all field sample plots.

Table 2 describes the distribution of tree species on the field sample plots. The distribution is calculated as the percentage of the total basal area.

For further descriptions of the ground reference values, see table 3.

Table 2: The distribution of species for the separate project and the overall distribution for the dataset based on the basal area.

		Species		
Project		**Spruce**	**Pine**	**Deciduous**
1	**MEV**	91 %	2 %	7 %
2	**Sig/Fles**	43 %	45 %	12 %
3	**Modum**	57 %	31 %	12 %
	Total	59 %	30 %	11 %

Table 3: Each variable's average ground reference values are displayed for each project and the entire dataset. Min and max observed ground reference values are also displayed.

	Basal area (m^2/ha)			Min (field)	Max (field)
	Project	**N**	**Field**	**m2/ha**	**m2/ha**
1	MEV	116	29.8	5.2	62.1
2	Sigdal - Flesberg	267	24.1	4.2	54.7
3	Modum, Asker, Lier	169	29.1	7.7	66.7
	Total	552	26.8	4.2	66.7

	Dominant height (m)			Min (field)	Max (field)
	Project	**N**	**Field**	**m**	**m**
1	MEV	116	20.7	8.8	31.4
2	Sigdal - Flesberg	267	20.1	11.2	30.2
3	Modum, Asker, Lier	169	20.9	11.7	37.4
	Total	552	20.5	8.8	37.4

	Site index (m)			Min (field)	Max (field)
	Project	**N**	**Field**	**m**	**m**
1	MEV	116	16.5	5.6	26.1
2	Sigdal - Flesberg	267	13.8	6.0	23.0
3	Modum, Asker, Lier	169	14.7	6.0	26.0
	Total	552	14.6	5.6	26.1

	Number of trees (n/haa)			Min (field)	Max (field)
	Project	**N**	**Field**	**n/ha**	**n/ha**
1	MEV	116	831	160	1640
2	Sigdal - Flesberg	267	670	40	2000
3	Modum, Asker, Lier	169	708	160	1760
	Total	552	716	40	2000

	Age (year)			Min (field)	Max (field)
	Project	**N**	**Field**	**yr**	**yr**
1	MEV	116	60.6	18	183
2	Sigdal - Flesberg	267	89.7	20	217
3	Modum, Asker, Lier	169	86.2	17	235
	Total	552	82.5	17	235

2.2.2 Forest resource map – SR16

SR16 is a nationwide prediction map of forest attributes that covers all forested areas in Norway. It gives an overview of the extent and characteristics of Norway's forest resources. SR16 predictions are produced through automated processes as a combination of existing maps (AR5), terrain models, 3D remotely measured data (ALS and photogrammetry) and ground reference values from manual measurements at field sample plots used by the Norwegian NFI (NIBIO, 2023). NFI field sample plots were primarily used to provide annual updates for regional or national statistics and policy-making (Rahlf et al., 2021; Tomppo et al., 2010). However, after the introduction of SR16, ground reference values from NFI field sample plots serve a primary role as calibration data for prediction models in the same manner as ground reference values for field sample plots in FMIs. NFI field sample plots used by SR16 are distributed over all forested areas in Norway according to a permanent 3×3 km grid.

SR16 predictions of forest attributes were extracted for each field sample plot by weighting the 16×16 m cell predictions intersecting the field sample plot with the individual cells area included within the plot (Bollandsås et al., 2023). Some SR16 predictions might result from several weighted intersecting SR16 cells within the same field sample plot.

SR16 calculates the site index using an area-based method with ALS data as the explanatory variable and ground reference values from the Norwegian NFIs field sample plots. Additionally, the statistic model utilises AR5 (area resource map and area classification system), terrain models and climatic data for predicting the H^{40} site index for Norway spruce, Scots pine and European white birch (NIBIO, 2023).

Ground reference values and SR16-predictions might be related to different points in time (table 1). The data were not forecasted or backcasted to represent the same year due to the relatively small timespan between the acquisitions of ground reference values and SR16 predictions.

2.3 Data analysis

2.3.1 Accuracy analysis

In some circumstances, the state of the field sample plots at the time of ALS acquisition and at the time of the FMI field inventory may differ significantly. This can happen for several reasons, such as undetected disturbances in SR16 or incorrect classifications of harvests in SR16. In these cases, the FMI field inventory may have acquired ground reference values representing full stocking, despite the actual state of the field sample plots being very different. This might result in large outliers significantly affecting the results of analyses (Bollandsås et al., 2023). Therefore, field sample plots with an extremely large disparity between the ground reference values and SR16 predictions were excluded by applying Rosners's test (Rosner, 1983) to each plot separately to automatically detect outliers that differed significantly from the rest of the observations. The Rosner test was applied for each project and variable independently. This resulted in the detection of five outliers in total that were removed.

To analyse the systematic differences, ground reference values for variables of interest were compared against SR16 predictions by assessing the difference (D_i) between the ground reference value (y_i) and SR16 prediction ($\ddot{y}_i$) for each field sample plot. Further, the mean difference (MD and MD%) was analysed as the average difference between the ground reference values and SR16 predictions for the individual projects and the total dataset. Additionally, the root mean squared error (RMSE and RMSE%) was calculated to address the concentration of the data around the line of best fit, thus revealing the standard deviations of the residuals (prediction errors). The mean difference (MD, MD%) and the root mean squared errors (RMSE, RMSE%) were calculated as follows:

$$D_i = y_i - \ddot{y}_i \tag{1}$$

$$MD = \frac{\frac{1}{n}\sum_{i=1}^{n}(D_i)}{Y} \tag{2}$$

$$MD(\%) = \frac{\frac{1}{n}\sum_{i=1}^{n}(D_i)}{Y} \times 100 \tag{3}$$

$$RMSE = \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(D_i)^2}}{Y} \tag{4}$$

$$RMSE\% = \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(D_i)^2}}{Y} \times 100 \tag{5}$$

where n = the number of plots, y_i = ground reference value for the forest attribute in plot i, $\ddot{y}_i$ = the predicted forest attribute from SR16 in plot i, Y = the mean ground reference value for the forest attribute, and D_i is the difference between the ground reference value and SR16 prediction in plot i.

The minimum (Min) and maximum (Max) observed differences between ground reference values and SR16 predictions were determined for the individual projects and the total dataset (table 6).

2.3.3 Loss analysis

Long-term timber production computations were made with GAYA (Eid, 2000; Hoen & Eid, 1990; Hoen & Gobakken, 1997). GAYA is a large-scale forestry scenario model based on the simulation of stand-level treatments and linear programming for solving management problems (Eid, 2000; Lappi, 1992). All model components are deterministic (Eid, 2000). Eid (2000) suggests that economic calculations and stand projections rely heavily on the “average tree” of each stand, i.e. the basal area mean diameter (D_{ba}), the mean height weighted by basal area (H_L) and the number of stems/ha (N). Consequently, the projections are based on diameter increment functions (Blingsmo, 1984). The diameter increment is predicted with age, dominant height, site quality, N and D_{ba} as independent variables. Height development models (Braastad, 1977; Tveite, 1976; Tveite, Bjørn, 1977) were predicted with H_{L}, age and site quality as independent variables, whereas a mortality model (Braastad, 1982) used N as the independent variable.

Optimal silvicultural management strategies maximising the NPV were simulated using ground reference values. Suboptimal silvicultural management strategies were simulated using presumably erroneous SR16 predictions to calculate the maximised NPV for the alternate scenario. Projections were performed for ten five-year periods assuming all treatments took place in the middle of the five-year period. Treatments included final harvest and immediate planting or natural rejuvenation, depending on the forest conditions. A real annual rate of discount of 3 % was applied in this study.

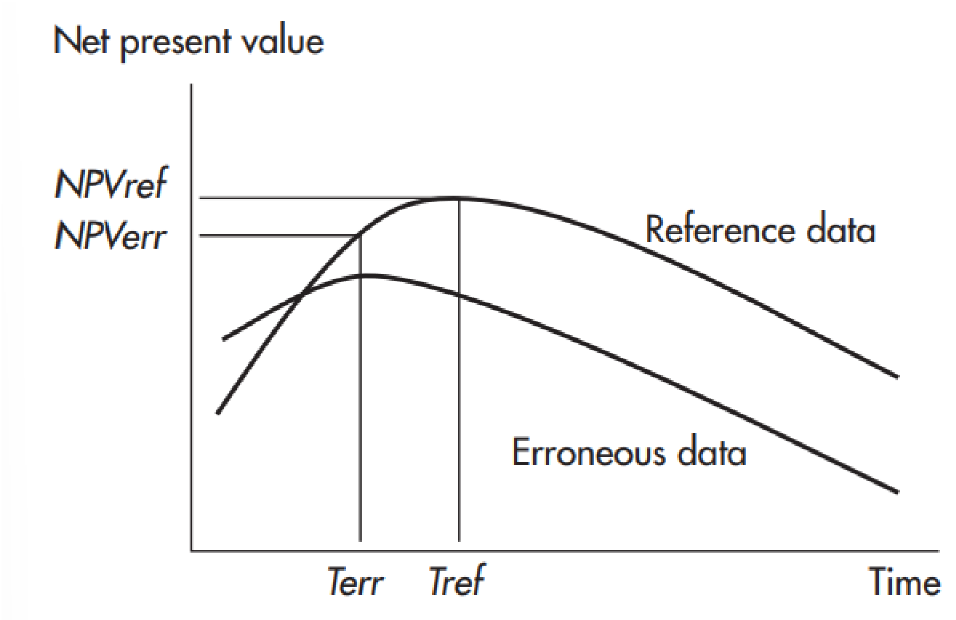

Figure 3: (Eid, 2000) An illustration of how NPV losses can appear due to erroneous inventory data. *Use of uncertain inventory data in forestry scenario models and consequential incorrect harvest decisions. Silva Fennica, 34: 89-100.*

Figure 3 illustrates how NPV losses may appear due to erroneous inventory data. The upper line is an indication of the development of the NPV close to the final harvest based on the ground reference values, where. In contrast, the lower line represents the NPV from erroneous data. Harvesting decisions based on erroneous data could result in the final harvest being conducted at time *Terr* instead of *Tref*. The resulting NPV losses can be illustrated as the difference between *NPVref* and *NPVerr* (Eid, 2000).

The expected losses can be calculated using Eid's (2000) example where $NPVref_i$ = the NPV of stand number i (i=1, 2, …, n) for the ground reference values, whereas $NPVerr_i$ is the NPV of SR16 predictions for stand number i (i=1, 2, …, n). The NPV loss caused by an error in the data for stand number i can then be calculated as:

$$NPVloss_i = NPVref_i - NPVerr_i \tag{6}$$

Expected NPV losses of all stands within a project or dataset can be calculated as follows:

$$NPVloss = \left(\sum_{i=1}^{n} NPVloss_i\right) / n \tag{7}$$

where $NPVloss_i$ is the NPV loss for stand number i ($i=1, 2, \ldots, n$) and n is the total number of stands within the dataset or project.

The timber prices used in the calculations were based on the average price over five years (2017 – 2022), consisting of assortment prices for sawn- and pulpwood for Norway spruce and Scots pine on the Norwegian timber marked. Prices used for European white birch are composed of mean pulp- and sawnwood prices combined over the same period (SSB, 2022) (table 4).

Table 4: The average assortment prices for pulp- and sawnwood for Norway spruce, Scots pine and European white birch between 2018 to 2022. The average price during this period is used as assortment prices for the economic analysis. Prices are expressed in Norwegian kroner (NOK).

Assortment	Average prices/year (NOK)					Average
	2018	2019	2020	2021	2022	
Spruce - sawnwood	517	523	457	564	654	**543**
Spruce - pulpwood	286	344	286	253	306	**295**
Pine - sawnwood	473	483	453	546	628	**517**
Pine - pulpwood	266	328	274	245	284	**279**
Birch - sawnwood	351	470	605	560	608	**405**
Birch - pulpwood	260	312	269	263	350	

As of 2023, planting costs NOK 5 – 6 per plant without subsidies (Viken-Skog, 2022). The cost of planting is reduced by government-created subsidies created to stimulate increased carbon sequestration and by using private forest funds with tax advantages. This was assumed to reduce the direct cost to 25% of the original costs (table 5).

Table 5: The prices of planting for Norway spruce, Scots pine and deciduous trees. Due to subsidies and other benefits, the direct share of cost is assumed to be 25%. Prices are expressed as Norwegian kroner (NOK).

	Norway Spruce	Scots Pine	Deciduous	Share of cost
Cost (NOK/plant)	6	6	8	25%

NPV losses were calculated for an overall SR16 scenario that used all SR16 predictions (scenario 2). Additionally, differentiating independent effects of isolated variables for SR16 predictions included a series of secondary scenarios (a-e) as follows:

1) Scenario 1: Stand estimates using ground reference values (reference option).
2) Scenario 2: Stand estimates using all SR16 predictions.
    a. Scenario 2a: Stand estimates isolating SR16 basal area.
    b. Scenario 2b: Stand estimates isolating SR16 dominant height.
    c. Scenario 2c: Stand estimates isolating SR16 site index.
    d. Scenario 2d: Stand estimates isolating SR16 number of trees/ha.
    e. Scenario 2e: Stand estimates isolating SR16 age.

The dataset is comprised of data representing diverse forest conditions geographically and biologically. Therefore, the results were separated according to the separate projects.

3. Results

3.1 Accuracy results

The results from the statistical analysis are presented as the difference between ground reference values and SR16 predictions as relative (MD%, RMSE%) and absolute (MD, RMSE) results presented for each variable (G, Hdom, SI, N and A) independently for each project and the entire dataset (table 6). Additionally, scatterplots highlight the distribution of prediction errors as the relationship between the ground reference values (X-axis) and the SR16 predictions (Y-axis) (figures 4 to 7).

The overall accuracy of SR16 predictions resulted in MD% values of 9.7% for G, -2.4% for Hdom, 7.5% for SI, 6.6% for N and 2.3% for A. Corresponding RMSE% values were 29%, 9%, 24%, 34%, and 41% for G, Hdom, SI, N and A, respectively (table 6).

Locally, MD% of SR16 predictions showed a wide range of variations ranging from 1.0 to 18.2% for G, -1.0 to -4.8% for Hdom, 0.0 to 12.9% for SI, -0.8 to 19.3 % for N, and -8.0 to 16.5% for A. Corresponding RMSE% values ranged locally from 26 to 30% for G, 9 to 10% for Hdom, 20 to 28 % for SI, 31 to 36% for N, and 40 to 43% for A (table 6).

Table 6: The average differences between ground reference values against SR16 predictions which includes the observed max, min, MD, MD%, RMSE and RMSE%.

Basal area (m2/ha)					Difference				
				Min	Max	MD		RMSE	
Project	N	Field	SR16	m^2/ha	m^2/ha	m^2/ha	%	m^2/ha	%
1 MEV	116	29.8	30.1	-23.1	26.3	0.3	1.0	7.8	26.1
2 Fles/Sig	267	24.1	26.0	-13.7	18.1	1.9	7.9	6.9	28.7
3 Modum	169	29.1	34.4	-15.5	25.3	5.3	18.2	8.8	30.3
Total	552	26.8	29.4	-23.1	26.3	2.6	9.7	7.7	28.7
Dominant height (m)					**Difference**				
				Min	Max	Average		RMSE	
Project	N	Field	SR16	m	m	m	%	m	%
1 MEV	116	20.7	19.7	-7.5	5.9	-1.0	-4.8	2.0	9.8
2 Fles/Sig	267	20.1	19.6	-5.8	5.1	-0.5	-2.5	1.9	9.4
3 Modum	169	20.9	20.7	-5.0	5.9	-0.2	-1.0	1.8	8.8
Total	552	20.5	20.0	-7.5	5.9	-0.5	-2.4	1.9	9.3
Site index (m)					**Difference**				
				Min	Max	Average		RMSE	
Project	N	Field	SR16	m	m	m	%	m	%
1 MEV	116	16.5	16.5	-9.8	10.0	0.0	0.0	3.2	19.7
2 Fles/Sig	267	13.8	14.7	-7.6	8.6	0.9	6.5	3.2	23.5
3 Modum	169	14.7	16.6	-8.0	10.0	1.9	12.9	4.1	27.7
Total	552	14.6	15.7	-9.8	10.0	1.1	7.5	3.5	24.0
Number of trees (n/ha)					**Difference**				
				Min	Max	Average		RMSE	
Project	N	Field	SR16	n/ha	n/ha	n/ha	%	n/ha	%
1 MEV	116	830.7	868.5	-711.1	808.9	37.8	4.6	257.2	31.0
2 Fles/Sig	267	670.3	664.9	-872.8	458.2	-5.4	-0.8	221.5	33.1
3 Modum	169	707.9	844.4	-504.2	623.8	136.5	19.3	255.6	36.1
Total	552	715.5	762.7	-872.8	808.9	47.2	6.6	239.8	33.5
Age (yr)					**Difference**				
				Min	Max	Average		RMSE	
Project	N	Field	SR16	yr	yr	yr	%	yr	%
1 MEV	116	60.6	70.6	-99.1	88.0	10.0	16.5	25.9	42.8
2 Fles/Sig	267	89.7	93.6	-112.8	115.1	3.9	4.3	38.5	43.1
3 Modum	169	86.2	79.3	-130.4	59.8	-6.9	-8.0	34.7	40.3
Total	552	82.5	84.4	-130.4	115.1	1.9	2.3	35.4	41.1

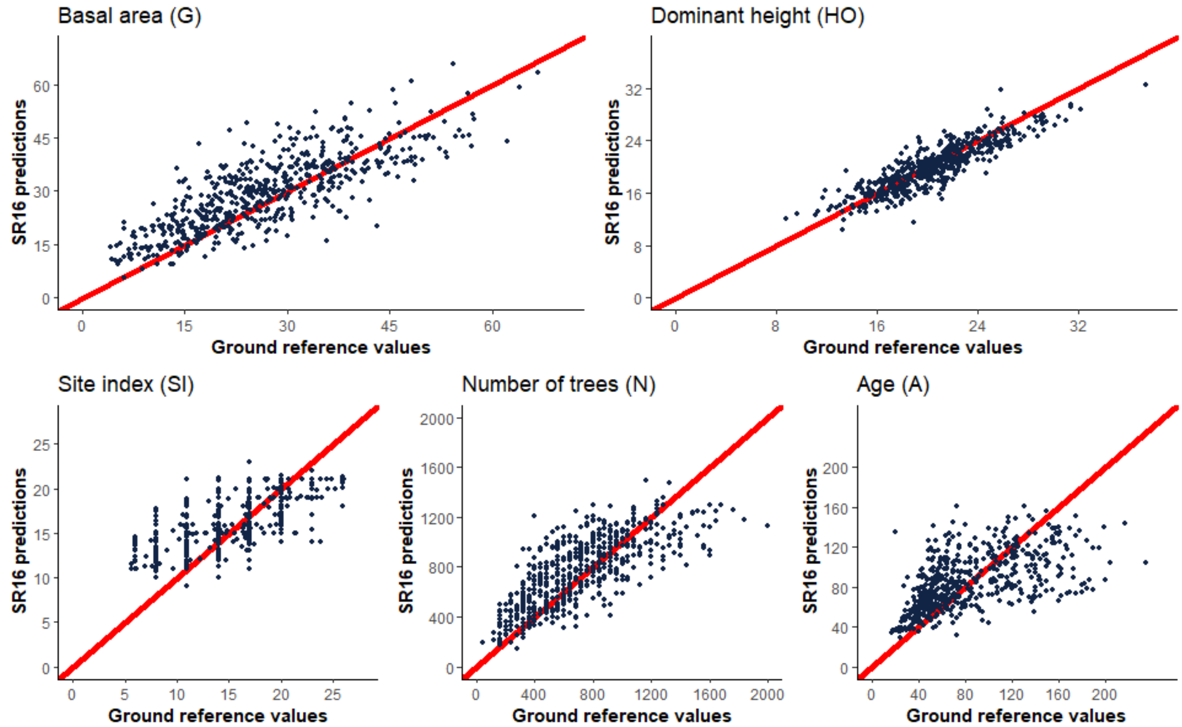

Figure 4: Overall scatterplot visualisation. Scatterplots show the relationships between the ground reference values and SR16 predictions. An overweight of points on one side of the line could mean unreliable estimates from SR16.

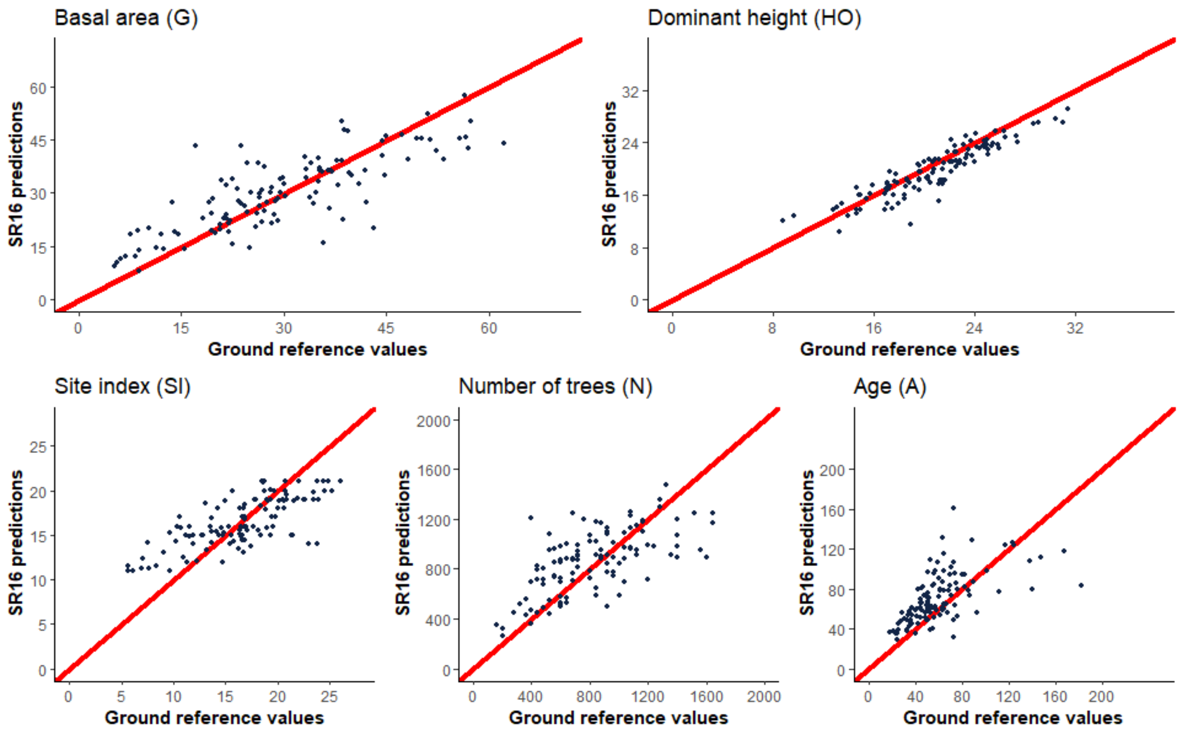

Figure 5: Scatterplot visualisation for project one (MEV) for the variables of interest. Scatterplots show the relationships between the ground reference values and SR16 predictions. An overweight of points on one side of the line could mean unreliable estimates from SR16.

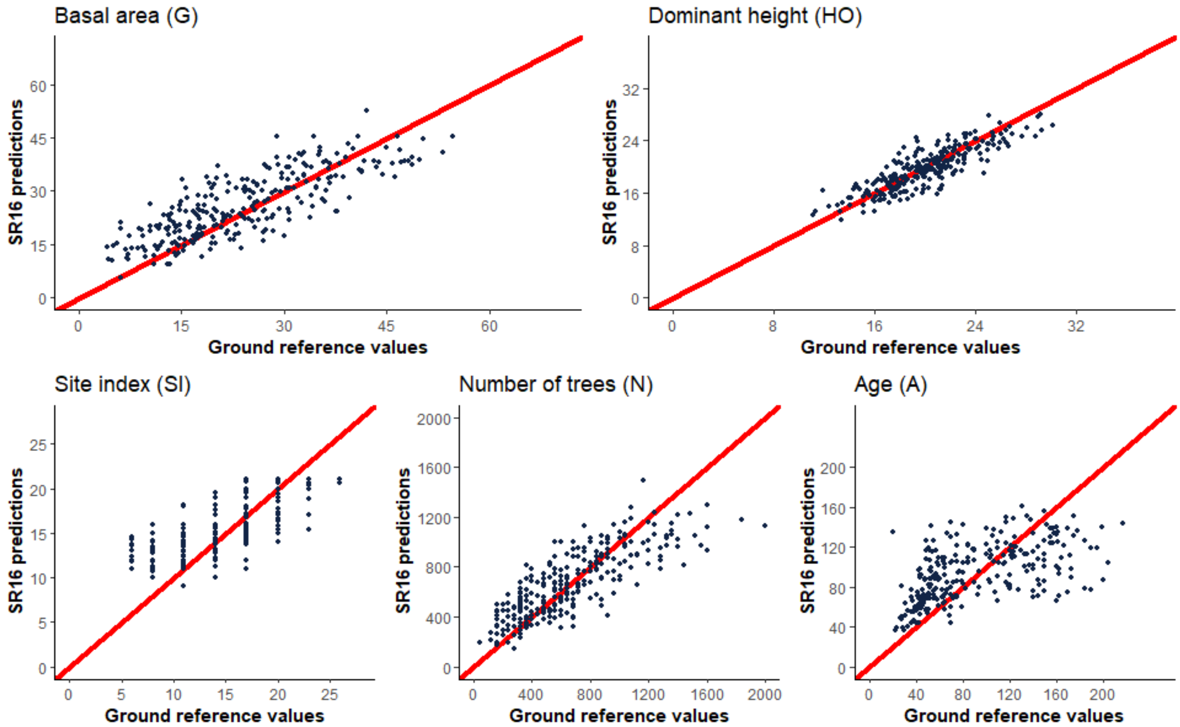

Figure 6: Scatterplot visualisation for project two (Sigdal and Flesberg) for the variables of interest. Scatterplots show the relationships between the ground reference values and SR16 predictions. An overweight of points on one side of the line could mean unreliable estimates from SR16.

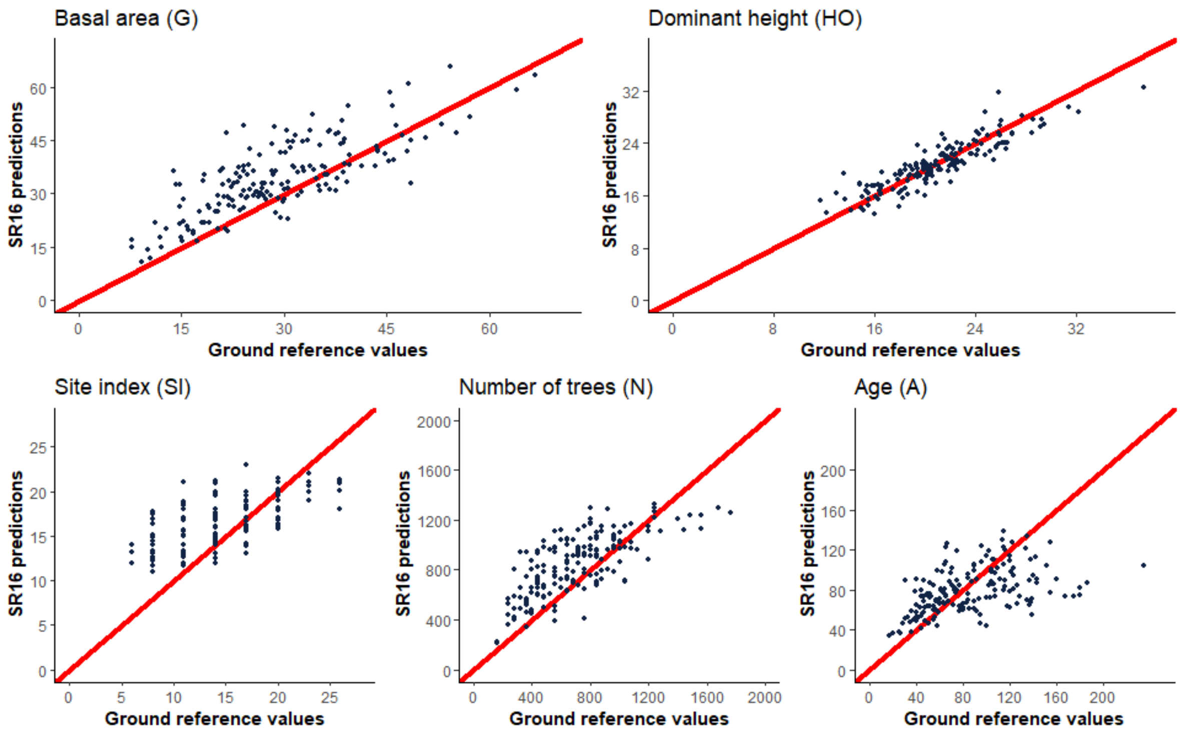

Figure 7: Scatterplot visualisation for project three (Modum, Lier and Asker) for the variables of interest. Scatterplots show the relationships between the ground reference data and SR16 predictions. An overweight of points on one side of the line could mean unreliable estimates from SR16.

The scatterplots highlight the relationship between the ground reference values and SR16 predictions. Results indicate significant overpredictions of G, SI, N and A; however, the magnitude of overpredictions varied significantly between individual projects and overall results. For SI, plots under 17 H^{40} were observed to be generally overpredicted. However, plots with an SI over 17 H^{40} seemed to a lesser extent to be underpredicted. Prediction errors of A can be seen to be generally overpredicted at stand ages below 120 years, whereas stand ages over 120 years seems to be underpredicted.

3.2 Loss results

The economic analysis was performed on the condition that each field sample plot represents an individual stand in GAYA and constitutes an area of one hectare. The results are highlighted in accompanying tables (tables 7, 8, 9 and 10) and diagrams (figure 8) illustrating expected economic losses overall for the dataset, including results for the individual projects, and expected losses when isolating the separate variables of interest.

The total value for the overall dataset using ground reference values was NOK 48 295 083. Using SR16 predictions resulted in a total loss of NOK 402 814. The average loss per hectare was 728 NOK/ha, constituting to an average loss of 0.83%. On the other hand, the max registered loss was NOK 19 904. Isolating SR16 predictions in separate analyses resulted in an average NPV loss ranging from NOK 98/ha to 561/ha. The results show that A and SI inflicted the most significant NPV reductions (table 7).

Table 7: Loss results for the entire dataset displayed as min, max, the total sum of losses, in addition to average losses and the total NPV. The column SR16 represents overall results utilising all variables, whereas SR16 G = isolated basal area, SR16 Hdom = isolated Hdom, SR16 SI = isolated SI, SR16 N = isolated N and SR16 A = isolated A.

TOTAL	Scenario 1	Scenario 2					
	1) Reference option	SR16	SR16 G	SR16 Hdom	SR16 SI	SR16 N	SR16 A
Net present value (NOK)	48 295 083	47 892 269	48 240 256	48 240 932	48 157 445	48 220 305	47 984 574
Min loss (NOK/ha)	0	0	0	0	0	0	0
Average loss (NOK/ha)	0	728	99	98	249	135	561
Max loss (NOK)	0	19 904	5 338	11 750	8 271	11 750	17 509
Sum loss (NOK)	0	402 814	54 827	54 151	137 638	74 778	310 509
Stands with loss	0	186	83	48	106	85	145
Stands without loss	552	366	469	504	446	467	407
Max loss (%)	0 %	69.00 %	46.65 %	47.72 %	45.45 %	47.72 %	61.14 %
Average loss (%)	0 %	0.83 %	0.11 %	0.11 %	0.28 %	0.15 %	0.64 %

Another way to view the results of the economic analysis is to split up the dataset and review the results of the individual project themselves due to substantial variation in forest conditions that could affect SR16 predictions and the potential impact the variables could have on the behaviour of GAYA.

The total value for project one using ground reference values was NOK 13 157 927. Using SR16 predictions on all variables resulted in a total loss of NOK 168 490. The average NPV reduction per hectare was NOK 1 453/ha, which accounts for an average NPV reduction of 1.28%. Furthermore, the max loss for an individual stand amounted to NOK 19 904. Isolating the various variables resulted in an average loss that varied between NOK 31/ha to 999/ha depending on the variable isolated. Age accounts for most economic losses (table 8).

Table 8: Loss results for project one (MEV) displayed as min, max, the total sum of losses, in addition to average losses and the total NPV. The column SR16 represents overall results utilising all variables, whereas SR16 G = isolated basal area, SR16 Hdom = isolated Hdom, SR16 SI = isolated SI, SR16 N = isolated N and SR16 A = isolated A.

MEV	Scenario 1	Scenario 2					
	1) Reference option	SR16	SR16 G	SR16 Hdom	SR16 SI	SR16 N	SR16 A
Net present value (NOK)	13 157 927	12 989 437	13 137 515	13 154 281	13 121 502	13 148 764	13 042 035
Min loss (NOK/ha)	0	0	0	0	0	0	0
Average loss (NOK/ha)	0	1 453	176	31	314	79	999
Max loss (NOK)	0	19 904	5338	1 223	7 116	1 781	17 509
Sum loss (NOK)	0	168 490	20412	3 646	36 425	9 163	115 892
Stands with loss	0	55	19	12	36	21	44
Stands without loss	116	61	97	104	80	95	72
Max loss (%)	0 %	69.00 %	46.65 %	29.22 %	45.45 %	3.10 %	39.98 %
Average loss (%)	0 %	1.28 %	0.16 %	0.02 %	0.28 %	0.07 %	0.88 %

Secondly, the total value for project two using the ground reference values was NOK 18 904 733. The total economic loss of using SR16 predictions was NOK 151 205. The average economic loss of using SR16 predictions resulted in a loss of 564 NOK/ha, an average reduction of 0.80% net present value. The highest recorded loss in a stand was NOK 17 221. Isolating separate SR16 variables resulted in an average economic loss ranging from NOK 95/ha to 435/ha. The results suggest that age is responsible for the most significant economic reduction (table 9).

Table 9: Loss results for project two (Sigdal and Flesberg) displayed as min, max, the total sum of losses, in addition to average losses and the total NPV. The column SR16 represents overall results utilising all variables, whereas SR16 G = isolated basal area, SR16 Hdom = isolated Hdom, SR16 SI = isolated SI, SR16 N = isolated N and SR16 A = isolated A.

SIGDAL-FLESBERG	Scenario 1	Scenario 2					
	1) Reference option	SR16	SR16 G	SR16 Hdom	SR16 SI	SR16 N	SR16 A
Net present value (NOK)	18 904 733	18 753 528	18 879 160	18 878 098	18 852 541	18 863 428	18 788 235
Min loss (NOK/ha)	0	0	0	0	0	0	0
Average loss (NOK/ha)	0	564	95	99	195	154	435
Max loss (NOK)	0	17 221	2 361	6 207	6 888	7 689	17 221
Sum loss (NOK)	0	151 205	25 573	26 635	52 192	41 305	116 498
Stands with loss	0	76	45	23	37	44	62
Stands without loss	268	192	223	245	231	224	206
Max loss (%)	0.00 %	51.10 %	29.81 %	47.72 %	8.62 %	47.72 %	48.05 %
Average loss (%)	0.00 %	0.80 %	0.14 %	0.14 %	0.28 %	0.22 %	0.62 %

Finally, the total value of project three using the ground reference values was NOK 16 232 740. Applying SR16 predictions for all variables resulted in a total loss of NOK 83 119. The average NPV reduction using SR16 predictions for all variables was 492 NOK/ha or a 0.51% NPV reduction. The max loss experienced in an individual stand was NOK 14 289. Isolating SR16 variables resulted in average NPV reductions ranging between NOK 52/ha to 462/ha. Isolated SR16 age accounted for an average loss nearly identical to when all variables were used (table 10).

Table 10: Loss results for project three (Modum, Lier and Asker) displayed as min, max, the total sum of losses, in addition to average losses and the total NPV. The column SR16 represents overall results utilising all variables, whereas SR16 G = isolated basal area, SR16 Hdom = isolated Hdom, SR16 SI = isolated SI, SR16 N = isolated N and SR16 A = isolated A.

MODUM	Scenario 1	Scenario 2					
	1) Reference option	SR16	SR16 G	SR16 Hdom	SR16 SI	SR16 N	SR16 A
Net present value (NOK)	16 232 740	16 149 621	16 223 898	16 208 870	16 183 719	16 208 430	16 154 621
Min loss (NOK/ha)	0	0	0	0	0	0	0
Average loss (NOK/ha)	0	492	52	141	290	144	462
Max loss (NOK)	0	14 289	2 518	11 750	8 271	11 750	14 289
Sum loss (NOK)	0	83 119	8 842	23 870	49 021	24 310	78 119
Stands with loss	0	55	19	13	33	20	39
Stands without loss	169	114	150	156	136	149	130
Max loss (%)	0,00 %	31.93 %	31.26 %	35.03 %	12.07 %	7.41 %	61.14 %
Average loss (%)	0,00 %	0.51 %	0.05 %	0.15 %	0.30 %	0.15 %	0.48 %

Figure 8 presents expected losses overall and for the individual variables, where results indicate that most losses occur below 50 years of age. Accordingly, the figure shows that A and SI cause most of the observed NPV losses at stands below 50 years.

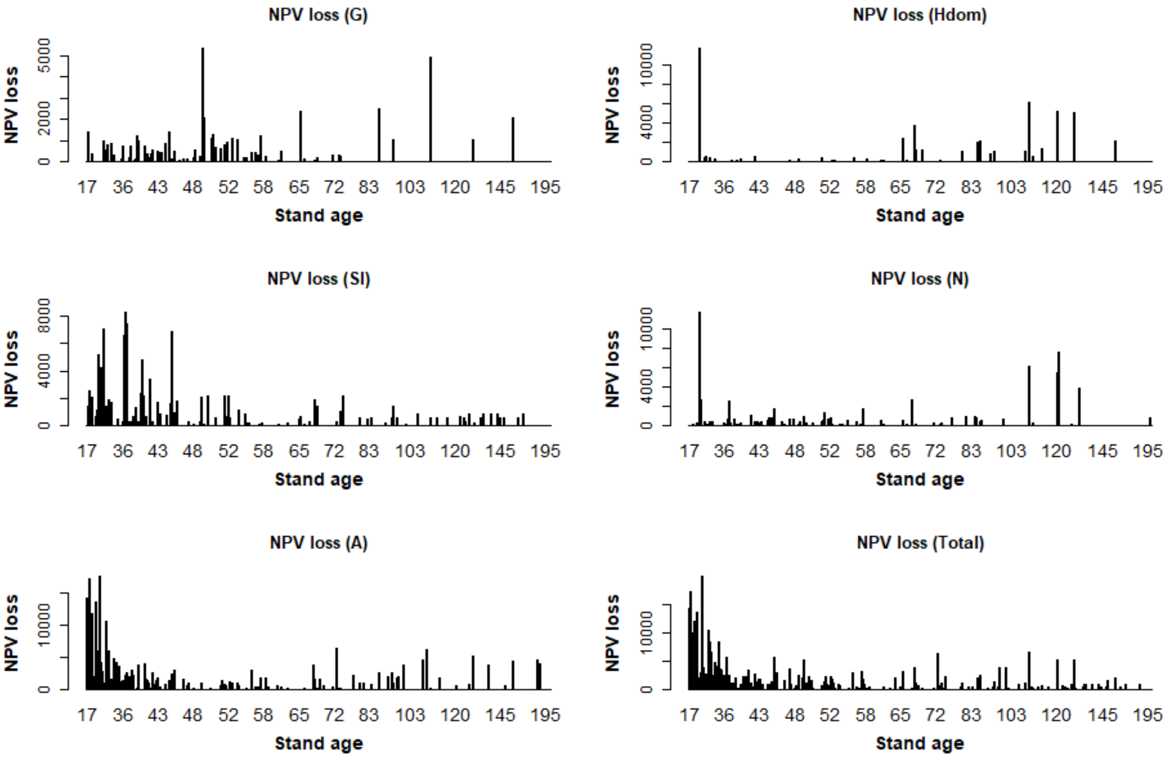

Figure 8: Barplots indicating overall NPV losses illustrated as NOK/ha for each isolated variable and overall SR16 scenario by stand age.

4. Discussion

4.1 Accuracy analysis

This study aimed to assess the accuracy of predictions from the SR16 forest resource map by comparison against ground reference values based on 552 field sample plots from several FMI projects in south-eastern Norway. An additional assessment of the economic costs caused by erroneous stand predictions was performed using the long-term forest simulator, GAYA. Bollandsås et al. (2022; 2023) undertook similar analyses using ground reference values and SR16 predictions from projects two and three. However, the study was conducted on the variables of V, G, Hm and Hdom. Furthermore, the present study assessed prediction errors for SI, N and A, in addition to Hdom and G. The results highlighted the importance of assessing results locally, which resulted in significant variations of prediction errors for the regional FMI projects.

It was expected that SR16 predictions would not be as accurate as the ground reference values. However, it was a surprise that the results varied significantly between the individual project areas. Regional prediction models, like the ones used in SR16, use NFI field observations as calibration data from a larger region to produce predictions for forest attributes at a local level. However, using NFI field observations as calibration data in prediction models can struggle to provide accurate local predictions of forest attributes, leading to FMI-specific differences observed in Bollandsås et al.'s (2023) study. The results from the present study, which included SI, N, and A as additional variables, underline previous studies' findings linked to FMI-specific differences. For example, the overall MD% for A was 2.4%, whereas MD% values of 16.5%, 4.3%, and -8.0% were observed at projects one, two, and three, respectively (table 6). Similar variations were observed for the other variables, indicating that the FMI-specific differences were not limited to a single forest attribute.

SR16s utilisation of NFI plots as ground reference values might introduce unwanted consequences in poorly adapted models that tend to generalise forest conditions due to a small sampling intensity. Poorly adapted models struggle to link ground reference values and ALS data representing smaller geographical areas. For example, poorly adapted ALS models might struggle to form a relationship between stem properties and distinct geographical patterns like latitude, elevation, and soil properties at a local level (Næsset, 2014). The present study and Bollandsås et al. (2023) provide evidence regarding distinct geographical patterns that suggest these traits are especially noticeable for assessments of local FMI projects. An overrepresentation of the average forest conditions for the area from which the data are collected is a general challenge of prediction models developed from empirical data (Bollandsås et al., 2023). A single FMI could be comprised of forest conditions that are, on average, different from those represented by the field sample plots used as calibration data. Consequently, systematic prediction errors could occur for smaller spatial domains (Bollandsås et al., 2023). However, since SR16 estimates generally seem to provide more dissimilar estimations for forest conditions locally, providing property-specific data could yield even more pronounced dissimilarities (Bollandsås et al., 2023). Neither the present study nor the study of Bollandsås et al. (2023) included property-specific data at the scope of an average forest property to illustrate the potential consequences of individual properties. The property-specific data used for project one does not provide a general guideline for property-specific data due to its large size not being representative of the average forest property.

For smaller domains, predicting the magnitude of prediction errors could be challenging when external models are applied without additional ground reference values from the area of interest (Bollandsås et al., 2023). In cases with ground reference values from field sample plots, the average prediction error could be observed by subtracting observed plot values with corresponding predictions (Bollandsås et al., 2023). Plot observations for calibration of local effects with predictions from a regional model from SR16, might provide a cost-effective way of supporting local planning of silvicultural management planning, especially since the number of local field sample plots could potentially be substantially smaller than the standard practice in operational FMIs (Bollandsås et al., 2023).

Nilsson et al. (2017) reported an absolute MD% that ranged from 16 to 22% for G. whereas Bollandsås et al. (2023) reported an absolute MD% that ranged from -7 to 6% for Hdom and -17 to 41% for G. In the present study, the overall MD% range for G ranged from 1 to 18%, and Hdom ranged from – 1 to – 5%, which is lower than the ones reported by Nilsson et al. (2017) and Bollandsås et al. (2023).

RMSE% measures the distance between the residuals to the line of best fit and illustrates how concentrated the data is around it. RMSE% values in this study ranged from 26 to 30% for G, 9 to 10% for Hdom, 20 to 28% for SI, 31 to 36% for N and 40 to 43% for A (table 6). The results imply no significant difference in the perceived variation internally between the projects and the total estimate. However, external variations between estimates for different variables emphasise the previous confirmation of how ALS data results in significantly lower RMSE% values for Hdom. Notably, the RMSE% for A in this study was higher than that for any other variable. Earlier studies such as Nilsson et al. (2017) reported RMSE % from 20 to 27% for G in a leave-one-out-cross-validation study for three independent areas in Sweden. Correspondingly, Bollandsås et al. (2023), partially using the same data as this study, compared SR16 predictions against ground reference values, resulting in RMSE% ranging from 22 to 46% for G and 6 to 17% for HO. The study from Bollandsås et al. (2023) utilised data from various geographical regions and forest conditions, which might have resulted in more significant variations in RMSE% compared to the present study.

Hauglin et al. (2021) studied overall plot level RMSE% values ranging from 31 to 33% for G using non-stratified and species-specific SR16 models. The study recommended including separate models for each main tree species to improve prediction accuracy. However, Bollandsås et al. (2023) did not observe a significant improvement in their study using 12 stratified models compared to the three models used by Hauglin et al. (2021). Despite not including species-specific or stratified models, the RMSE% values for G and Hdom in this study are still comparably smaller than the RMSE% reported by Hauglin et al. (2021) and Bollandsås et al. (2023). It is possible that differences in field measurement protocols, such as variations in sampling designs and plot sizes, could have influenced the RMSE% results reported by Bollandsås et al. (2023) compared to those found in this study.

Bollandsås et al. (2023) suggested that providing general guidance on where SR16 predictions perform well is challenging. Using a variable importance analysis (VIP-analysis), Bollandsås et al. (2023) elaborate that the observed factors explaining the variability of differences between SR16 predictions and ground reference values were predominantly represented in variables describing forest and canopy structure. Of several forest attributes describing the forest and canopy structure, the proportion of deciduous trees at the plot level was one of the major sources of explaining variability in observed differences between the ground reference value and SR16 predictions. Results from the present study indicate more significant prediction errors for G and SI in project two and three, possibly linked to a higher proportion of deciduous trees at plot level compared to project one (table 2). Previous studies (Liang et al., 2007; Næsset, 2005) suggested that an increased proportion of deciduous trees in a plot effect derived ALS metrics when all other factors are kept equal.

One issue that arose during the comparison of results was the difference in methodology with Bollandsås et al. (2023). During the acquisition of data for the present study for data, the time interval between the acquisition of ground reference values and SR16 predictions was short. As a result, growth models were not used to simulate forest conditions to the equivalent year for both datasets. Instead, the data were used as they were with minor deviations, as the deviations were deemed insignificant enough to avoid introducing more significant errors that could occur using growth models. Conversely, Bollandsås et al. (2022; 2023) utilised various growth models to backcast SR16 predictions to the FMI field plot acquisition date. Due to the differing methodologies used, it is challenging to determine the extent to which the backcasting impacts the comparability of results between the two studies.

4.2 Loss analysis

As Bollandsås et al. (2023) pointed out, decisions regarding the particular use of data should be based not only on the desired levels of accuracy but also on the data acquisition costs related to the suitability for decision-making (Kangas, 2010). Therefore, Bollandsås et al. (2023) suggested that further studies should focus on this topic using a loss analysis as an analytical method.

Table 7 shows that the total overall average loss was a 0.83% reduction of NPV. In contrast, individual variables ranged from an NPV reduction of 0.11% to 0.64%. NPV reductions are caused by inaccurate predictions, resulting in a delayed or premature final harvest and/or wrong rejuvenation method. According to Eid (2000)**,** a given error level would result in more significant NPV losses for A and SI than losses from other variables. With this in mind, it was unsurprising that these two variables were the leading cause of most expected losses. Eid (2000) suggests that site index directly affects the development of the "average" tree, ie. Importance for diameter growth and height development because these effects heavily influence decisions regarding the timing of final harvest and rejuvenation method. Therefore, erroneous SI predictions might result in significant NPV losses. However, most losses seem to be attributed to inaccurate predictions related to age. An erroneous age prediction plays an even more prominent role in the timing of final harvests (Eid, 2000).

In the same manner as the assessment of prediction accuracy, results varied significantly for the loss analysis when the result was reviewed locally. Therefore, loss results from the individual projects can be viewed in tables 8, 9 and 10.

Regarding prediction accuracy, project one had the most precise predictions among the reviewed projects. However, the magnitude of prediction errors did not necessarily correspond with reductions in NPV. Project one had the largest overall observed NPV reduction, of which the majority of NPV losses could be attributed to a significant overprediction of A. The results align with those of Eid (2000) regarding the potential of erroneous predictions of A. On the other hand, the relationship between the magnitude of significant prediction errors resulted only in minor NPV reductions for Hdom compared to the other projects.

Project two comprises almost half of the dataset and aligns more closely with the overall observed results. However, unlike project one, the magnitude of prediction errors for A in project two does not correlate well with the corresponding NPV reductions. For instance, a prediction error of 4.3% for A in project two resulted in an average NPV reduction of 0.62%. In contrast, a prediction error of 16.5% for A in project one resulted in an average NPV loss of 0.80% (tables 6, 8 and 9). This might suggest no clear correlation between the magnitude of prediction errors and corresponding NPV losses between projects one and two.

Project three displayed significant prediction errors for G, SI, N and A. However, despite the large magnitude of these errors, the total NPV reduction for this project was still significantly lower than what was observed for the other projects. These results are surprising but could be explained by a large underprediction of A, which could lead to significantly lower NPV losses compared to what an equivalent overprediction might impose. On the other hand, Eid (2000) explains that A plays an even more significant role than SI when determining the time of the final harvest. A large underprediction of A would extend the timespan before the final harvest, whereas a large overprediction of SI would shorten the timespan before the final harvest. Therefore, the prediction errors for SI and A are likely to counteract each other, resulting in lower NPV overall losses than if both variables were overestimated or underestimated. However, an isolated SI exhibited the most significant observed NPV reduction among the projects.

Previous research has demonstrated the usefulness of loss analyses for evaluating the accuracy of forest resource maps, such as the national forest resource map (SR16) in Norway. Bollandsås et al. (2022) reported an average NPV loss of 2.4% utilising data from SR16. From a total of 48 stands, 36 stands reported a reduction in NPV. On the other hand, replacing SR16 predictions for A and SI with ground reference values reduced the total NPV loss to 0.056 % affecting just 5 out of 48 stands. Comparably, NPV losses using SR16 predictions in the current study were overall 0.83%, whereas NPV losses were 1.28%, 0.80% and 0.51% for the respective projects. Bollandsås et al. (2022) attributed the large proportion of NPV losses from SI to the generally poor adaptability of SR16 predictions that did not span the width of variation seen in the ground reference values. In contrast, NPV losses stemming from A were resulted from systematic over-predictions of SR16 A. The site index of the most productive areas was generally underestimated. Although this study did not perform similar scenario analyses, the findings suggest similarities with Bollandsås et al.'s (2022) study, indicating that the highest proportion of observed NPV losses were resulted from SR16 predictions for A and SI.

It is essential to carefully evaluate and compare the results with the study of Bollandsås et al. (2022), given that the study utilised a small dataset consisting of only 48 field sample plots located in homogenous forest conditions with a predominance of old-growth forests in highly productive areas. These areas tend to have a high value of information (VOI) and may be more susceptible to significant NPV reductions if incorrect management decisions are made (figure 9). This could affect the comparability with the present study. On the other hand, the present study included SR16 predictions for A and SI for all field sample plots accounting for various forest conditions. The introduction of various forest conditions in the present study could provide more realistic results than Bollandsås et al.'s study (2022), as seen by lower overall NPV losses in the present study. Consequently, the results from the loss analysis in the present study could suggest that an SR16-based approach generally performs better than Bollandsås et al.'s (2022) results.

	I	II	III	IV	V
23	-	-	-	**1**	**1**
20	-	-	-	**1**	**1**
17	-	-	-	**2**	**1**
14	-	-	-	**2**	**2**
11	-	-	-	**3**	**2**
8	-	-	-	**3**	**3**
6	-	-	-	-	**3**

Figure 9: (Eid, 2022). The value of information regarding the priority of the final harvest of forest stands, 1 = top priority, 2 = secondary priority, and 3 = third priority. *Personal communication, Beslutning – verdien av informasjon. Ås: NMBU*

In light of the findings by Bollandsås et al. (2022), replacing SR16 predictions for A and SI with ground reference values may offer a promising approach to assess loss analyses accurately. This could result in considerable reductions of inventory costs by using ground reference values for A and SI while supplementing with SR16 predictions for other variables. The inventory cost per hectare for an FMI range between NOK 100 – 200/ha but depends on the property size. If a forest owner utilises the forest fund and other subsidies to purchase an FMI, regular costs for a forest property of 100 hectares would exceed NOK 30/ha

(Bollandsås et al., 2022). It was suggested by Bollandsås et al. (2022) that the economic loss of using SR16 predictions instead of a local FMI represented losses of a completely different magnitude, even when limitations associated with the study's data material are accounted for. Although this study resulted in significantly lower NPV losses associated with using SR16 predictions, the magnitude of these losses would still outweigh the costs of conducting an FMI inventory and potential NPV losses due to FMI data. Bollandsås et al. (2022) illustrated that replacing SR16 predictions for A and SI with ground reference values resulted in NPV losses of NOK 49/ha, whereas replacing A and SI for an FMI inventory with ground reference values resulted in a loss of NOK 64/ha.

Nevertheless, it should be noted that neither the current study nor Bollandsås et al. (2022) included inventory costs as an additional factor in the loss analyses. Therefore, it is difficult to fully assess this approach's economic viability and determine how reducing manual measurements could improve the utility of SR16 predictions in strategic forest planning.

Noordermeer et al. (2018) presented two methods of SI determination as "the (1) direct and (2) indirect method". The direct method was calculated by regressing field observations of age-height SI against canopy height metrics derived from ALS data from the first point in time and changes in ALS metrics reflecting canopy height growth during the observation period of 15 years. The indirect method was calculated by modelling Hdom for the two points in time using the ALS metrics as predictors. Then, SI was derived from the initial Hdom, the estimated Hdom, and the length of the observation period using empirical SI curves. The direct method resulted in an RMSE of 1.78 m H^{40} for Norway spruce and 1.08 m H^{40} for Scots pine, whereas the indirect method resulted in an RMSE of 1.82 m H^{40} obtained for both species (Noordermeer et al., 2018). Comparably, the overall obtained RMSE from this study was 3.5 m H^{40}. The new and improved methods of determining SI proposed by Nordermeer et al. (2018) could be introduced to SR16 predictions. However, the methods require data from at least two ALS campaigns covering the same area of interest. Therefore, it might not be viable for the full SR16 coverage.

To the best of our knowledge, there is limited literature explicitly investigating the use of loss analyses for evaluating SR16 predictions. While there have been studies using similar methods in other contexts, there is a gap in research on this particular topic, performed on the scope and using the variables done in this study.

At the same time, it is essential to consider the limitations of the loss approach. The economic implications of an error can vary depending on the context in which it occurs. For example, a significant prediction error for tree height may be more costly in the context of timber production than in the context of carbon sequestration. In other words, it is essential to interpret loss results cautiously and consider the specific economic implications of prediction errors in each case. In addition to considering the limitations of the loss approach, it is also important to recognise the potential consequences of using inaccurate inventory data in forest management scenarios. Eid (2000) investigated the use of uncertain inventory data in forestry scenario models and found that even minor errors in inventory data could lead to substantial changes in forest management decisions. This underscores the importance of accurate inventory data, a critical factor in developing reliable forest management models. When using loss analyses to evaluate the accuracy of inventory data, it is essential to consider the potential long-term costs of inaccurate data, as the consequences of incorrect forest management decisions can compound over time.

5. Conclusion

The results from this study highlight the potential benefits and weaknesses of using predictions from the Norwegian SR16 forest resource across a large diversity of forest conditions. It can be seen that prediction errors varied depending on the individual projects, of which areas with a significant proportion of deciduous trees contributed to significant prediction errors. Economic losses resulting from prediction errors were mainly related to age and, occasionally, site index. However, the magnitude of prediction errors did not entirely explain the observed NPV losses.

This study shows that SR16 predictions deliver accurate results for larger areas. However, the predictions struggle to capture the complete range of variations in local forest conditions and therefore are not suitable as a fully-fledged replacement for an FMI. On the other hand, as shown in the economic analysis, isolated G, Hdom and N did not result in significant economic losses and can, according to the assumptions of the loss analysis, provide satisfactory results if used with ground reference values for age and site index as shown by Bollandsås et al. (2022). Nonetheless, SR16 remains a valuable source of information which can be helpful in many contexts.

Further research should assess the methods of determining SI presented by Noordermeer et al. (2018) in the context of possible integration of SI determination into SR16. In addition, further research could also include assessing inventory costs and economic losses of replacing SR16 predictions for A and SI with ground reference values across a broad range of forest conditions.

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