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Long-term strategic forest planning based on biased remote sensing predictions

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ABSTRACT

Accurate forest data is essential for informed decisions regarding forest policy and management. Traditionally collected through field surveys, this type of data has increasingly been produced with remote sensing (RS). RS provides comprehensive resource maps produced with data from sensors, including airborne laser scanning (ALS) and satellite imagery. However, RS predictions can include large uncertainties, including both random and systematic errors. The systematic errors often stem from the problem of regression towards the mean, whereby small true values are overestimated while large true values are underestimated. These errors pose challenges for effective forest management planning since they can lead to wrong assumptions about forest conditions, for example, that a forest conforms to average conditions due to reduced variability. In this study, we quantified the differences between expected and realised outcomes in forest planning informed by RS predictions, specifically evaluating inventories based on ALS and optical satellite imagery. The evaluation was made according to a business-as-usual scenario with additional concerns about biodiversity and carbon sink targets. The satellite-based forest inventory, more impacted by both general uncertainty and regression towards the mean, performed worse than ALS. Our results indicate that reliance on RS predictions led to 10% to 12% overestimated harvest levels, with notable fluctuations over time, alongside a decrease in net present value of -6% to -9%. Furthermore, carbon stocks were unintentionally reduced in the satellite-based plans, with overestimations ranging from 8% to 24%. Across both RS methods, achieving stable development for biologically valuable forests proved difficult. Our findings underscore the relevance of these issues for forestry and are important to ongoing policy development related to forest monitoring and planning.

INTRODUCTION

Forests and their ecosystem services are critical for life on Earth (Brockerhoff et al. 2017). The provisioning of these services relies on the functioning of forest ecosystems (Hooper et al. 2005). To ensure a consistent supply of goods such as wood, energy, and non-wood forest products, forest managers and policymakers must assess both the likely and preferred future trajectories of forest ecosystems. Forest scenario analysis and planning have been developed for this purpose, providing methodologies to simulate and schedule possible forest management activities while evaluating their economic, ecological, and social impacts (e.g., Eggers et al. 2019).

Forest scenario analysis and planning, irrespective of their scale, depend on data representing the current state of forests (Eriksson and Borges 2014). This type of data enables forecasting based on various management regimes, including biodiversity and the provisioning of ecosystem services (Nilsson et al. 2012). Advances in methods and technology have resulted in the widespread availability of wall-to-wall remote sensing (RS) data, presented as forest resource maps (e.g., Reese et al. 2003, Hansen and Loveland 2012, Kotivuori et al. 2016, Nilsson et al. 2017, Astrup et al. 2019). These maps are used for assessments of the current state of forests (e.g. Schuck et al. 2003), policy development (e.g., Seebach et al. 2012), mapping the supply of ecosystem services (e.g., Orsi et al. 2020), and input for forest planning models (e.g., Flisberg et al. 2022, Wilhelmsson et al. 2022, Ulvdal et al. 2023). The creation of forest resource maps typically involves parametric or non-parametric regression models (e.g., Andersen et al. 2005, Zald et al. 2016), which link RS data, such as laser beam hits at various heights or pixel colour, with ground-truth measurements, such as basal area from geo-positioned field plots. These models are applied to larger areas, producing predictions for all raster elements in the wall-to-wall map. However, this model-based RS inventory approach introduces uncertainty-related challenges. Like most inventory methods, random errors affect the data quality. However, perhaps more influential is the issue of regression toward the mean (Stigler 1997, Barnett et al. 2005).

Regression toward the mean causes models to overestimate small true values and underestimate large ones, reducing the variance in predicted values compared to the true values (Ståhl et al. 2024). When such errors also correlate with the true values rather than the predictions, they are classified as Berkson-type errors (Carroll et al. 2006, Kangas et al. 2023). Errors of Berkson-type in RS-based predictions have been shown to influence forest planning results, e.g., regarding the final layout of harvest areas when using spatial optimisation on erroneous data (Islam et al. 2012). Various methods, including calibration and imputation, have been explored to mitigate these errors. For instance, the landscape distribution of stem volume can be preserved by imputing RS-based predictions with national forest inventory plot data (Barth et al. 2012). Another approach is to apply histogram matching using k-nearest-neighbour algorithms (Gilichinsky et al. 2012). Lindgren et al. (2022) demonstrated that classical calibration (e.g. Tellinghuisen 2000) can effectively mitigate the effects of regression towards the mean. However, none of these studies have quantified the long-term impact of such errors on decisions or plans based on data affected by regression towards the mean.

Numerous studies have examined the effects of uncertain data more generally. Typically, these studies simulate erroneous data and compare forecasts based on that data with those based on data considered to be true (e.g., Holopainen et al. 2010, Islam et al. 2010, Duvemo et al. 2014, Ruotsalainen et al. 2021). Some of these studies address errors in RS-based resource maps, but the errors are often simulated, and the study areas are relatively small. Given the growing use of forest resource maps in forest scenario analysis and planning, further research is needed to understand how uncertainties, such as Berkson-type errors, affect forecasts and decision-making (Fassnacht et al. 2023). This need is underscored by recent policy developments in the European Union, where suggestions for new regulations on forest monitoring and planning emphasise increased use of RS (Bontemps et al. 2022).

This study aims to assess the impact of using RS data in long-term forest planning and to quantify the discrepancies between expected and realised provisioning of ecosystem services and biodiversity. We analysed data from airborne laser scanning (ALS) and optical satellite imagery, both subject to random errors and regression toward the mean in varying degrees. We evaluated their use as inputs in forest planning models, describing a business-as-usual scenario extended with targets for biodiversity conservation and carbon sequestration. The models were implemented and solved with the decision support system Heureka PlanWise (Lämås et al. 2023).

MATERIAL AND METHODS

Data and pre-processing

The RS-based predictions evaluated in this study were gathered from two forest resource maps: the SLU Forest Map, derived from optical satellite imagery in 2010, and a similar map obtained from ALS in 2019.

Satellite predictions

The SLU Forest Map provides predictions for volume, Lorey's mean height, mean age, and species proportion, presented on 25x25 m raster elements covering all of Sweden. These predictions were modelled using optical satellite imagery from Landsat 7 Enhanced Thematic Mapper and k-nearest-neighbour imputation based on national forest inventory plots (for details, refer to Reese et al. 2003).

ALS predictions

The ALS-based map from 2019 has a resolution of 12.5x12.5 m and includes attributes derived from regression models between ALS data and national forest inventory plot data. These attributes include volume, Lorey's mean height, average diameter at breast height (D_{bh}), and stand basal area (for details, see Nilsson et al. 2017). Raster elements with a predicted tree height of <3 m are excluded from the public version of the ALS map due to concerns about the quality of the predictions, while the full data product was retained for our analyses.

Field-surveyed reference data

To evaluate RS-based maps, we utilised high-quality reference data gathered for long-term forest planning. The reference data originated from two independent inventories conducted in 2010 and 2019 on a forest holding encompassing approximately one million hectares of productive forestland in Sweden. These inventories involved systematic surveys of circular field plots (radius: 3-10 m), wherein individual tree data and stand properties were recorded to provide unbiased stand-level estimations.

Measurement protocols varied according to the average tree height on the plots. For plots with established trees (average height >4 m), all trees >4 cm in diameter at breast height (1.3 m above ground) were calipered, and tree species were identified. A subset of calipered trees was randomly selected for height and age measurements, with age determined through the count of annual rings on increment cores. Dominant trees required for site index estimation were also measured for height. On plots dominated by saplings, height measurements of main stems replaced calipering. Each plot underwent detailed site characterisation, including descriptions of vegetation, climate, soil, terrain, and natural values.

The number of plots per stand ranged from approximately 6 in smaller stands to 13 in larger ones, with plot radius standardised within each stand. Stands were randomly selected through stratified sampling, with inclusion probabilities proportional to stand area. Stratification was based on auxiliary data on stand age and standing volume from the forest owner's stand inventory, with at least three stands sampled per stratum. Representative stand areas were calculated as the total stratum area divided by the number of sampled stands.

The inventory design followed established protocols used for the decision support system Heureka PlanWise, a widely used tool among forest companies and researchers in Sweden (for details, refer to Lindgren 1984, Jonsson et al. 1993, Lämås et al. 2023). All attributes needed

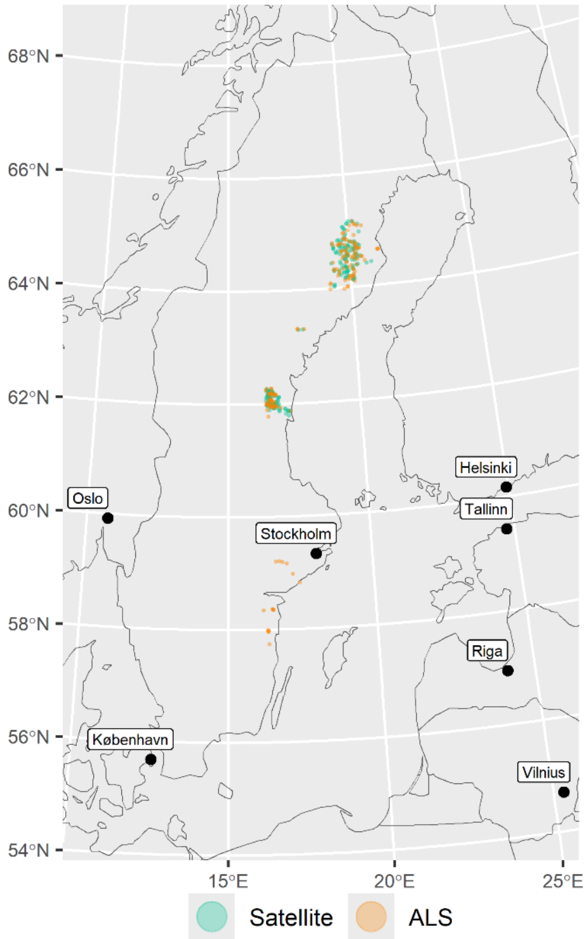

Figure 1. The positions of the included stands shown with coloured points. Satellite indicates those stands surveyed in 2010 used with the satellite map. ALS indicates those stands surveyed in 2019 used with the ALS map. ALS is airborne laser scanning. Projection: SWEREF 99 TM (EPSG:3006). Source of country borders and positions of cities: Natural Earth.

to run Heureka PlanWise were collected in the field inventory. Heureka PlanWise is described below.

Standardisation of age distributions

Only those field-surveyed stands covered by the footprint of the 2019 ALS map were included in the analyses, resulting in 198 of 1,070 stands from 2010 and 152 of 800 stands from 2019 being included further (map of included stands in Figure 1). To ensure that the two inventories were comparable on the forest level, random values from a uniform distribution were drawn repeatedly and assigned as new representative areas for the remaining stands until the same age distribution was achieved. This process also maintained the total area represented in the original field inventories. After this adjustment, the inventories from both years matched the general age distribution of forest land owned by forest companies in Sweden.

Finalised stand averages

We calculated stand averages from the RS-based predictions for the corresponding field-surveyed stands using the satellite map for stands surveyed in 2010 and the ALS map for those surveyed in 2019. This involved calculating the area-weighted average of each attribute across the raster elements intersecting each stand polygon.

Heureka PlanWise can be used either with data on a single-tree level, i.e. tree lists, or data made from stand averages. When using the latter, Heureka PlanWise generates a tree list corresponding to the averages with models included in the system. The satellite map needed to be complemented with missing attributes in the form of stand averages to make it possible to generate tree lists for each stand with Heureka PlanWise. The complementation was done using regression models developed from freely available Swedish national forest inventory plot data from 2017-2021. For more details about the complementation, refer to Appendix A.

Furthermore, to run Heureka PlanWise, more information than what was available from RS sources was needed, which is why the RS-based predictions for the included stands in both maps were complemented further with averages from the field survey of each stand. The sources of all attributes for these RS-based, but complemented, stand inventories are presented in Table 1.

Table 1. An overview of the attributes and their sources for the completed remote sensing-based stand inventory datasets. ALS refers to airborne laser scanning, while satellite refers to optical satellite imagery. Species proportion was calculated based on volume for the following species: Picea abies *(L.) H. Karst.,* Pinus sylvestris *L.,* Betula *spp. (*Betula pendula *Roth or* Betula pubescens *Ehrh.),* Pinus contorta *Douglas ex Loudon,* Fagus sylvatica *L.,* Quercus *spp. (*Quercus robur *L. or* Quercus petraea *(Matt.) Liebl.), and other deciduous species. D_{bh} refers to the mean basal area-weighted tree diameter at breast height.*

Attribute for stand	Satellite	ALS
Volume (m^3ha^{-1})	only used for modelling	not used
Lorey's mean height (m)	satellite	ALS
Basal area (m^2ha^{-1})	modelled	ALS
D_{bh} (cm)	modelled	ALS
Mean age (years)	satellite	field survey
Number of stems (ha^{-1})	modelled	not used
Species proportion (0-1)	satellite	field survey
Soil moisture (categorical)	field survey	field survey
Vegetation type (categorical)	field survey	field survey
Site index (m)	field survey	field survey
Technical accessibility (categorical)	field survey	field survey

Simulation of tree lists

Tree lists were generated for the stands based on both RS-based stand inventories with Heureka PlanWise (v.2.21.3.0). This was not needed for the reference data since it was already at the individual tree level.

Examination of data and errors

New stand averages were calculated from the tree lists generated in Heureka PlanWise and were compared with the corresponding field-surveyed averages (Figure 2).

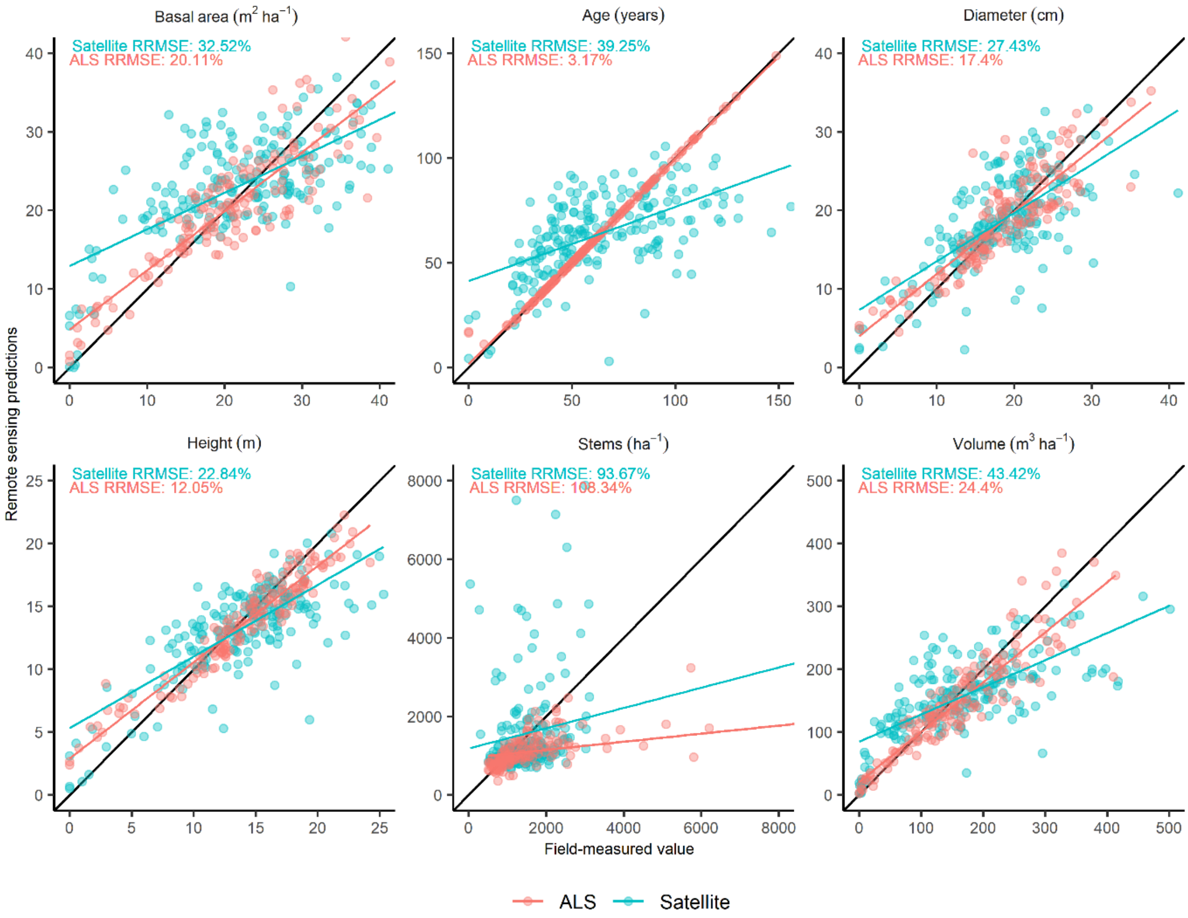

Figure 2. The relation between field-measured reference data (x-axis) and complemented remote sensing predictions (y-axis) from remote sensing-based forest inventories with optical satellite imagery (blue) and ALS (red) for the attributes basal area, mean age, basal area weighted diameter at breast height, Lorey's mean height, number of stems, and volume. Each point represents averages for one stand as calculated by Heureka PlanWise. The coloured lines are the least square linear relationships. The black line is the 1:1 relationship. Note that the values for basal area, diameter and stems per hectare in the satellite map were assigned according to the functions in Tables A1-A3 in the Appendix and that age in the ALS map is the same as the field-measured age. RRMSE refers to the relative root mean square error.

Figure 2 clearly shows that the RS-based predictions from both RS-based stand inventories regress to the mean since the slope of the least square lines is smaller than the 1:1 lines. This indicates that the small reference values are overestimated while the large reference values are underestimated. To further determine that the errors in the RS-based predictions resulted from regression to the mean and thus of Berkson-type, we calculated error correlations and examined the empirical variances of both the errors and the predictions. Furthermore, we performed a paired t-test grouped on three equally sized quantiles (defined individually per attribute) to check for local bias.

Descriptive statistics for the finalised stand inventories are presented in Table 2.

Table 2. Descriptive statistics (area-weighted averages) for the completed RS-based stand inventories compared to the reference data. D_{bh} refers to the mean diameter at breast height. ALS stands for airborne laser scanning, and satellite refers to optical satellite imagery. D_{bh} refers to the mean basal area-weighted tree diameter at breast height. Field indicates that the source was the field-survey

Year	**Source**	**Volume**	**Lorey's mean height**	**Basal area**	**D_{bh}**	**Mean age**	**Number of stems**	**Site productivity**
		(m^3ha^{-1})	(m)	(m^2ha^{-1})	(cm)	(years)	(ha^{-1})	($m^3ha^{-1}year^{-1}$)
2010	field	125.3	10.9	17.1	14.9	50.4	2,074	5.3
2010	satellite	123.8	10.7	18.9	15.0	51.4	2,488	5.3
2019	field	121.6	11.2	16.4	14.8	52.1	2,158	4.2
2019	ALS	114.2	11.4	16.8	15.8	53.6	1,261	4.1

The errors in the RS-based predictions correlated more with the corresponding reference data than with the predictions (Table 3). This relationship was true for all variables except the predicted number of stems in the satellite map. Moreover, the empirical variances of the predicted values were smaller than those of the reference data for all variables except the number of stems in the predictions based on satellite data (Table 4). Furthermore, the biases were generally positive for small reference values and negative for large reference values (Table 5). These results imply that the errors of the predictions in the study were generally of Berkson type and that the models had a regression towards the mean.

Table 3. The correlation between errors and their corresponding field-measured values in stands and the correlation between errors and their corresponding stand predictions for both the satellite and ALS maps. D_{bh} is the mean basal area weighted diameter at breast height. ALS is airborne laser scanning. Satellite is optical satellite imagery. D_{bh} refers to the mean basal area-weighted tree diameter at breast height.

	Satellite		**ALS**	
Attribute	Errors~Field	Errors~Prediction	Errors~Field	Errors~Prediction
Volume	0.79	0.10	0.50	0.11
Lorey's mean height	0.66	0.01	0.71	0.47
Basal area	0.74	0.02	0.53	0.08
D_{bh}	0.49	-0.31	0.45	-0.02
Mean age	0.78	-0.07	0.30	0.23
Number of stems	0.59	-0.64	0.98	0.28

Table 4. The empirical variance of RS-based predictions and the field-measured values for both the satellite and ALS map. D_{bh} is the mean basal area weighted diameter at breast height. ALS is airborne laser scanning. Satellite is optical satellite imagery. D_{bh} refers to the mean basal area-weighted tree diameter at breast height.

	Satellite		**ALS**	
	Field	Prediction	Field	Prediction
Volume (m^3ha^{-1})	9,847	3,807	8,219	6,209
Lorey's mean height (m)	23	13	25	16
Basal area (m^2ha^{-1})	98	45	83	60
D_{bh} (cm)	42	35	48	38
Mean age (years)	902	354	752	725
Number of stems (ha^{-1})	1,425,087	1,569,503	3,785,745	179,955

Table 5. Results from a paired t-test for both ***RS****-methods. The data for each attribute was divided into three equally sized parts defined by the 1/3 and 2/3 percentiles. A positive bias indicates that the* ***RS****-metod overestimated the reference value, and vice versa. A large p-value indicates that the difference is non-significant, i.e. that there is no bias.* D_{bh} *refers to the mean diameter at breast height. ALS stands for airborne laser scanning, and satellite refers to optical satellite imagery.*

Method	**Attribute**	**Part of range**	**Bias**	**p-value**	**Number of stands**
ALS	Age	1/3	+0.79	0.09	50
ALS	Age	2/3	0.00		49
ALS	Age	3/3	0.00		50
ALS	Basal area	1/3	+2.13	0.00	50
ALS	Basal area	2/3	-0.28	0.54	49
ALS	Basal area	3/3	-2.94	0.00	50
ALS	D_{bh}	1/3	+1.09	0.01	50
ALS	D_{bh}	2/3	+0.69	0.09	49
ALS	D_{bh}	3/3	-1.42	0.01	50
ALS	Height	1/3	+0.58	0.02	50
ALS	Height	2/3	-0.22	0.14	49
ALS	Height	3/3	-1.58	0.00	50
ALS	Stems	1/3	+51.53	0.03	50
ALS	Stems	2/3	-170.54	0.00	49
ALS	Stems	3/3	-1723.66	0.00	50
ALS	Volume	1/3	+7.22	0.00	50
ALS	Volume	2/3	-10.57	0.00	49
ALS	Volume	3/3	-33.26	0.00	50
Satellite	Age	1/3	+17.65	0.00	65
Satellite	Age	2/3	+8.64	0.00	65
Satellite	Age	3/3	-24.86	0.00	65
Satellite	Basal area	1/3	+7.45	0.00	65
Satellite	Basal area	2/3	+1.48	0.01	65
Satellite	Basal area	3/3	-5.82	0.00	65
Satellite	D_{bh}	1/3	+2.55	0.00	66
Satellite	D_{bh}	2/3	+0.93	0.06	64
Satellite	D_{bh}	3/3	-2.55	0.00	65
Satellite	Height	1/3	+1.68	0.00	65
Satellite	Height	2/3	-0.35	0.08	65
Satellite	Height	3/3	-3.30	0.00	65
Satellite	Stems	1/3	+388.16	0.00	65
Satellite	Stems	2/3	+91.06	0.55	65
Satellite	Stems	3/3	-496.27	0.05	65
Satellite	Volume	1/3	+49.36	0.00	65
Satellite	Volume	2/3	-1.51	0.77	65
Satellite	Volume	3/3	-76.74	0.00	65

SIMULATING FOREST DEVELOPMENT AND MANAGEMENT ACTIVITIES USING HEUREKA PLANWISE

To assess the impact of relying on RS-based stand inventories for forest management planning, we generated long-term plans based on the forest stand inventories described above.

Heureka PlanWise

Heureka PlanWise is built around a simulator that generates treatment programmes at the stand level according to user-defined rules and an optimisation module that selects the optimal combination of treatment programmes for each stand based on user-stated preferences (Lämås et al. 2023). Thus, Heureka PlanWise is based on the model I formulation, where a treatment programme is an explicit sequence of forest management activities and non-management in one stand during the planning horizon (Johnson and Scheurman 1977). The simulator forecasts the tree layer based on current forest data and possible management activities (Fahlvik et al. 2014). It includes models for various ecosystem services, such as harvested wood output (e.g. Flisberg et al. 2014), carbon storage (e.g. Lundmark et al. 2018), and biodiversity indicators (e.g., Eggers et al. 2022). The treatment programmes are divided into five-year periods. The user defines management strategies and rules to generate multiple alternative treatment programmes per stand, allowing the simulator to vary the timing and type of management activities.

Management strategies

For both RS-based stand inventories, we generated treatment programmes under seven management strategies: typical Nordic even-aged forestry, intensive forestry, selection forestry, actively promoted broad-leaves forestry, passively promoted broad-leaves forestry, closer-to-nature forestry, and unmanaged forestry (see Table 6). Each strategy, except for selection forestry and unmanaged forestry, also included a variant with extended rotation lengths of 50 years. The strategies were defined to reflect business-as-usual forest management in the Nordics as well as potential alternatives. The alternatives were defined with aims other than the highest financial return in mind.

Table 6. An overview of the management strategies used in the study.

Strategy	Min. rotation length	Max. rotation length	Retention	Regeneration method	Stand proportions after cleanings and thinnings
Typical Nordic even-aged forestry	Lowest legal age	Lowest legal age + 10 years	According to certifications, i.e. 10 trees and 3 high stumps ha^{-1} at final felling	Planting of 2,500 conifer seedlings ha^{-1}	90% of regeneration species and 10% of broad-leaves
Intensive forestry	Lowest legal age	Lowest legal age	According to certifications, i.e. 10 trees and 3 high stumps ha^{-1} at final felling	Planting of 2,500 genetically improved conifer seedlings ha^{-1}. *Pinus contorta* on poorer sites	95% of regeneration species and 5% of other species
Selection forestry	Not applicable	Not applicable	Not applicable	Advance growth	Not applicable
Active promotion of broad-leaves	Conifer stands: lowest legal age Broad-leaf stands: 80 years	Conifer stands: lowest legal age + 10 years. Broad-leaf stands: 90 years	20 trees and 3 high stumps ha^{-1} at final felling	Planting of 2,000 seedlings ha^{-1}. *Populus tremula* on rich sites, otherwise *Betula pubescens*.	100% of broad-leaves OR 40% of *Betula* spp. and 60% of regeneration species
Passive promotion of broad-leaves	Conifer stands: lowest legal age Broad-leaf stands: 80 years	Conifer stands: lowest legal age + 10 years. Broad-leaf stands: 90 years	20 trees and 3 high stumps ha^{-1} att final felling	Seed trees for *Pinus sylvestris* stands on drier and poorer sites, otherwise planting of approximately 2,500 conifer seedlings ha^{-1}	100% of broad-leaves OR 40% of *Betula* spp. and 60% of regeneration species
Closer-to-nature forestry	Lowest legal age + 25 years	Lowest legal age + 50 years	70 trees and 3 high stumps ha^{-1} at final felling and 3 high stumps ha^{-1} at thinning	Seed trees	100% of broad-leaves OR 40% of *Betula* spp. and 60% of planted species
Unmanaged	Not applicable	Not applicable	Not applicable	Not applicable	Not applicable

For typical even-aged forestry, we simulated the standard practices for certified Nordic forestry. This strategy involved mechanical soil preparation two years post-final felling, planting of conifer seedlings in the subsequent year, cleaning at 2-6 meters tree height, up to two thinnings, and a final felling. The intensive forestry strategy mirrored the even-aged approach but also incorporated fertilisation and the planting of exotic tree species in appropriate stands. Selection forestry involved repeated selection fellings every 20 years. In the active promotion of broad-leaves, planting was exclusively done with Betula pubescens or Populus tremula (L.), with broad-leaves prioritised as future-trees during cleanings and thinnings. The passive promotion of broad-leaves included conifer planting, yet broad-leaves were prioritised as future-trees in subsequent cleanings and thinnings. Closer-to-nature forestry utilised only seed trees for regeneration, emphasised the leaving of broad-leaves in cleanings and thinnings, and maintained higher retention of trees post-treatment compared to other strategies. In unmanaged forestry, the forest was left without intervention. For all strategies, excluding unmanaged forestry, 10% of each stand's area was designated as retention patches, not including retention of standing trees and high stumps.

MAKING PLANS WITH THE HELP OF OPTIMISATION

To identify the optimal treatment programmes for each stand, independently for each RS-based inventory, we formulated and solved two distinct optimisation problems that reflect varying decision-maker priorities.

Optimisation models

The HARVEST optimisation problem was designed for a decision-maker focused on maximising economic returns and ensuring stable or increasing harvest levels. This problem seeks the plan that delivers the highest net present value (NPV) while adhering to certification standards and legal requirements and maintaining or increasing harvest levels over time (see Equations 1-10). In contrast, the BIO-CARBON problem was tailored for a decision-maker with similar economic and regulatory objectives as HARVEST but with additional constraints of preserving carbon storage in living tree biomass and maintaining the area of ecologically significant forests (see Equations 1-14). Ecologically significant forests were defined based on indicators established by the Swedish Parliament's environmental objectives (The Swedish Environmental Protection Agency 2024). The NPVs in both cases were calculated using a 3% discount rate.

The detailed formulation of the optimisation problems is provided in the form of a mixed integer programming model presented in the subsequent equations.

(1) $$maximise\ \ Z = \sum_{i=1}^{I} \sum_{j=1}^{J_i} n_{ij} a_i x_{ij}$$

Subject to

(2) $$x_{ij} \in [0,1] \qquad \forall\, i \in I, \forall\, j \in J_i$$

(3) $$y_{sp} \in \{0,1\} \qquad \forall\, p \in P, \forall\, s \in S$$

(4) $$\sum_{j=1}^{J_i} x_{ij} = 1 \qquad \forall\, i \in I$$

(5) $$\sum_{s=1}^{S} y_{sp} = 1 \qquad \forall\, p \in P$$

(6) $$\sum_{i=1}^{I} \sum_{j=1}^{J_i} b_{ijp} a_i x_{ij} \leq 0.5 \sum_{i=1}^{I} a_i \qquad \forall\, p \in P$$

(7) $$\sum_{i=1}^{I} \sum_{j=1}^{J_i} d_{ijp} a_i x_{ij} \leq 5e \sum_{s=1}^{S} f_s y_{sp} \sum_{i=}^{I} a_i \qquad \forall\, p \in P$$

(8) $$y_{sp} g_s \leq \frac{\sum_{i=1}^{I} \sum_{j=1}^{J_i} h_{ijp} a_i x_{ij}}{\sum_{i=1}^{I} a_i} \qquad \forall\, p \in P, \forall\, s \in S$$

(9) $$\sum_{i=1}^{I} \sum_{j=1}^{J_i} k_{ijp} a_i x_{ij} \leq 2.5e \sum_{s=1}^{S} f_s y_{sp} \sum_{i=}^{I} a_i \qquad \forall\, p \in P$$

(10) $$\sum_{i=1}^{I} \sum_{j=1}^{J_i} v_{ijp+1} a_i x_{ij} \geq \sum_{i=1}^{I} \sum_{j=1}^{J_i} v_{ijp} a_i x_{ij} \qquad \forall p \in P$$

(11) $$\sum_{i=1}^{I} \sum_{j=1}^{J_i} c_{ijp} a_i x_{ij} \geq \sum_{i=1}^{I} \sum_{j=1}^{J_i} c_{ijp-1} a_i x_{ij} \qquad \forall p \in P$$

(12) $$\sum_{i=1}^{I} \sum_{j=1}^{J_i} l_{ijp} a_i x_{ij} \geq \sum_{i=1}^{I} \sum_{j=1}^{J_i} l_{ijp-1} a_i x_{ij} \qquad \forall p \in P$$

(13) $$\sum_{i=1}^{I} \sum_{j=1}^{J_i} m_{ijp} a_i x_{ij} \geq \sum_{i=1}^{I} \sum_{j=1}^{J_i} m_{ijp-1} a_i x_{ij} \qquad \forall p \in P$$

(14) $$\sum_{i=1}^{I} \sum_{j=1}^{J_i} o_{ijp} a_i x_{ij} \geq \sum_{i=1}^{I} \sum_{j=1}^{J_i} o_{ijp-1} a_i x_{ij} \qquad \forall p \in P$$

Where,

Z is the objective function given the set of restrictions,
x_{ij} is the proportion of stand i assigned to the treatment programme j,
y_{sp} is a binary variable that helps in the calculation of the allowable annual harvest area decided by Swedish law,
I is the set of stands,
J_i is the set of treatment programmes for stand i,
P is the set of periods,
S is the set of area classes defined by Swedish law regarding allowable annual harvest area,
n_{ij} is the NPV per hectare from forest management in stand i according to treatment programme j,
a_i is the representative area of stand i,
b_{ijp} is 1 for stand i with treatment programme j in period p if the age of the stand is lower than 20 years, otherwise 0,
d_{ijp} is 1 for stand i with treatment programme j if the stand is subjected to clear cut in period p, otherwise 0,

e is an area factor from Swedish law, taking the value 0.014 if the average site productivity of the forest holding is larger than 8 $m^3ha^{-1}year^{-1}$, 0.011 if it is between 8 and 4 $m^3ha^{-1}year^{-1}$, otherwise 0.009,
f_s is a correction factor from Swedish law taking the value 1.4 for $s = 1$, 1.8 for $s = 2$, 2.2 for $s = 3$, 2.8 for $s = 4$,
g_s is an area class proportion from Swedish law taking the value 0 for $s = 1$, 0.26 for $s = 2$, 0.51 for $s = 3$, 0.76 for $s = 4$,
h_{ijp} takes the value 1 for stand i with treatment programme j in period p if the mean age of the stand is older than a rotation age, otherwise 0. The rotation age is 70 years if the average site productivity of the forest holding is larger than 8 $m^3ha^{-1}year^{-1}$, 90 years if it is between 8 and 4 $m^3ha^{-1}year^{-1}$, otherwise 110 years,
k_{ijp} takes the value 1 for s stand i with treatment programme j in period p if the stand is subjected to fertilisation, otherwise 0,
v_{ijp} is the harvested volume per hectare in stand i with treatment programme j in period p,
c_{ijp} is the carbon stock of living trees per hectare in stand i with treatment programme j in period p,
l_{ijp} is 1 for stand i with treatment programme j in period p if the stand is older than 120 years in boreal-nemoral and nemoral forests or 140 years in boreal forests, otherwise 0,
m_{ijp} is 1 for stand i with treatment programme j in period p if at least 25% of the basal area is broad-leaf and the stand is older than 60 years in boreal-nemoral and nemoral forests or 80 years in boreal forests, otherwise 0, and
o_{ijp} is 1 for stand i with treatment programme j in period p if the stand has more than 60 large trees per hectare, otherwise 0. A conifer is considered large if the D_{bh} is wider than 45 cm; the corresponding value for broad-leaves is 35 cm.

Equation (1) defines the objective of maximising the NPV across all stands in the forest. Eq. (2) states that x_{ij} is a continuous variable between 0 and 1, while Eq. (3) states that y_{sp} is a binary variable. Eq. (4) sets the maximum area constraint, ensuring that the proportions of assigned treatment programmes in each stand sum to 1. Eq. (5), together with Eq. (3), ensures that only one area class is used by forcing the sum of y_{sp} to be equal to 1 in each period. In line with Swedish law, Eq. (6) ensures that the area of forests younger than 20 years remains below 50% of the total area in all periods. Eq. (7) limits the harvested area so that it does not exceed the allowable harvest area, which is calculated using Eq. (8). Notably, the factor 5 adjusts the annual value to a periodic one. Eq. (9) restricts the area subject to fertilisation to less than half of the allowable harvest area. Eq. (10) enforces a non-declining harvest, while Eq. (11) mandates non-declining carbon storage in living tree biomass. Eq. (12) preserves a non-declining area of old-growth forests, Eq. (13) maintains the area of mature forests rich in broad-leaf trees, and Eq. (14) ensures a non-declining area of forest with large trees. Note that Eqs. (11 - 14) are specific to the BIO-CARBON optimisation problem.

Outcomes from the optimisation

The two optimisation problems were solved independently using treatment programmes generated from each RS-based forest inventory to produce management plans. The optimsiation module in Heureka PlanWise was used to build the problem in Zimpl. The problem was then passed on to Gurobi 10 for solving, employing a traditional branch and bound algorithm with a relative gap tolerance of 1% (Land & Doig 1960).

The outcomes, measured in terms of NPV, harvest volumes, carbon storage, and the area of ecologically significant forests, represent what decision-makers might expect when following these plans, assuming the RS-based predictions are accurate. These expected outcomes are referred to as EXPECTATION.

To evaluate what would happen in real forests if decisions on future management were made using RS-based stand inventories, we simulated the implementation of these management decisions using field-surveyed reference data as input. Heureka PlanWise forecasted the outcomes for stand development, as well as indicators of ecosystem services and biodiversity, following the same sequences of management determined from using the corresponding RS-based stand inventories of matching stands. The resulting outcomes are referred to as REALISATION.

As a reference, we also solved the two optimisation problems using treatment programmes generated solely from the field data as input. The outcomes for the resulting plans are denoted REFERENCE, as they represent the optimal plans assuming perfect information.

To aid in digesting the results, we highlight two key comparisons. The first is the difference between REALISATION and EXPECTATION; a negative difference in this comparison indicates that the actual outcomes fell short of the expected ones, signalling an over-optimistic expectation. The second important comparison is between REALISATION and REFERENCE; a negative difference here suggests suboptimality, revealing that decisions based on RS data were less optimal than those derived from field data. This kind of suboptimality is often denoted regret (Bell 1982; Kangas et al. 2015). In the same tradition, an overestimation of the optimal value, i.e. EXPECTATION vs. REFERENCE, can be denoted disappointment (Bell 1985).

RESULTS

Net present value

Our findings indicate a potential risk of overestimating NPV when relying on RS-based stand inventories (Table 7). The discrepancy between the expected and realised NPV was more pronounced for satellite-based plans than ALS-based plans. A similar trend was observed for suboptimality, i.e. the difference between the realised and reference NPV.

Table 7. The results for the net present value for both remote sensing-based stand inventories and each problem. Loss is the difference between the expected and the realised net present value. Suboptimality is the difference between the reference and realised net present value. Satellite refers to optical satellite imagery, and ALS to airborne laser scanning.

Data used	Problem	REALISATION	EXPECTATION	REFERENCE	Loss	Suboptimality
		SEK ha^{-1}	SEK ha^{-1}	SEK ha^{-1}		
Satellite	HARVEST	51,469	56,345	56,626	-8.7%	-9.1%
Satellite	BIO-CARBON	51,515	56,202	55,214	-8.3%	-6.7%
ALS	HARVEST	49,318	53,056	52,842	-7.0%	-6.7%
ALS	BIO-CARBON	48,430	52,032	51,822	-6.9%	-6.5%

Harvest levels

The RS-based plans lead to uneven harvest levels during the planning horizon in REALISATION (Figure 3). A common pattern emerged where the initial expected harvest levels were lower than those realised during the first 10–15 years but generally surpassed them in later years, with brief exceptions. In these cases, realised harvest levels also exceeded those in REFERENCE, suggesting unsustainable over-harvesting. Over the 100-year period, the total suboptimality in harvested volume in REALISATION relative to REFERENCE was somewhat larger for ALS-based plans than for satellite-based plans (Table 8). Both the satellite-based and ALS-based plans got lower (EXPECTATION compared to REALISATION) harvest levels by 10-12%. EXPECTATION projected higher harvests than for both data sets, indicating an overestimation.

Table 8. The results for the average harvest level per hectare for both remote sensing-based stand inventories. Loss is the difference between the expected and the realised average harvest level. Suboptimality is the difference between the reference and realised average harvest level. Satellite refers to optical satellite imagery, and ALS to airborne laser scanning.

Data used	Problems	REALISATION	EXPECTATION	REFERENCE	Loss	Suboptimality
		$m^3ha^{-1}year^{-1}$	$m^3ha^{-1}year^{-1}$	$m^3ha^{-1}year^{-1}$		
Satellite	Both	4.4	5.0	4.8	-12%	-8.3%
ALS	Both	3.9	4.4	4.3	-10%	-8.7%

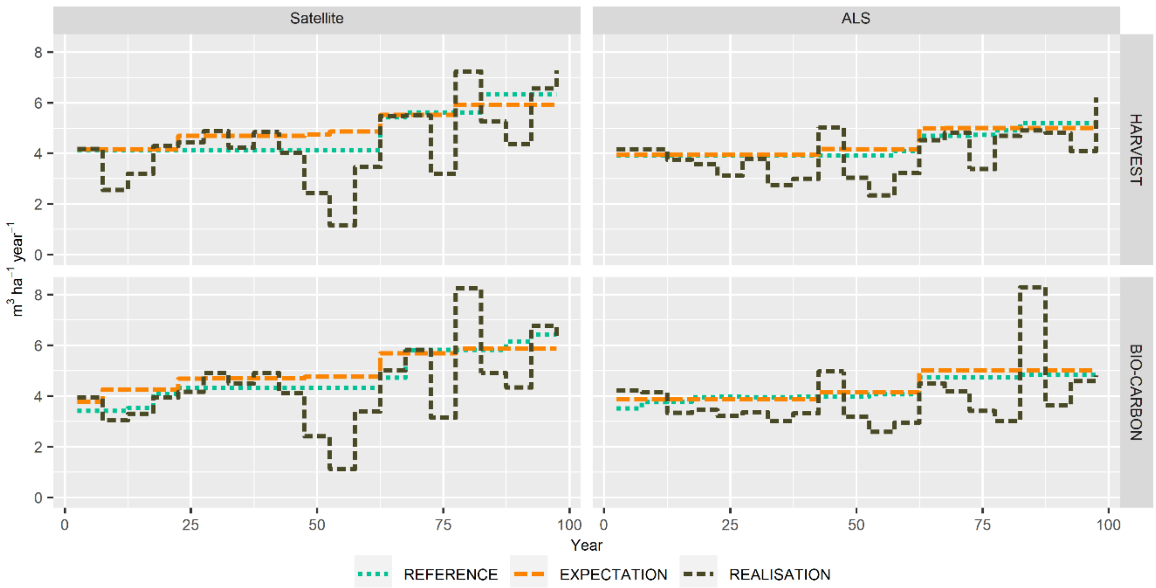

Figure 3. The average harvested volume per hectare and year according to the three outcomes REFERENCE, EXCPECTATION, and REALISATION and the problems HARVEST and BIO-CARBON. Satellite refers to optical satellite imagery, and ALS to airborne laser scanning.

Carbon stock

Figure 4 illustrates that satellite-based plans overestimated carbon stocks in EXPECTATION compared to REALISATION during the first 50 years, with differences ranging from 8% to 24%. In contrast, the ALS-based plans showed smaller deviations, from -3% to 7.5%. Despite the BIO-CARBON problem prohibiting any reduction in carbon stock, both ALS and satellite-based plans resulted in a realised carbon stock reduction of approximately 5% compared to the initial value after several years.

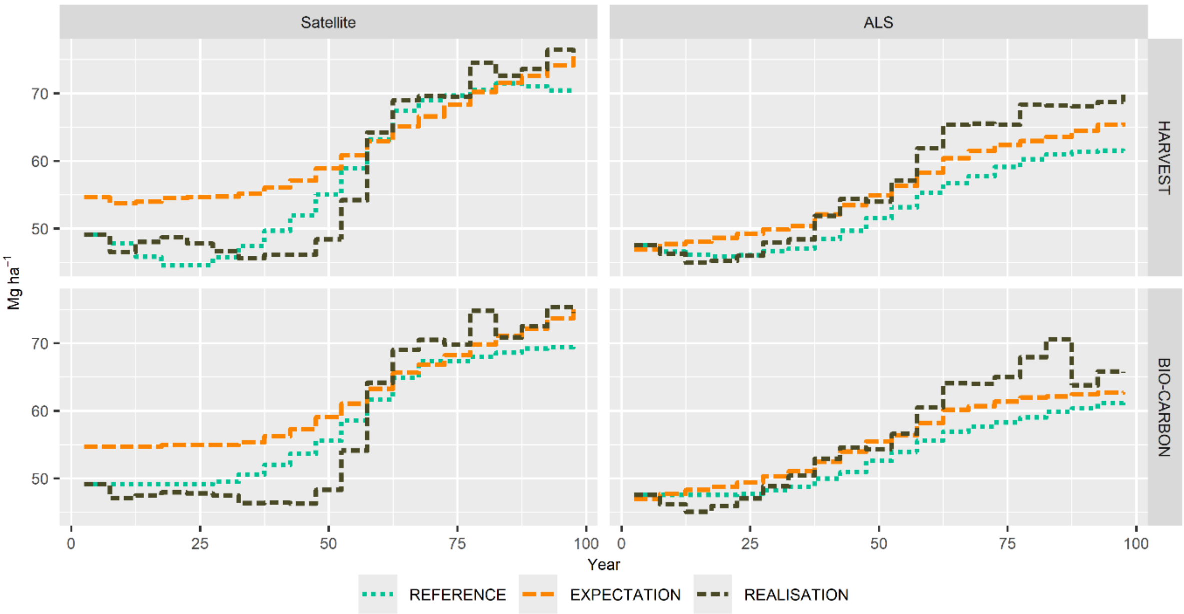

Figure 4. The average carbon stock per hectare according to the three outcomes REFERENCE, EXCPECTATION, and REALISATION and the problems HARVEST and BIO-CARBON. Satellite refers to optical satellite imagery, and ALS to airborne laser scanning.

Ecologically important forests

Figure 5 shows the development of the area proportion of forests that fulfilled any of the following criteria: it was older than 120 years in the south or 140 years in the north, had at least 60 large trees per hectare or had many mature broad-leaf trees. Satellite-based plans were less effective in identifying these ecologically valuable forests than ALS-based plans, causing EXPECTATION to be significantly lower than REALISATION early in the planning horizon, which contributed to an unintended decline in BIO-CARBON. In contrast, the ALS-based plans showed more alignment between REALISATION, EXPECTATION, and REFERENCE, though EXPECTATION was often equal to or lower than REALISATION over many periods.

Figures for the individual indicators are presented in Appendix B.

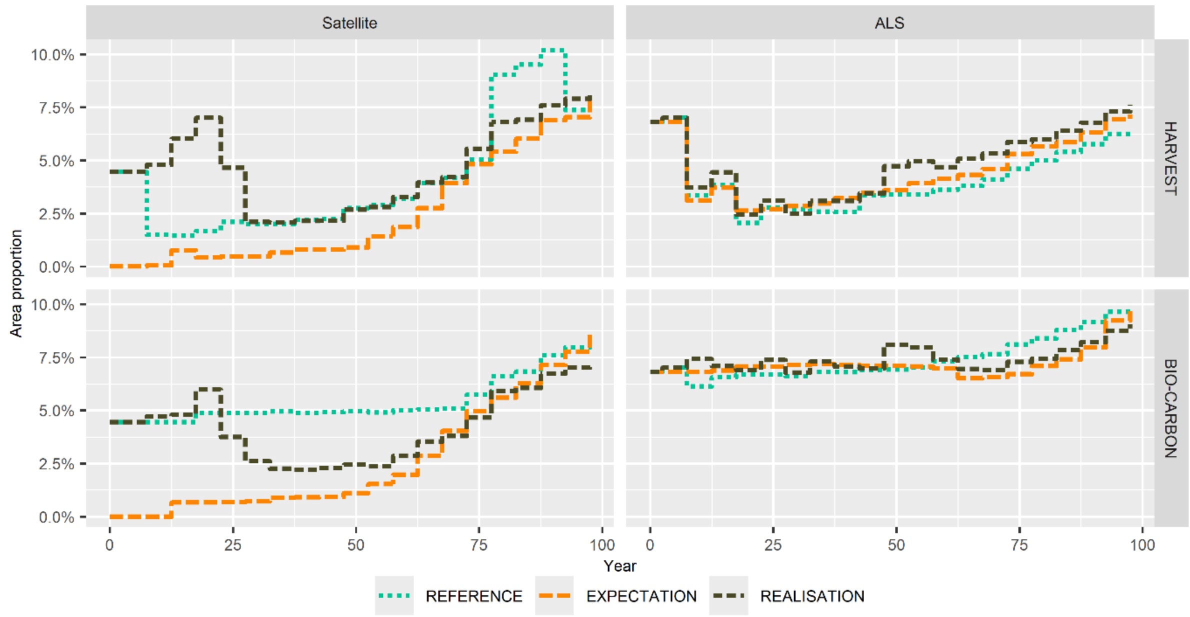

Figure 5. The area proportion of forest where any of the ecological indicators old forest, mature broad-leaf forests or forests with large trees were true according to the three outcomes REFERENCE, EXCPECTATION, and REALISATION and the problems HARVEST and BIO-CARBON. Satellite refers to optical satellite imagery, and ALS to airborne laser scanning.

Differences during the first 10 years

The first 10 years in a planning horizon are often considered most important, as it is very common to make a new long-term plan when that time has passed (Ulvdal et al. 2023). The relative changes for harvest levels, carbon stock, and the area of ecologically important forests compared to the reference during the first 10 years for the HARVEST-problem also show large deviations for this initial time (Table 9). Notably, harvest levels were almost 20% lower than what they should have been when planning with satellite data, even though the expectation was higher than the reference. Carbon stocks were overestimated, most significantly for the satellite data. Also, the area of ecologically important forests shows significant deviations from the reference levels.

Table 9. The relative changes for harvest levels, carbon stock, and the area of ecologically important forests compared to the reference during the first 10 years for the HARVEST-problem.

Method	Outcome	Harvest level	Carbon	Ecologically important forests
ALS	EXPECTATION	+0.10%	+0.52%	-4.22%
ALS	REALISATION	+5.92%	-0.30%	+3.51%
Satellite	EXPECTATION	+1.05%	+11.88%	-99.11%
Satellite	REALISATION	-18.18%	-1.28%	55.72%

DISCUSSION

Our study reveals that forest management planning based on data from RS-based forest inventories can lead to unexpected or undesirable outcomes. The realised results for ecosystem services and biodiversity indicators often diverged significantly from initial expectations. Notably, deviations were more pronounced in plans based on predictions from satellite data than those relying on predictions from ALS. This was expected since the satellite predictions generally had larger random errors and a more profound influence of regression toward the mean (Figure 2).

Across all indicators, i.e. NPV, harvest volume, carbon stock, and ecologically important forest area, the realised outcomes deviated from expectations. Note that absolute values from the evaluation of the two RS-based stand inventories should not be directly compared across inventories, as they represent slightly differing forests, despite efforts to standardise them. Rather, the focus should be on relative differences, such as the gap between expected and realised outcomes.

NPV, used as an overall measure of optimality, indicated that decision-making informed by RS could result in suboptimality, with reductions in NPV of at least -7% to -9%. The suboptimality was more pronounced in the satellite-based plans than those based on ALS predictions (Table 7), likely due to larger random errors and effects from regression towards the mean in satellite-derived predictions (Figure 2). The suboptimalities we report are likely conservative, as they reflect only the direct costs associated with mistimed or suboptimal treatments and their silvicultural consequences. For example, too early harvesting would result in lower timber volumes or smaller logs, both of which yield lower market prices and incur higher operational costs. The suboptimalities exclude indirect costs, such as those stemming from failures to meet industrial supply contracts. Additionally, some attributes in the RS-based inventories were gathered in the field, thus providing an unfair comparison to the reference data in favour of the RS-based inventories. However, the suboptimalities we report are consistent with or exceed those reported in other studies examining the impact of data quality on planning efficiency (e.g. Duvemo et al. 2014; Ruotsalainen et al. 2021).

While NPV is a useful metric for overall objective fulfilment, harvest levels are often more critical for forest companies and national scenario analyses (Hynynen et al. 2015; Ulvdal et al. 2023). Our findings demonstrate substantial fluctuations in realised harvest levels when planning is based on RS-based stand inventories (Figure 3). These levels were generally lower than both optimal and expected values, which poses potential challenges (Table 8). For example, the financial value of forest companies may depend on their projected harvest levels (Chudy & Cubbage 2020). Also, lower-than-expected harvests may hinder efforts to replace fossil fuels with wood-based materials, a key strategy for mitigating climate change (e.g. Gustavsson et al. 2017).

The sudden decrease in harvest levels after the first period for the satellite-based plans can be explained by the fact that some stands with harvests planned according to the predictions from satellite data had not reached the lowest allowable age for harvests according to the reference data (see Figure 6). These harvests were postponed to the earliest time points when they were allowed, resulting in lower harvests. This result is most likely an effect of regression towards the mean since relatively young forests, i.e. approximately 50 years, according to the reference data, were predicted to be older, i.e. approx. 75 years (Figure 6). This effect from regression towards the mean also led to cyclic patterns in harvest levels, which is an expected result of planning based on data with reduced variability of initial conditions, i.e. data that describe a too large portion of the forest as conforming to average conditions.

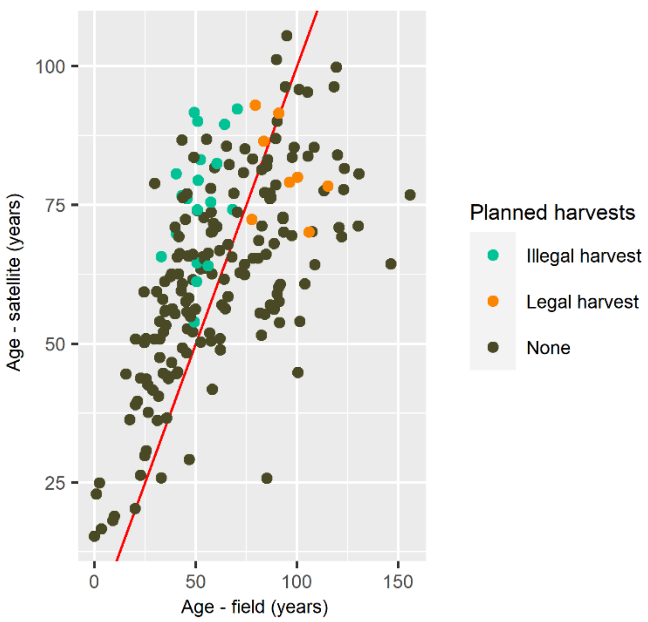

Figure 6. The stand ages according to both the reference data and predictions from satellite data, at year 0 in stands with planned harvests in the second period (year 5-10) of the problem HARVEST where decisions were based on the satellite-based predictions. The planned harvests are coloured depending on if the harvest in each stand was legal or not (depending on the age). The green-blue stands had not come to age and were therefore postponed. None indicates that no harvest were planned in either case in that period.

Keeping forests from becoming carbon sources is also a possible climate change mitigation strategy (Kirschbaum 2003), where short-term reduction is the key (Skytt et al. 2021). Our results indicate that forest management decisions informed by RS-based stand inventories may lead to reductions in carbon stocks despite intentions to increase them (Figure 4). Furthermore, the satellite-based plans substantially overestimated initial carbon storage levels, which raises concerns for carbon monitoring programs that rely on predictions based on satellite data.

Planning for ecological considerations with RS-based stand inventories as input also presents challenges. Satellite-based plans tended to underestimate the area of ecologically important forests (Figure 5), likely due to old forests missing from the dataset, which is explained by regression towards the mean. A correct assessment of old forests appeared to be very influential for the overall results for all three ecological indicators (see individual indicators in Appendix B).

In contrast, ALS-based plans yielded more accurate results, as forest age in this dataset was not predicted using RS (Table 1). Although methods for predicting forest age using a combination of ALS and satellite data exist, they remain uncertain, with relative root mean squared errors ranging from 16% to 50% (Schumacher et al. 2020). Nonetheless, advances in bi-temporal ALS suggest that it may become possible to improve age predictions in the future (Appiah Mensah et al. 2023). Including predicted ages instead of using the field-measured ages would probably negatively influence the results of the ALS-based plans.

Given the growing reliance on remotely sensed forest inventories (Fassnacht et al. 2023), we concur with calls for increased evaluation of these datasets. A persistent issue is the frequent presentation of forest resource maps without accompanying quality metrics, which may lead forestry professionals and policymakers to overlook the inherent uncertainties (Kangas et al. 2023). The need for such evaluations is underscored by the increasing emphasis on large-scale RS-based forest monitoring programs for policy development (Probeck et al. 2014; Linser et al. 2023). A recent European example illustrates the risks of basing policy on RS-derived data. Ceccherini et al. (2020) claimed that, from analysing satellite data, there was a rapid increase in harvested areas across Europe, particularly in the Nordic region. However, these findings were later contested both methodologically and with additional analyses of national field-based forest inventories (Palahí et al. 2021; Picard et al. 2021; Breidenbach et al. 2022). The questioned conclusions by Ceccherini et al. (2020) are not strictly related to random errors or biases in RS predictions but point to the uncertainties that may arise when RS-derived data are used to inform policy (European Commission 2024).

Our findings highlight potential risks when using RS data for forest scenario analysis and planning, particularly due to differences between expected and realised outcomes. There is, however, more to do in this field. For example, this study only acknowledged three indicators for ecologically important forests due to the lack of other models – which is a common problem (Hunault-Fontbonne & Eyvindson 2023). Another drawback was that we only included carbon stock in living trees when soil carbon, in reality, makes up a significant part of the total stock (Bradshaw & Warkentin 2015). The decision not to model soil carbon was based on the current uncertainties of the models implemented in Heureka PlanWise (Ortiz et al. 2013). Moreover, although the field survey data used for reference was of as high quality as practically possible, it may have included measurement and sampling errors (Lindgren 2000), contributing to some extent to the differences between field data and predictions based on remotely sensed data. The same is true regarding the generation of tree lists in Heureka PlanWise. These potential differences should, however, be rather negligible and should not impact the results in any significant way.

Future studies should consider the adaptive nature of forest planning, which incorporates periodic re-planning and data updates since this is how forestry operates (Ulvdal et al. 2023). Moreover, the lack of uncertainty-handling methods in our optimisation models reflects current practice, as forest companies in Sweden typically do not employ such techniques (de Pellegrin Llorente et al. 2023). Employing stochastic programming or similar methods could likely improve planning outcomes (Pasalodos-Tato et al. 2013). Likewise, this would also probably be the case for calibration techniques such as histogram matching (Gilichinsky et al. 2012).

Moreover, future studies should try to isolate the effect of regression towards the mean, as this is probably one major driver in some of the negative effects of using RS-derived data in forest planning. To do this, it is probably necessary to conduct some simulation of errors, where their characteristics could be controlled. Such a study would probably be challenging to design with similar real-world data as in this study. Regression towards the mean is no new problem in forest inventory and planning. Many inventory methods, especially those that, to some extent, are subjective, are affected in the same way (Ståhl 1992). Also, models that aim to describe forest growth and development over time are generally affected by the same problem. Nevertheless, the availability and periodicity of new RS-based predictions about forests, i.e.

forest resource maps, is drastically increasing, and many users probably do not reflect much about their uncertainty. This highlights the need to address the issue at hand.

CONCLUSIONS

Reliable data on forest resources is essential for informing future forest policy and management. Our findings indicate a suboptimality in NPV of -7% to -9% when using RS-based stand inventories influenced by regression towards the mean and other errors. Other indicators also showed substantial differences between expected and realised outcomes in plans based on predictions from RS. Harvest levels fluctuated significantly over time, occasionally exceeding sustainable harvest thresholds, while carbon stocks were unintentionally reduced. Notably, satellite-based plans significantly overestimated carbon stocks, while the degree of overestimation was less pronounced in plans based on ALS predictions. Achieving stable outcomes for biodiversity indicators proved challenging for all RS-based stand inventories, though ALS-based plans performed markedly better than the satellite-based plans.

Our results highlight the impact of uncertainties inherent in RS predictions, including the issue of regression towards the mean when such data is used in scenario analyses and planning models. These findings have important implications for ongoing policy development and potential regulations concerning large-scale forest monitoring and planning. While RS-based predictions remain a valuable tool for forest planning and policy, it is crucial to acknowledge their limitations. We recommend that decisions regarding forest management be supported by high-quality data or, at the very least, data with well-characterised uncertainties.

AVAILABILITY OF DATA AND MATERIAL

The original stand inventory and field survey data analysed during this study are unavailable since the data belongs to a third party (Holmen Skog AB) and may have financial implications.

The satellite map is freely available from the Swedish University of Agricultural Sciences' webpage: https://www.slu.se/en/environment/statistics-and-environmental-data/search-for-open-environmental-data/slu-forest-map/.

The public version of the ALS map is freely available from the Swedish Forest Agency's webpage: https://www.skogsstyrelsen.se/skogligagrunddata. The version used in this study is available for researchers upon reasonable request.

CODE AVAILABILITY

Data processing scripts in R and the Heureka PlanWise Project file are available from the corresponding author upon reasonable request.

CONFLICTS OF INTEREST

During the work with this study, Patrik Ulvdal were affiliated part-time with Holmen Skog AB, the company that provided data. Holmen also funded part of the study in the form of parts of the salary for Patrik Ulvdal. The other authors declare no competing interests.

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APPENDIX A

The satellite map needed to be complemented with missing attributes in the form of stand averages to make it possible to generate tree lists for each stand with Heureka PlanWise. The complementation was done by employing simple regression models developed from freely available Swedish national forest inventory plot data from 2017-2021 (Tables A1-A3). The predictive variables in the models were selected by conducting bidirectional step-wise regression analyses for each response variable. Logarithmic, quadratic, cubic, square root, raising to the power 10, raising to the power-e or reciprocal transformations of the predictive variables were allowed if all variables for the same response had the same transformation. Only stand averages from available predictions were used as input in the models to calculate the complementary attributes. The number of stems was only calculated for stands with height <7 m since stands of this height need that attribute in Heureka PlanWise, but others do not.

*Table A1. The linear models ($y = a + bx + cz + dq$) for assigning the number of stems per hectare in stands with heights <7 m based on the satellite map. Separate models based on dominant tree species group. y is the number of stems per hectare (ha^{-1}), a is a constant, x is the height (m), z is the volume ($m^3 ha^{-1}$), and q is the stand age (years). * indicates significance at the 0.001 level. The dominant species group is the species group encompassing more than 50 % of the total stand volume.*

Dominant species group in element	a	b	c	d	R^2	Number of observations
Coniferous (>50%)	5059.7*	-713.7*	52.1*	-0.85	0.45	3746
Deciduous (>50%)	5181.8*	-528.1*	83.4*	-22.00*	0.49	1776

Table A2. The power models ($y = e^a x^b z^c$) for assigning basal area weighted diameter at breast height (D_{bh}) in stands with heights >7 m based on the satellite map. Separate models based on dominant tree species group. y is the D_{bh} (cm), x is the height (m), and z is the mean age (years). All exponents had significance at the 0.001 level. The dominant species group is the species group encompassing more than 50 % of the total stand volume.

Dominant species group in element	a	b	c	R^2	Number of observations
Coniferous (>50%)	0.0836	0.807	0.179	0.76	16662
Deciduous (>50%)	-0.354	0.916	0.220	0.70	2953

Table A3. The linear models ($y = a + bx$) for assigning the basal area per hectare in stands with heights >7 m from the satellite map. Separate models based on dominant tree species or species group. y is the basal area ($m^2 ha^{-1}$), a is a constant, and x is the quota volume/height ($m^2 ha^{-1}$). An asterisk (*) indicates significance at the 0.001 level. Dominant species is the species with more than 60% of the volume. If no species makes up more than 60%, the same rule is applied to species groups, i.e. coniferous and deciduous species. If no group is larger than 60%, the stand is considered to be mixed.

Dominant species in element	a	b	R^2	Number of observations
Pinus sylvestris (>60%)	-0.795*	2.17*	0.98	8011
Picea abies (>60%)	-0.350*	2.13*	0.97	5029
Betula spp. (>60%)	-0.139	2.23*	0.96	1192
Pinus contorta (>60%)	-0.456*	1.95*	1.00	287
Quercus spp. (>60%)	-0.334*	2.31*	1.00	163
Fagus sylvatica (>60%)	-0.894*	2.45*	1.00	71
Coniferous (>60%)	-0.853*	2.17*	0.98	2061
Deciduous (>60%)	0.00811	2.26*	0.97	360
Unknown deciduous (>60%)	0.0778	2.25*	0.96	380
Mixed (i.e. none of the above)	-0.481*	2.19*	0.98	1162

APPENDIX B

Figures showing the development of the individual ecological indicators in Figure 5.

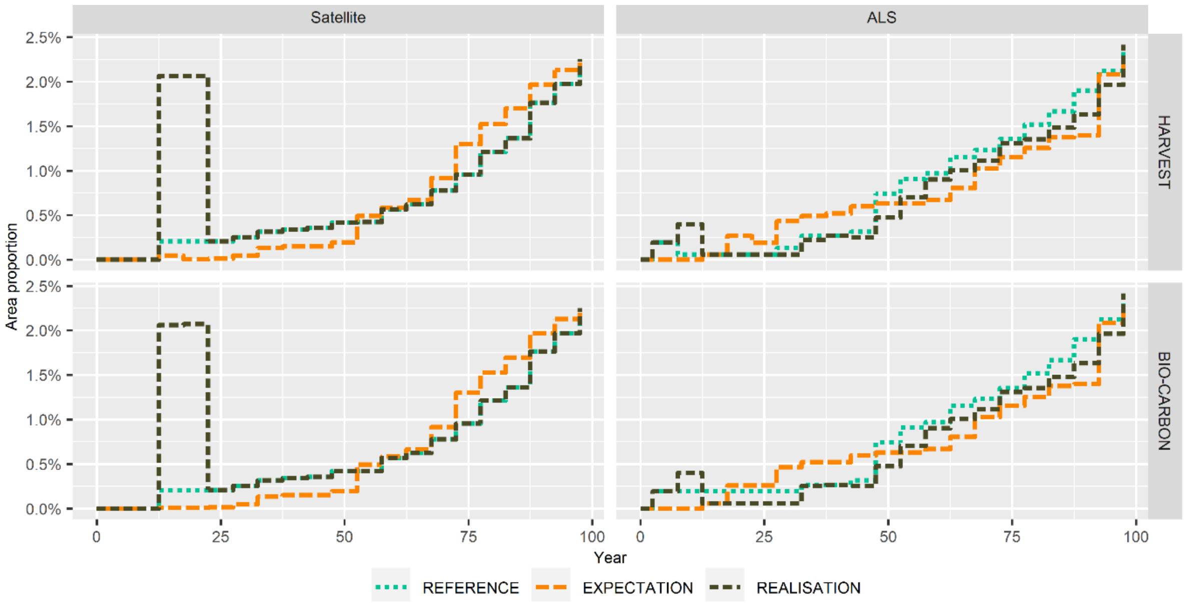

Figure B1. The area proportion of forests with more than 60 large trees per hectare according to the three outcomes (REFERENCE, EXCPECTATION, and REALISATION) and the two problems (HARVEST and BIO-CARBON). Satellite refers to optical satellite imagery, and ALS to airborne laser scanning.

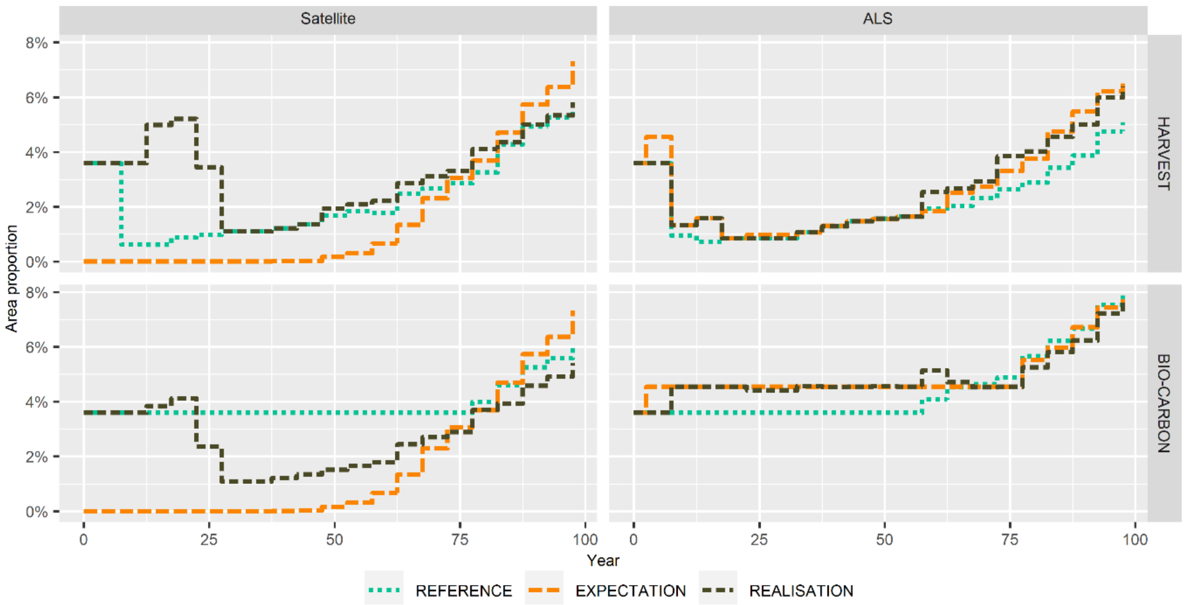

Figure B2. The area proportion of old forests according to the three outcomes (REFERENCE, EXCPECTATION, and REALISATION) and the two problems (HARVEST and BIO-CARBON). Satellite refers to optical satellite imagery, and ALS to airborne laser scanning.

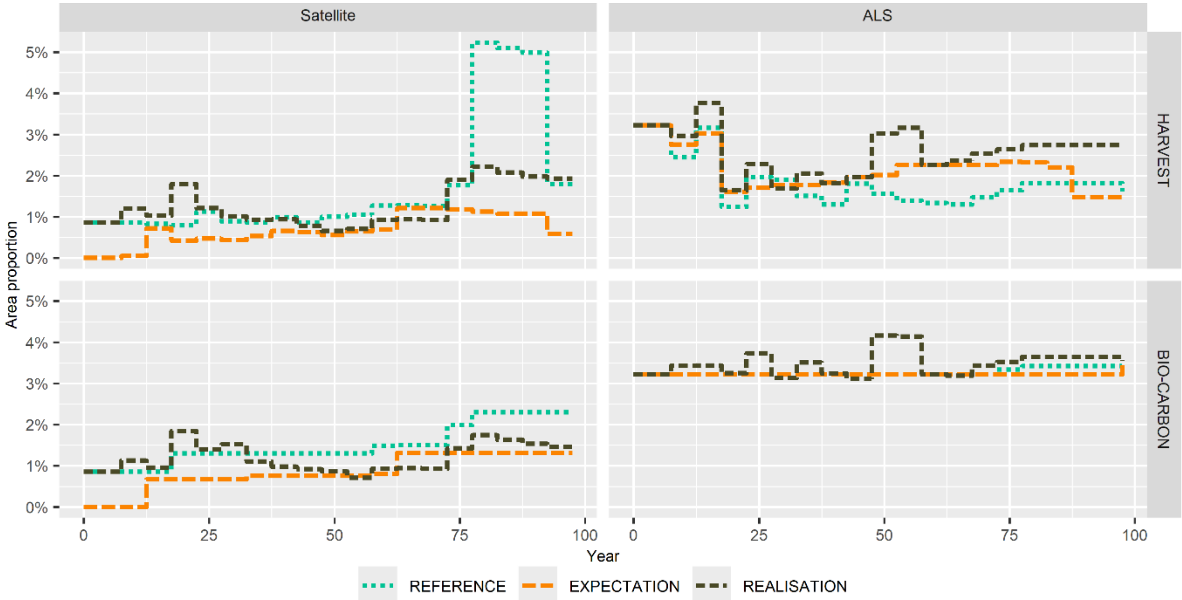

Figure B3. The area proportion of mature broad-leaf forests according to the three outcomes (REFERENCE, EXCPECTATION, and REALISATION) and the two problems (HARVEST and BIO-CARBON). Satellite refers to optical satellite imagery, and ALS to airborne laser scanning.