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From point clouds to forest management: Quantifying the sensitivity of a decision support framework to initialization data using close-range remote sensing

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ABSTRACT

Forest management faces profound uncertainty regarding future forest development, as climate change increasingly drives critical transitions in forest ecosystems. Decision support systems (DSSs) that integrate climate-sensitive forest models with assessments of biodiversity and forest ecosystem services (BES) can help systematically reduce uncertainty about the consequences of alternative climate and management pathways. However, assessing the reliability of DSS outputs requires a systematic evaluation of uncertainty sources across individual DSS components. A key challenge in this context is the DSS initialization, which is often constrained by limited data availability from traditional sources such as forest management plans and inventories, making it a major source of uncertainty. Recent advances in close-range remote sensing, particularly high-resolution LiDAR-based inventories, provide detailed information on forest structure and composition and offer new opportunities for improved DSS initialization. Nevertheless, the extent to which high-resolution LiDAR-based inventories can be used for DSS initialization, how they influence DSS outputs, and how they contribute to overall uncertainty remain largely unexplored. This study therefore aims to quantify the sensitivity of a DSS framework to initialization data using LiDAR-based forest inventory.

Our approach comprised (1) forest inventory sampling using terrestrial and unmanned aerial laser scanning (TLS/ULS), (2) initialization of the forest gap model ForClim, (3) simulation under alternative management and climate change scenarios, and (4) evaluation of BES outcomes. The study was conducted in a 3.6 ha structurally diverse and temperate forest stand in Switzerland. The combined TLS/ULS inventory served as reference data, from which sampling variants with different sample sizes were derived to represent varying levels of inventory detail. DSS sensitivity to initial stand resolution was assessed over a 70-year simulation period under three management intensities (no management, low-intensity, and high-intensity management), three climate scenarios (historical, RCP4.5, and RCP8.5), and 13 stand-level indicators aggregated into partial utilities for BES, such as biodiversity, timber, carbon sequestration and recreation.

Our results revealed that smaller sample sizes led to greater deviations from the reference simulation. This effect diminished over time and with increasing management intensity for most BES indicators. Although the inventory sample size was the dominant source of uncertainty during the initial simulation period, climate-related uncertainty increased with time. Our findings identify a 20–40 year tactical planning window during which high-resolution initialization is the primary determinant of DSS reliability, after which climate uncertainty becomes a more relevant factor in strategic planning. Future research should further exploit the potential of high-resolution LiDAR data by extracting additional information on forest composition and state, thereby enabling more robust decision support for long-term forest planning under climate change and increasing demands for BES provision.

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1. Introduction

The availability of information on the current state and condition of forests is steadily increasing, driven largely by advances in remote sensing technologies (Senf, 2022). In particular, Light Detection and Ranging (LiDAR) systems – such as unmanned aerial laser scanning (ULS), mobile laser scanning (MLS), and terrestrial laser scanning (TLS) – have substantial potential to complement traditional forest inventories (Holvoet et al., 2025; Kükenbrink et al., 2025; Maeda et al., 2025) and to reduce spatial uncertainties through cost-effective upscaling to larger areas (Mosig et al., 2026; Ma et al., 2025; Calders et al., 2020; Disney et al., 2019). High-resolution LiDAR enables the derivation of key forest attributes relevant for biodiversity assessments (Fol et al., 2023; Feigl et al., 2025) and economic valuation of trees (Larysch et al., 2025) by providing accurate single-tree information such as diameter at breast height (DBH), tree height, position (e.g., Liang et al., 2016), and tree species classification (e.g., Puliti et al., 2025).

In contrast to this increasing data availability, forest management faces profound uncertainties regarding future forest development trajectories, as climate change drives critical transitions in forest ecosystems (Patacca et al., 2023; Senf and Seidl, 2021). Uncertainty exists, for example, with regard to the future provision of forest ecosystem services, which is challenged by climate change as well as by trade-offs between biodiversity and ecosystem services (BES) (Blattert et al., 2024; Lecina-Diaz et al., 2024) and evolving societal demands for BES (e.g., Winkel et al., 2022). This contrast highlights an 'uncertainty paradox': while uncertainty about the current forest state is decreasing due to increasing high-resolution forest inventory data, the uncertainty about future pathways of long-term forest ecosystem development is increasing, e.g., due to climate change (Yousefpour and Hanewinkel, 2016; Senf, 2022). Consequently, long-term forest projection strategies must be developed based on the current state of knowledge (e.g., Huber et al., 2020).

Forest decision support systems (DSSs) offer a promising approach to addressing these challenges by combining forest models with multi-criteria decision analysis (MCDA) to evaluate multiple decision-relevant BES (Wolfslehner and Seidl, 2010; Vacik and Lexer, 2014; Blattert et al., 2017; Kangas et al., 2015; Segura et al., 2014). DSSs are increasingly recognized as essential tools for long-term forest planning, enabling the assessment of future forest trajectories under climate change and alternative management scenarios (Nordström et al., 2019; Blattert et al., 2017). In recent years, DSSs developed for Central European conditions (Thrippleton et al., 2021; Blattert et al., 2018) have evolved substantially, for example through the integration of climate-sensitive forest models (e.g., ForClim, Blattert et al., 2024), the integration of indices on forest structure and composition as proxies for biodiversity (e.g., deadwood, habitat trees, species and structural diversity) (Blattert et al., 2017, 2018) and the explicit consideration of disturbance mitigation strategies (Mutterer et al., 2025). However, DSSs still rely on forest inventory data (Thrippleton et al., 2023; Blattert et al., 2024), as model initialization (i.e., specifying the initial structure and composition of forest stands) remains a major challenge due to limited data availability from traditional sources such as forest management plans and conventional inventories (Mina et al., 2025).

Understanding uncertainty and sensitivity within DSSs across their individual components is therefore crucial, following the concept of the "cascade of uncertainty" (Lindner et al., 2014). Previous studies have shown that uncertainties in forest model outputs arises from multiple sources, including model selection (Bugmann and Seidl, 2022), assumptions regarding soil conditions and management implementation, model structure, and climate change projections (Huber et al., 2021; Djahangard et al., 2024; Snell et al., 2018; Maxwell et al., 2022; Walker et al., 2003). Moreover, Temperli et al. (2013) demonstrated that the sampling resolution of initial forest inventory data can significantly affect short-term BES projections, while long-term projections tend to be more robust to initialization uncertainty.

In this context, remote sensing (e.g., LiDAR) offers substantial potential to address DSS initialization needs, with the prospect of delivering consistent single-tree level information across larger areas. To date, remote sensing data have primarily been integrated into simulation frameworks at coarser spatial resolutions based on ULS data (Cattaneo et al., 2024) or used as supplementary information for forest management plans (Thom et al., 2022). At broader airborne scales, Nahorna et al. (2024) compared four inventory approaches based on airborne laser scanning (ALS) within a forest simulation framework and showed the importance of information quality for decision making in timber harvesting operations. At close range, Neudam et al. (2023) demonstrated the feasibility of using MLS data to initialize forest growth simulations to evaluate silvicultural treatments. However, a critical knowledge gap remains regarding the sensitivity of DSSs and corresponding BES projections to initialization data. A systematic assessment of uncertainty in DSS initialization data is therefore essential to ensure robust interpretation of simulation results.

This study addresses this gap by integrating LiDAR-based inventory into DSS initialization and systematically quantifying the propagation of initial-state uncertainties across individual DSS components. Specifically, we investigate the influence of inventory sample size, based on a high-resolution LiDAR reference inventory combining ULS and TLS data. In addition, we compare this reference inventory with a low-cost ULS inventory, identifying the role of species classification and structural detection for accurate DSS initialization regarding forest composition and structure. The following research questions were formulated:

- RQ1: To what extent does inventory sample size contribute to uncertainty in long-term BES provision under alternative climate change and management intensities?
- RQ2: What are the effects on BES when initializing the DSS with low-cost ULS data versus reference data?
- RQ3: What are the main drivers of uncertainty within a DSS over the simulation period, considering sample size, management intensity, climate scenarios and climate models?

To address these questions, we collected high-resolution LiDAR data using ULS and TLS systems for a 3.6 ha heterogeneous forest stand. A comprehensive reference forest inventory was derived by combining ULS and TLS data and applying state-of-the-art point cloud processing techniques. Based on this reference inventory, we implemented a systematic sampling approach to generate 18 different sample sizes. These datasets were used to initialize a forest DSS that has recently been applied in Swiss forest enterprises (Thrippleton et al., 2021; Blattert et al., 2024; Mutterer et al., 2025). Overall, the simulation framework integrates 20 inventory sample sizes (including the reference inventory and a low-cost ULS-based inventory), 20 climate model projections for RCP4.5 and RCP8.5, one historical climate scenario, and three forest management intensities. We subsequently quantify sensitivity and uncertainty associated with inventory sample size across 13 forest indicators and aggregated BES utilities, accounting for simulation time, management strategies, and climate scenarios.

2. Material and methods

2.1. Study site

The study site is located in the municipal forest district of Stein am Rhein in the Swiss canton of Schaffhausen. The area of interest (AOI) covers 3.6 ha, ranges in elevation from 620 to 638 m a.s.l., and is part of the larger forest district Oberwald (Fig. 1). Based on data from the nearby Schaffhausen weather station, mean annual temperature during the reference period 1991–2020 was 9.9 °C and the total annual precipitation amounted to 966 mm (MeteoSchweiz, 2024).

The AOI lies within the colline vegetation zone. Potential natural vegetation is primarily classified as a woodruff-beech forest (*Galio*

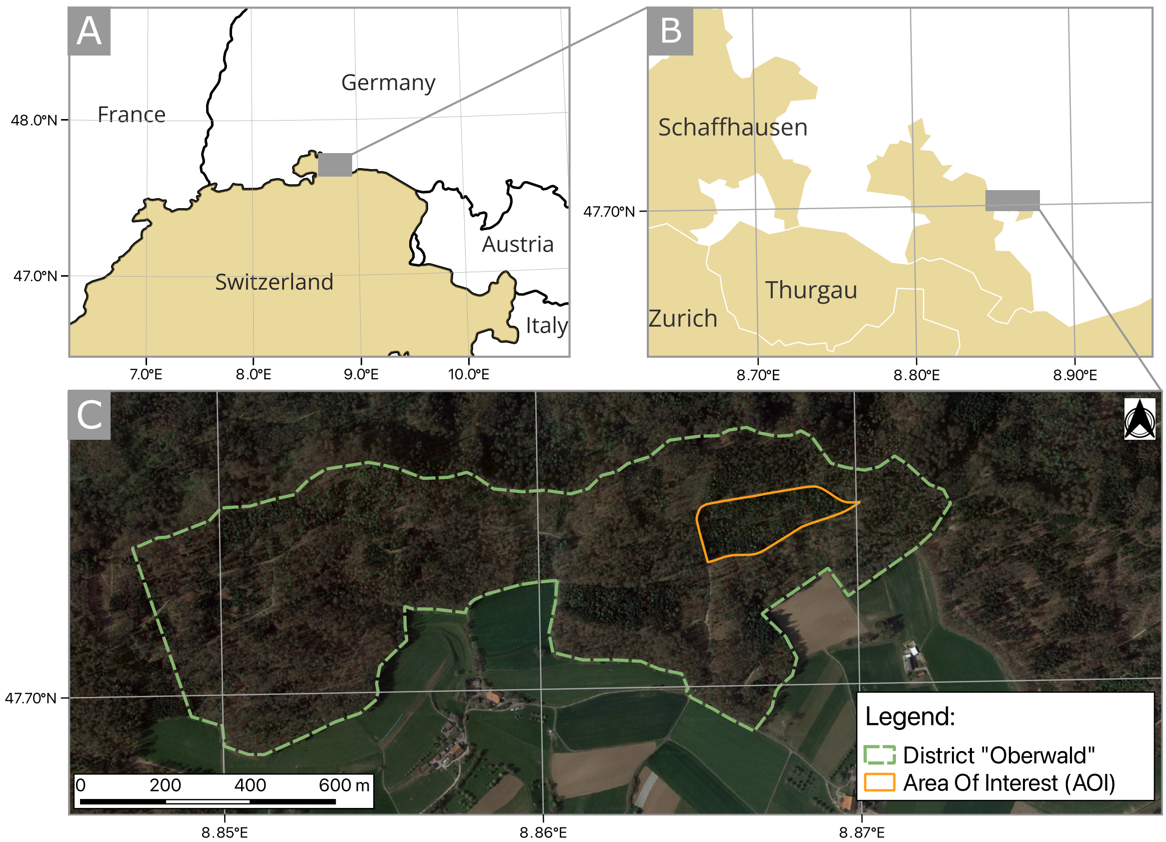

Fig. 1. Study site showing the area of interest (AOI) within the Oberwald forest district (Stein am Rhein, Switzerland). Orthophoto: © 2025 Google, CNES/Airbus, Maxar Technologies.

odorati-Fagetum typicum, with transitions to *Luzulo-Fagetum*) (Brang et al., 2020). The current forest composition is dominated by Norway spruce (*Picea abies*) and silver fir (*Abies alba*), mainly in pole wood and small timber stages. The stand is further mixed with small to large timber of European larch (*Larix decidua*), Douglas fir (*Pseudotsuga menziesii*), and Scots pine (*Pinus sylvestris*). Structural diversity is high, with denser areas characterized by limited understory and more open sections supporting a well-developed understory (Gini-index of 0.39; see Supplementary Material S4.1). Thus, the study site features a spatially diverse forest composition and structure, making it suitable for analyzing the influence of sample size on BES projections (see Section 2.3). Forest management objectives primarily focus on timber production, reflecting the site's productive growing conditions.

2.2. Decision support system

The DSS consists of three core components (Thrippleton et al., 2021): (i) a database containing environmental parameters and forest composition (see Section 2.2.1); (ii) a forest growth model (see Section 2.2.2); and (iii) indicators for assessing BES (see Section 2.2.3).

2.2.1. Database: Forest inventory based on LiDAR

The database underlying the forest growth model comprises environmental data, forest inventory information, and management settings (Thrippleton et al., 2021). As the forest inventory represents the focus of this study, only this component is described in detail here; remaining elements are presented in Section 2.2.2.

The forest inventory was derived from high-resolution LiDAR data acquired using two LiDAR systems: unmanned aerial laser scanning (ULS) and terrestrial laser scanning (TLS). Technical specifications of both systems are summarized in Table 1. All point clouds were georeferenced to the Swiss coordinate system LV95 (EPSG:2056) by aligning them with the Swiss surface 3D dataset (swisstopo, 2024) using an iterative closest point (ICP) approach.

Forest inventory processing comprised the following steps: (1) fusion of ULS and TLS point clouds to improve spatial completeness (Balestra et al., 2024), (2) individual-tree segmentation, (3) derivation of single-tree attributes (DBH, height, position), (4) tree species prediction, and (5) inventory validation. Detailed processing workflows are provided in Supplementary Material S2.1.

ULS-TLS fusion was employed to create a reference dataset that mitigates canopy occlusion in ULS data and range limitations in TLS data, thereby ensuring a near-complete representation of canopy and understory structures. Fusion was performed using the *merge* function of the *CspStandSegmentation* package (Frey and Schindler, 2024a). Individual trees were delineated using the deep learning approach *ForAINET* (F-score: 85.1%, as reported in Xiang et al. (2024)). Single-tree attributes (DBH, height, and position) were calculated using the forest inventory function of the *CspStandSegmentation* package. Tree species were predicted using the deep learning model *DetailView* (Frey and Schindler, 2024b) (overall accuracy: 76.9 – 93.8%, as reported in Puliti et al., 2025).

Inventory validation was conducted through visual comparison with a point cloud density raster and by evaluating the tree detection rate (TDR; see Supplementary Material S2.3). The resulting inventory derived from combined ULS and TLS data is provided in Supplementary Material S2.2 and served as the reference dataset for the DSS sensitivity analysis. The methodology for deriving the low-cost inventory based solely on ULS data is described in Supplementary Material S3.1.

2.2.2. Forest growth model: ForClim

Future forest development was simulated using ForClim version 4.1 (Bugmann, 1996; Marano et al., 2025). ForClim is a forest gap model belonging to the broader class of dynamic vegetation models.

Table 1
Technical specifications of the applied LiDAR systems.

LiDAR system	Device	Sensor	Scanning time	Date	Resolution
ULS	DJI Matrice 600 (DJI Co., Ltd, Shenzhen, China)	Hesai XT32-M2X (Hesai Technology Co., Ltd., Shanghai, China)	~ 8 min	July 2024	31 cm @ 50 m
TLS	Leica RTC360 (Leica Geosystems AG, Heerbrugg, Switzerland)	Equal to device	20.6 h (473 setups)	September 2024	6 mm @ 10 m

It simulates key demographic processes, such as establishment, growth, mortality, and competition, based on ecological and physiological principles (Huber et al., 2020). Gap models are particularly well suited for simulating structurally complex forests, such as uneven-aged and mixed stands, while requiring relatively limited input data. Their core assumptions trace back to the JABOWA model (Botkin et al., 1972) and have been refined over subsequent decades to enhance realism and predictive capacity (Bugmann, 2001).

ForClim has been extensively validated across a wide range of environmental conditions (Huber et al., 2021; Mina et al., 2017; Gutiérrez et al., 2016; Fischer et al., 2025). It is climate-sensitive and therefore capable of capturing climate-driven shifts in species composition and distribution (Huber et al., 2021; Gutiérrez et al., 2016; Takolander et al., 2019). Since a core aim of DSSs is to address long-term uncertainties driven by climate change impacts, ForClim is a well-suited model for the objectives of this study.

Simulations covered a 70-year period (2025–2095) and were initialized using five main inputs: (1) high-resolution forest inventory data, (2) forest management scenarios, (3) historical climate data, (4) climate projections, and (5) soil data. Model simulations were conducted using the R package *rforclim* (v. 1.01.001) (Hiltner and Marano, 2025).

(1) **High-resolution forest inventory**. LiDAR-derived data included four single-tree attributes: spatial position, species, DBH, and height (see Section 2.2.1). Trees were assigned to patches using a 20×20 m grid (400 m^2), representing the size of a typical canopy gap in mature stands (Bugmann, 1996, 2001). Patches intersecting the AOI by less than 50% were excluded, while basal area density in remaining boundary patches was adjusted to match original stand density by duplicating trees (see Supplementary Material S2.4). All 31 parameterized tree species were included to allow for potential species shifts. The setup of inventory sampling variants used for sensitivity analysis is described in Section 2.3.1.

(2) **Forest management scenarios**. Three management scenarios were implemented: a no-management scenario (NO), and two plenter management regimes based on single-tree selection using DBH thresholds and target basal area equilibria. The low-intensity 'plentering' scenario (LOW) targeted a basal area of 40 $m^2\,ha^{-1}$, while the high-intensity scenario (HIGH) targeted 20 $m^2\,ha^{-1}$. In both cases, the DBH threshold was set to 70 cm, with interventions applied at 10-year intervals starting in 2025. The implemented plenter management regimes reflect the current management practice for the study area.

(3) **Historical climate data**. Historical climate conditions for the period 1981–2010 were incorporated using ForClim's *weather generator*, which relies on monthly temperature and precipitation statistics (Bugmann, 1996; Huber et al., 2021). Preprocessing involved log-transforming precipitation data, calculating monthly means and standard deviations, and estimating cross-correlations between precipitation and temperature following the approach of Blattert et al. (2024).

(4) **Climate change data**. Data were derived from the Swiss 'CH2018' dataset, which provides daily temperature and precipitation time series from 1981 to 2099 at 2 km spatial resolution (CH2018, 2018). Ten EUR11 climate models (EURO-CORDEX, 12 km grid) were selected for each of the RCP4.5 and RCP8.5 scenarios, representing a wide set of possible emission trajectories covering uncertainties related to climate change pathways. Daily data were aggregated to monthly values. Simulations were run independently for each climate model, and indicator outputs were subsequently averaged to account for inter-model variability (Djahangard et al., 2024; Lindner et al., 2014) while preserving within-model extremes.

(5) **Soil data**. Mean soil water holding capacity for the AOI was derived from high-resolution soil maps (25×25 m; Baltensweiler et al., 2024). Soil properties included clay, sand, gravel, fine earth density, and soil depth. These variables were further processed to derive silt content and soil texture using the R packages *soilDB* (Beaudette et al., 2025) and *soil_texture* (Moeys, 2025).

2.2.3. Indicators for BES and aggregation of partial utilities

In total, 13 indicators were calculated for all climate scenarios and grouped into four BES categories: biodiversity, recreation, timber production, and carbon sequestration (C-seq). Indicator selection and computation followed established DSS methodologies (Blattert et al., 2018; Thrippleton et al., 2021; Blattert et al., 2024). All indicators are derived from forest structural attributes simulated by ForClim and serve as proxies for the utilities of BES. For example, the biodiversity indicators comprise structural and compositional proxies (i.e., deadwood, habitat trees, species and structural diversity). An overview of all indicators and associated weights is provided in Table 2, with detailed descriptions included in Supplementary Material S1.

For each BES group, indicators were normalized using value functions and transformed into utility scores ranging from 0 (lowest utility) to 1 (highest utility) (Blattert et al., 2017). Aggregated partial utilities were then calculated by weighting individual indicator utilities as follows:

$$PU_{a,p,m,cs} = \sum_{i \in I_a} \lambda_i u(x_{i,p,m,cs}) \tag{1}$$

where $PU_{a,p,m,cs}$ represents the partial utility of BES group a in period p under management strategy m and climate scenario cs, I_a denotes the set of indicators for BES group a, λ_i is the weight assigned to indicator i, and $u(x_{i,p,m,cs})$ is the normalized utility value of indicator i per BES group a ($i \in I_a$) (based on Blattert et al., 2024; Thrippleton et al., 2021).

2.3. Sensitivity analysis of the DSS framework

2.3.1. Development of sampling variants

A systematic sampling approach was developed to derive forest inventories at different spatial resolutions. Forest inventory sample plots were created using the patch-based ForClim design (see Supplementary Material S2.4), where each patch represents a sample plot with an area of 400 m^2. Sampling variants were generated using a farthest-point sampling approach (Eldar et al., 1997; Nuñez-Penichet et al., 2022), starting with the patch closest to the geographic center of the AOI (Fig. 2).

From this central patch, a systematic five-step sampling procedure was applied, beginning with five patches and progressing to a maximum of 85 patches. When multiple candidate patches were equidistant during the selection process, one was chosen at random. This approach was selected to maximize spatial dispersion and reduce spatial autocorrelation compared to random sampling, thereby ensuring that the

Table 2
Overview of BES categories, indicators, and assigned weights (λ_i) adapted from Blattert et al. (2024).

BES	Indicator	λ_i
Biodiversity	Shannon index alpha	0.25
	Post-hoc index alpha	0.25
	Total deadwood volume ($m^3\,ha^{-1}$)	0.25
	Number of habitat trees per ha (DBH > 70 cm)	0.25
Recreation	Mean height of 100 largest trees (per ha)	0.22
	Variation in tree size (Post-hoc index)	0.17
	Variation in tree species (Shannon index)	0.11
	Stand density index (SDI)	0.17
	Deadwood – harvest residue ($m^3\,ha^{-1}$)	0.22
	Deadwood – natural mortality ($m^3\,ha^{-1}$)	0.11
Carbon sequestration (C-seq)	Includes: above- and belowground biomass, deadwood, harvesting residues, natural mortality, harvested wood products, substitution of non-timber products, substitution of fossil fuels ($t\,C\,ha^{-1}$)	1
Timber production	Timber harvested ($m^3\,ha^{-1}\,yr^{-1}$)	0.8
	Productivity ($m^3\,ha^{-1}\,yr^{-1}$)	0.2

Table 3
Overview of the simulation setup.

	Levels	No. simulations	Details provided in
Management	NO, LOW, HIGH	3	Section 2.2.2
Climate	HIST (1), RCP4.5 (10), RCP8.5 (10)	21	Section 2.2.2
Sample size	1.1%–100%, ULS	20	Section 2.3.1
Total		1260	

sampled patches represent the spatial variability in forest structure across the AOI. To reduce potential bias caused by edge effects, tree densities of patches intersecting the AOI boundary were adjusted by replicating individual trees to achieve the same basal area as a complete patch (see Supplementary Material S2.4).

To account for stochasticity in the ForClim simulations (Bugmann et al., 1996; Bugmann, 2001), each sampling variant was replicated to match the 90 reference patches. When the division was uneven, additional patches were randomly selected from the respective sampling variant and the resulting selections were stored to ensure reproducibility. This replication strategy isolates the statistical sensitivity of the DSS framework but inherently suppresses landscape-level stochasticity that would be captured by a true 90-patch inventory. In addition to the 18 sampling variants, a low-cost ULS approach was included (methods described in Supplementary Material S3.1).

Each ForClim simulation was executed with the same simulation settings (i.e. ForClim seedValue = 1) (see Table 3). The computational demand for the 1260 simulations amounted to approximately 8 core-hours and were carried out on a Lenovo ThinkPad T14 with an AMD Ryzen 7 PRO 4750U processor (1.70 GHz, 8 cores), 32 GB RAM, running Windows 11 Pro (64-bit). The general ForClim simulation setup is described in Section 2.2.2.

2.3.2. Analysis of BES indicators and their partial utilities

The analysis of the sampling variants covered the specified simulation period, management intensities, and climate data, including climate models and climate scenarios (see Section 2.2.2). In addition, the BES indicators described in Section 2.2.3 were integrated into the analysis.

In a first step, all 18 sampling variants and the ULS data were analyzed by visualizing basal area trajectories over the simulation period, accounting for both climate and management scenarios. This exploratory analysis was used to identify sensitive sample sizes and to select a subset for further evaluation: 1.1%, 5.6%, 11.1%, 22.2%, 33.3%, 50%, and ULS data.

In a second step, relative differences between these seven selected sample sizes (including ULS) and the reference data were calculated for each BES indicator and visualized using heatmaps for the HIST climate scenario. In a third step, mean deviations of partial utilities were computed for the selected sample sizes across three time periods: short (2025–2045), mid (2050–2070), and long (2075–2095). Climate change scenarios and their variability across climate modes (±1 SD) were incorporated for visualization. This workflow allowed assessment of the effects of different sample sizes throughout the entire DSS pipeline.

2.3.3. Variance component analysis

A variance component analysis (VCA) was conducted for each indicator and involved multiple steps. First, deviations between each sample size (including ULS data) and the reference data were calculated (Eq. (2)). Second, the mean variance for each component and year was calculated across all possible combinations while holding the remaining components constant (Eq. (4)). The components considered were sample size, management intensity, climate model, and climate scenario.

For the mean variance associated with climate scenarios, indicator values were first averaged across climate models for each scenario (Eq. (3)), after which the variance between scenarios was calculated (Eq. (4)). For the mean variance associated with climate models, the historical climate scenario was excluded. Third, the total variance across all components was calculated for each year (Eq. (5)). Finally, the proportional contribution of each component to the total variance was determined (Eq. (6)).

$$D_{s,m,cs,cm,t} = I_{s,m,cs,cm,t} - I_{ref,m,cs,cm,t} \tag{2}$$

where $I_{s,m,cs,cm,t}$ is the indicator value at year t for sample size s, management intensity m, climate scenario cs, and climate model cm. $I_{ref,m,cs,cm,t}$ is the corresponding reference value.

$$\bar{D}_{s,m,cs,t} = \frac{1}{N_{cm}} \sum_{cm} D_{s,m,cs,cm,t} \tag{3}$$

where $\bar{D}_{s,m,cs,t}$ represents the mean deviation averaged across all climate models cm.

$$\sigma_c^2(t) = \frac{1}{N_{\text{fixed}}} \sum_{\text{fixed combinations}} \mathrm{Var}_c(D_{s,m,cs,cm,t}) \tag{4}$$

where $\sigma_c^2(t)$ is the mean variance at year t for component $c \in \{\text{sample size, management, climate model, climate scenario}\}$. This

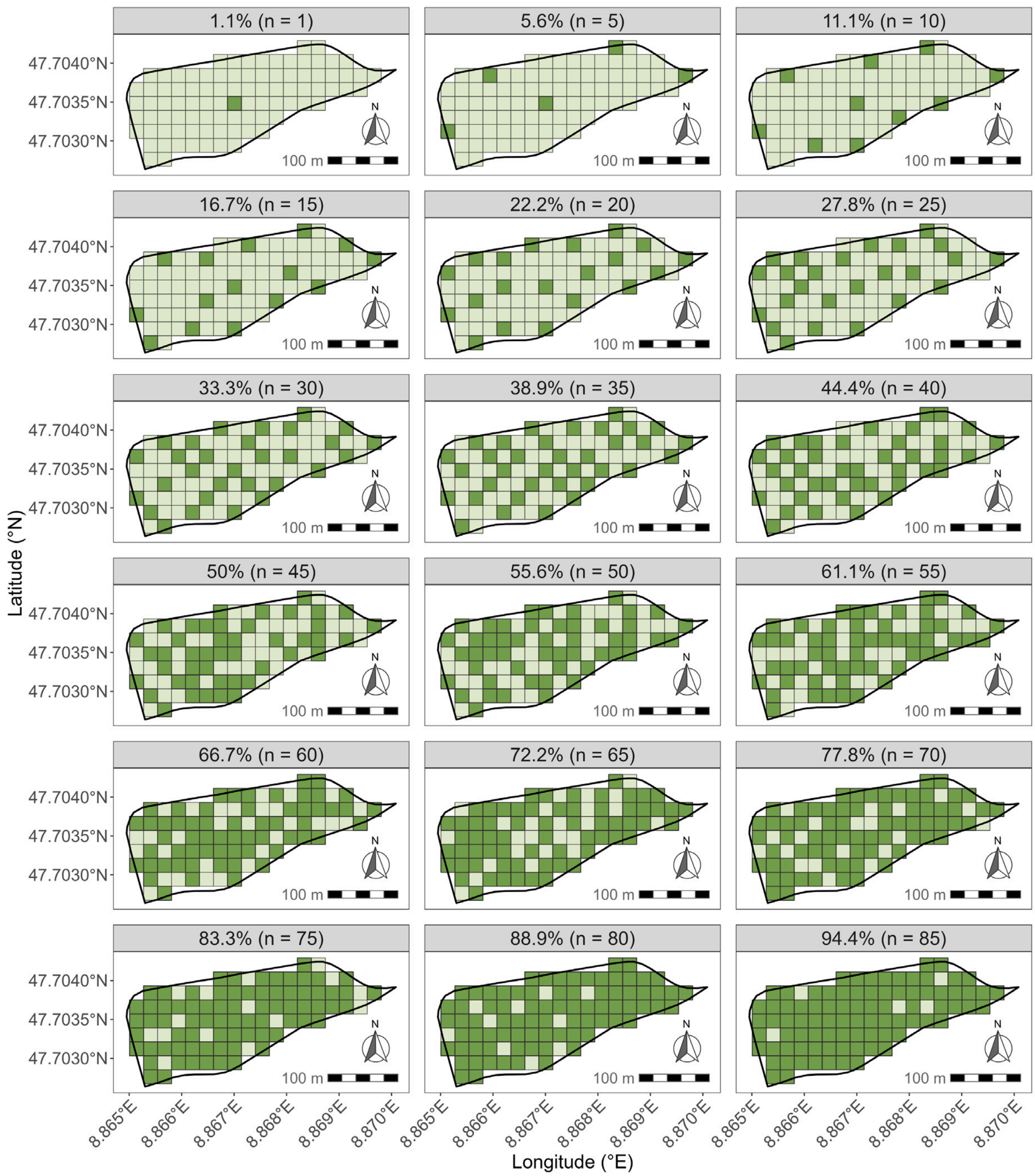

Fig. 2. The systematic sampling approach produced multiple inventory sample sizes, enabling an assessment of the sensitivity of the DSS framework to initial inventory data.

is calculated by (1) fixing the values of the three components other than c, (2) computing the variance of D across all levels of c, and (3) averaging across all combinations of the fixed components. The number of levels per component is: sample size ($N_s = 19$, reference data excluded), management ($N_m = 3$), climate model ($N_{cm} = 20$), and climate scenario ($N_{cs} = 3$).

$$\sigma^2_{\text{total}}(t) = \sum_c \sigma^2_c(t) \tag{5}$$

where σ^2_{total} is the total variance across all components at year t.

$$P_c(t) = \frac{\sigma^2_c(t)}{\sigma^2_{\text{total}}(t)}, \quad \text{with} \quad \sum_c P_c(t) = 1 \tag{6}$$

where $P_c(t)$ represents the proportional contribution of component c to the total variance at year t.

3. Results

3.1. Basal area trajectories for different inventory sample sizes

Basal area increased steadily over the simulation period under historical climate conditions (HIST) and without management intervention (NO). In contrast, under low (LOW) and high (HIGH) management intensities, basal area development was primarily controlled

Fig. 3. Basal area trajectories for different inventory sample sizes (reference data = combined ULS and TLS data) and ULS data, stratified by management intensity (NO, LOW, HIGH) and climate scenario (HIST, RCP4.5, RCP8.5).

by the prescribed harvesting cycles (reference data in Fig. 3). Under climate change scenarios (RCP4.5 and RCP8.5), basal area declined, particularly under NO and LOW management. This decline was mainly driven by a distinct reduction of Norway spruce abundance (see Supplementary Material S2.5 for tree species composition).

Across management intensities and climate change scenarios, smaller inventory sample sizes generally led to an underestimation of initial basal area (Fig. 3). Over time, this underestimation converged toward the reference trajectories, reflecting the model's demographic vegetation processes (growth and establishment) reaching a site-specific equilibrium, largely independent of the initial sampling deficit. This convergence occurred more rapidly under HIGH management intensity; by the end of the simulation period, basal area trajectories across sample sizes were nearly aligned with the reference data. The smallest sample size (1.1%) exhibited the strongest initial underestimation but also the steepest increase over time, particularly under NO management. Under RCP8.5, this led to a slight overestimation toward the end of the simulation period.

In contrast to the sampling variants, which converged to the reference data over time, the ULS data progressively diverged from the reference data. This divergence resulted from initial tree species misclassifications, which propagated through long-term growth dynamics (see Supplementary Material 3.2 for species composition). Overall, climate change effects on basal area development were similar across sample sizes and the reference data.

3.2. Impact of inventory sample size on BES indicators

Relative differences between reference data and selected sample sizes varied across management intensities and BES indicators over the simulation period (HIST climate scenario shown in Fig. 4). Across all indicators, smaller sample sizes resulted in larger deviations from the reference data, manifesting as both under- and overestimation. With increasing sample size, higher management intensity, and longer simulation horizons, deviations decreased for most indicators.

The Shannon diversity indicator exhibited a distinct pattern for the smallest sample size (1.1%) under LOW management, going from strong underestimation (−63.9%) at the beginning to a pronounced overestimation (69.8%) at the end of the simulation period. The C-seq indicator showed a considerable overestimation under HIGH management during the mid-simulation period, particularly for smaller sample sizes (e.g., 68.1% overestimation for the 1.1% sample size in 2070). This effect was attributed to the calculation of above- and below-ground carbon stocks ('Carbon ABG'), where initial biases relative to the reference data propagated throughout the simulation (see Supplementary Material S4.3).

For most indicators, relative differences between ULS data and the reference data remained approximately constant or increased slightly over time, especially under NO management. Introducing management interventions (LOW and HIGH) reduced the overall deviations compared to the reference data.

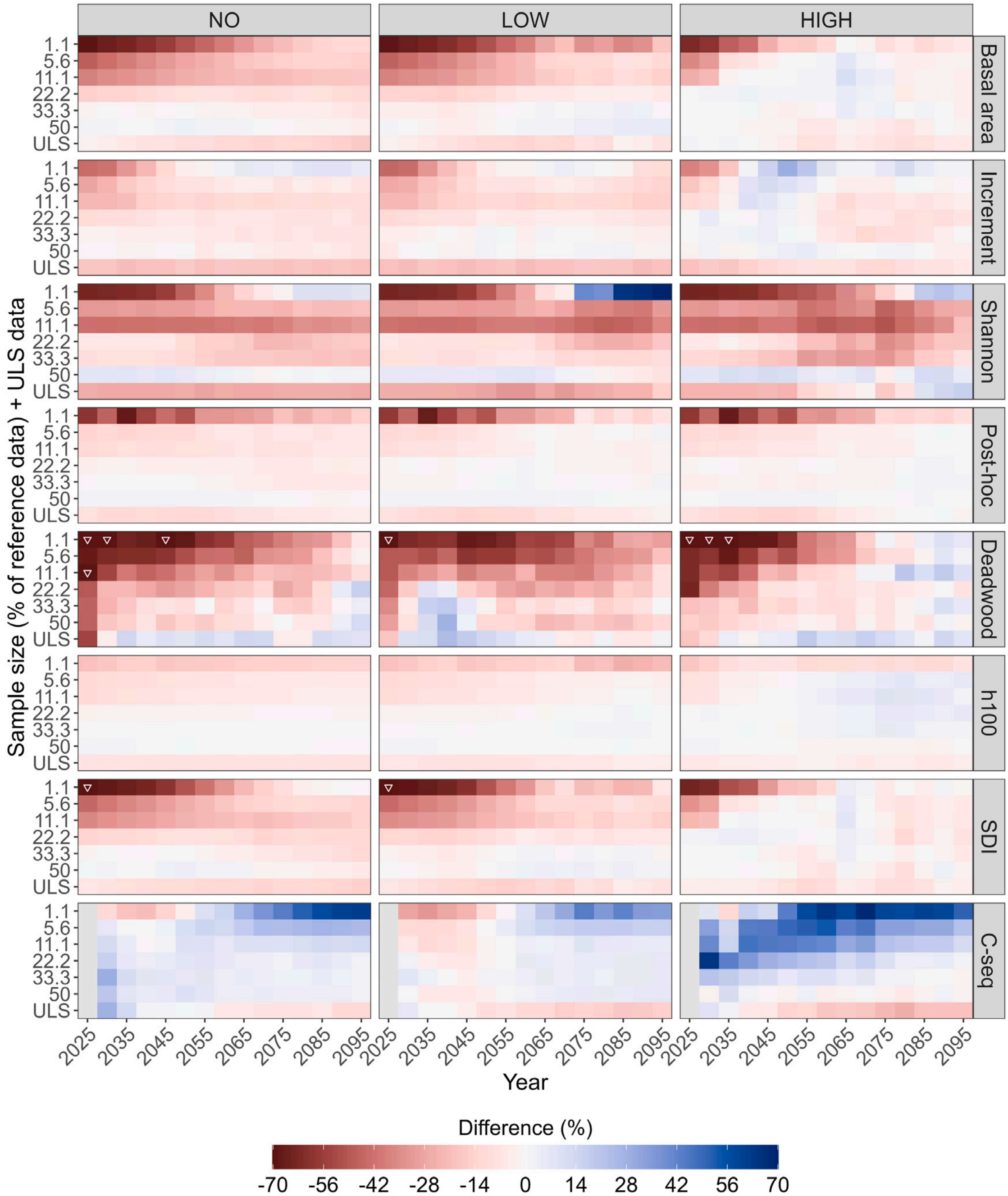

Fig. 4. Relative differences (%) between reference data and selected sample sizes (including ULS data) for BES indicators under historical climate conditions (HIST) and three management intensities (NO, LOW, HIGH). The triangle ▾ indicates capped values at −70%. Climate change scenarios are shown in Supplementary Material S4.2.

The indicators timber harvested and habitat trees were excluded from the main results, as they were directly determined by the prescribed harvesting cycles and management intensities (see Supplementary Material S2.6).

3.3. Partial utilities of BES considering climate variability

The partial utilities were shifting in various degrees across three time periods (short-, mid-, and long-term) due to climate change impacts and the selected sample sizes (Fig. 5). For the reference data, the utility scores for biodiversity and recreation were only slightly affected by climate change. However, C-seq and timber distinctly deviated from HIST in the long-term, with significant climate change variability. Original mean partial utilities were presented in Supplementary Material S2.7.

Smaller sample sizes exhibited substantial deviations in the short term for biodiversity, recreation, and C-seq across all climate change scenarios. Over time, these differences generally converged toward the corresponding reference scenarios. In contrast, deviations for timber increased with simulation duration, a pattern primarily driven by the dominant influence of the prescribed timber harvesting cycles (see Supplementary Materials S2.6).

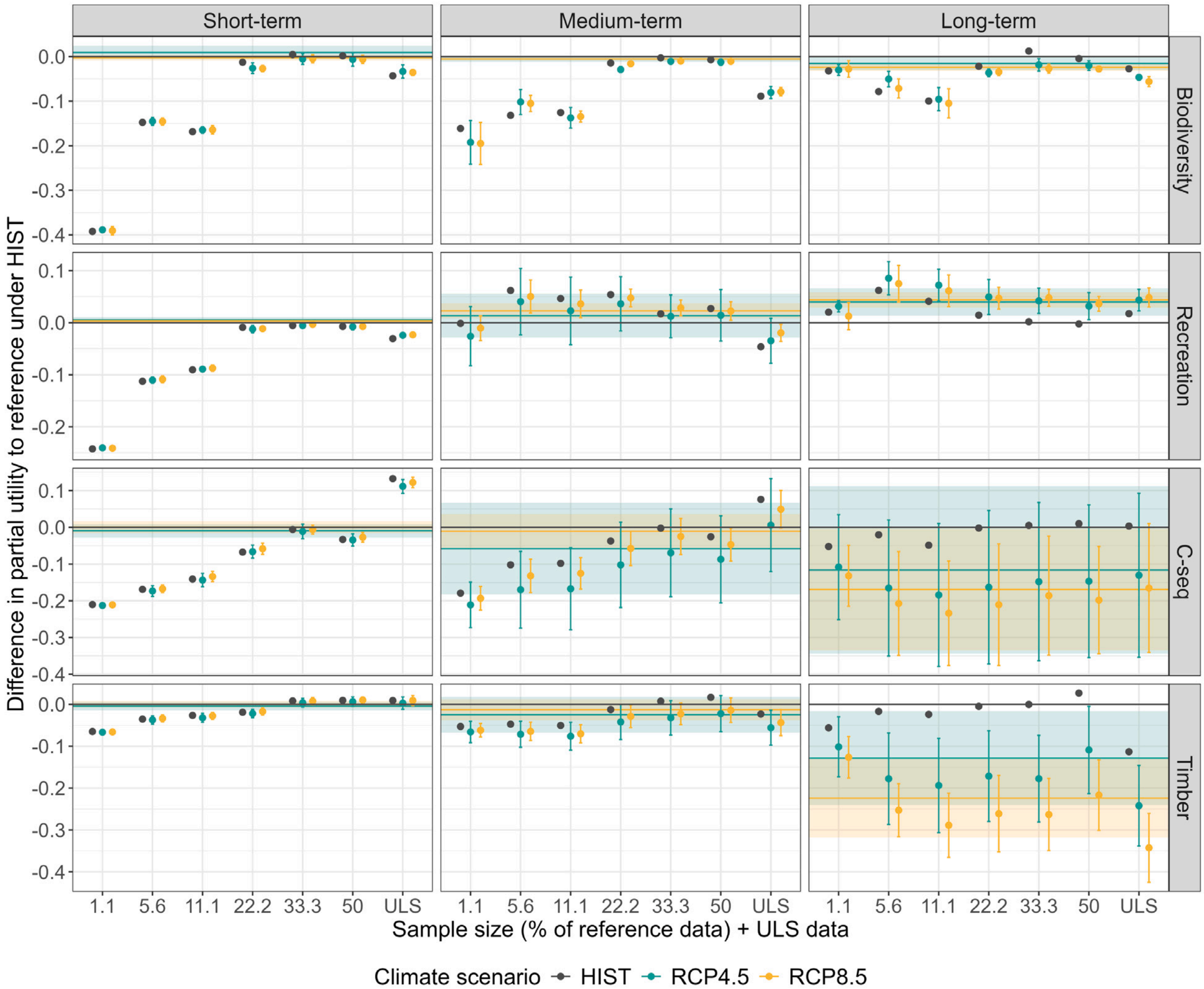

Fig. 5. Differences in partial utility scores for BES groups (aggregated indicators) relative to the reference scenario. Climate change scenarios RCP4.5 and RCP8.5 are shown with ± 1 standard deviation to illustrate variability across climate models (shaded area). Values are averaged over 20-year periods: short (2025–2045), medium (2050–2070), and long term (2075–2095). Results shown for LOW management; NO and HIGH management are provided in Supplementary Material S4.4.

3.4. Sources of uncertainty over the simulation period

The VCA identified inventory sample size as the dominant source of uncertainty for most indicators throughout the simulation period (Fig. 6; for methodology see Section 2.3.3). This pattern was particularly pronounced for basal area, increment, Shannon index, Post-hoc index, h100, and SDI. At the beginning of the simulation, sample size dominated uncertainty (e.g., 2025: increment = 91%, Post-hoc index = 99.3%). Over time, its contribution declined in favor of increasing influence from climate model, climate scenarios, and management intensity (e.g., 2095: SDI = 31.9%, h100 = 56.3%).

For the timber harvested and habitat trees indicators, sample size and management intensity contributed similar and relatively constant fractions of total variance, reflecting their direct dependence on management prescriptions. Deadwood was consistently influenced by climate model uncertainty, ranging from 15.1% in 2025 to 27.4% in 2085. In contrast, for the C-seq indicator, sample size became the dominant source of uncertainty toward the end of the simulation period, accounting for 81.1% of total variance in 2090.

Notably, sample size remained the dominant uncertainty source for increment, Shannon index, Post-hoc index, deadwood, and h100 even after 70 years of simulation. This highlights that initial inventory sample size continues to influence key structural and diversity-related metrics across the entire simulation horizon.

4. Discussion

4.1. The influence of forest structure on BES assessments

Our results showed that smaller forest inventory sample sizes led to substantial deviations of projected BES indicators from the reference data. In most cases, BES indicators underestimated reference values at the beginning of the simulation period and gradually converged over time (Figs. 3 and 4). These deviations at lower sample sizes can largely be explained by the replication of simulation patches, which resulted in more homogeneous forest structures and an insufficient representation of structural variability required for accurate BES estimation.

We found that a sample size of approximately one third of the reference inventory represented a saturation point, beyond which deviations from the reference data became marginal, particularly for structural indicators such as basal area and stand density index (SDI). However, this result is context-specific and reflects the moderate structural heterogeneity of the study stand (Gini = 0.39; see Supplementary Material S4.1). Forest stands with higher structural complexity would likely

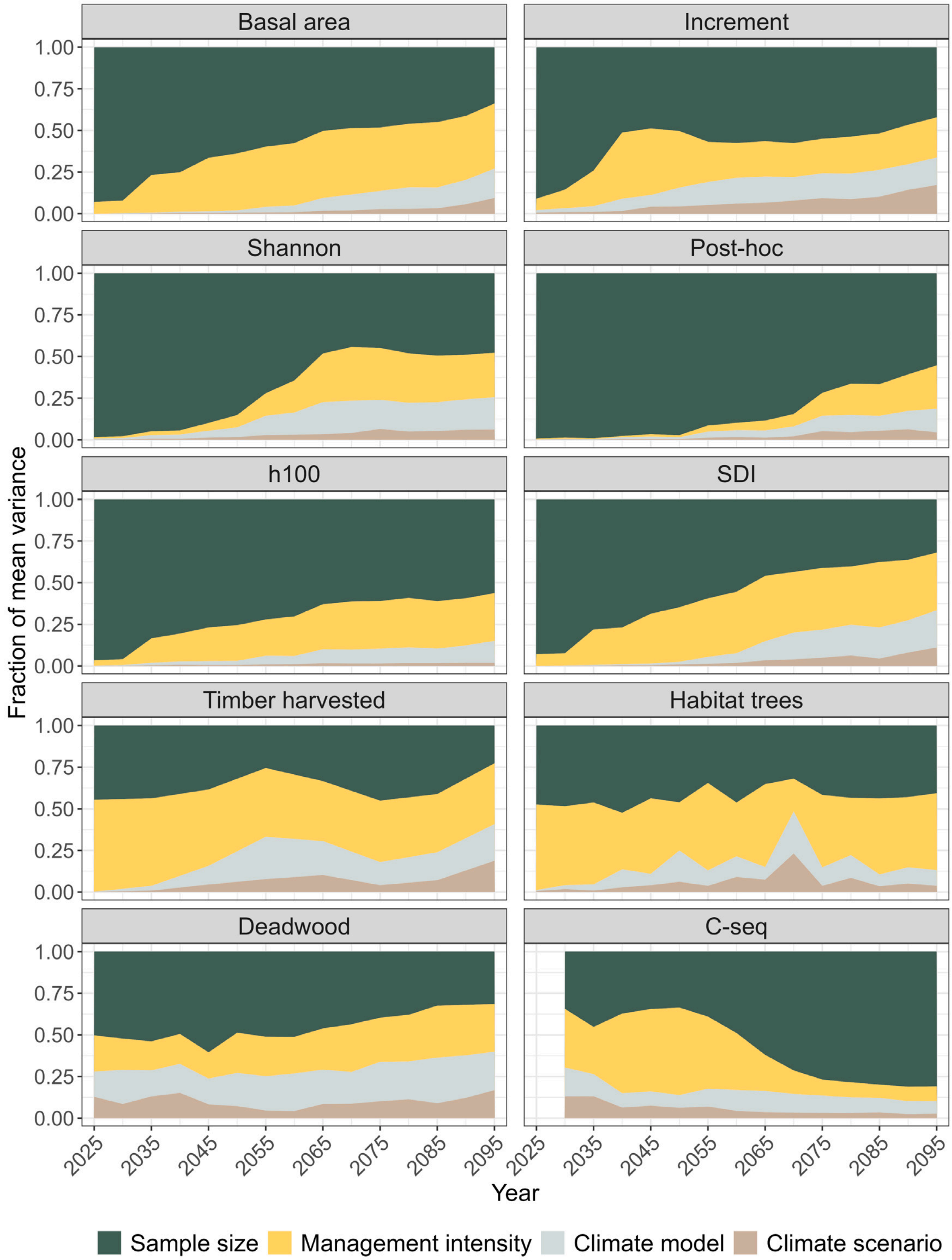

Fig. 6. Fraction of mean variance to sample size, management intensity, climate model, and climate scenario over the simulation period.

require higher sampling intensities to achieve comparable stability in indicator estimates.

With increasing simulation time and higher management intensity, deviations between sampling variants and reference data generally decreased. This convergence may be attributed to the long-term dominance of ForClim's demographic processes – establishment, growth, and mortality – which operate under consistent environmental parametrization (Bugmann, 2001). Management interventions further constrained structural variability by removing trees according to predefined harvesting rules, thereby reducing the influence of initial structural differences between sampling variants. In particular, HIGH management intensity acted as a homogenizing force: repeated harvesting toward an equilibrium basal area of 20 m^2 ha^{-1} dampened long-term effects of initial over- or underestimation.

However, these converging effects did not apply uniformly across all BES indicators or aggregated BES groups. More complex indicators, such as C-seq potential (composed of multiple carbon components) showed the opposite pattern, with deviations increasing over simulation time and management intensity (Fig. 4). The reason for this behavior was the calculation of the carbon compartment 'Carbon ABG' (above- and below-ground biomass carbon), which describes a carbon potential relative to the initial 'Carbon ABG' state (for further explanation see Supplementary Material S4.3). This indicates that for complex BES indicators, their design and composition need to be considered, as they might require higher initial data accuracy regardless of simulation horizon or management strategy. While Temperli et al. (2013) concluded that simulation periods exceeding 150 years may yield reliable results, our findings highlight that convergence strongly depends on indicator complexity. Simple indicators (e.g., basal area) converged within the 70-year horizon considered here, whereas complex indicators (e.g., C-Seq) and certain aggregated BES groups remained sensitive to initialization errors.

The importance of initial tree species composition became particularly evident when comparing low-cost ULS data with the reference inventory. Although ULS-derived inventories exhibited similar initial basal area, tree species composition differed substantially (see Supplementary Material S3.2). Under NO and LOW management approaches, these compositional discrepancies translated into larger deviations in basal area trajectories and more complex BES indicators such as C-seq (see Figs. 3 and 4). The progressive divergence of ULS trajectories highlights a fundamental limitation of DSS initialization: accurate structural metrics alone cannot compensate for species misclassification, as species identity determines growth, competition, and mortality processes in ForClim (Huber et al., 2018).

In summary, forest structure captured in the initialization data – particularly DBH distribution and tree species composition – was the main driver of sensitivity in BES projections, especially during the short-term projection period.

4.2. Comparing sources of uncertainty along the simulation period

Across the 70-year simulation horizon, inventory sample size was the dominant source of variance for most indicators, although the relative importance of other uncertainty sources – climate models, climate scenarios, and management intensity – increased over time (Fig. 6). The contribution of management intensity to total variance increased steadily, reducing the relative influence of sample size. Nevertheless, for several indicators, sample size remained a major uncertainty source even in 2095, indicating that a 70-year horizon was insufficient to fully compensate for imprecise inventory data for certain structural metrics. Thus, the reliability of DSS outcomes could be improved by higher-quality forest inventory data, particularly for indicators describing structural forest characteristics and under short-term or unmanaged trajectories.

Because the three management approaches pursue different objectives, they introduced a controllable and intentional source of variance, especially for indicators directly linked to management actions, such as timber harvested and habitat trees. This underscores the strong influence of forest management on simulated forest dynamics (Maxwell et al., 2022; Yousefpour and Hanewinkel, 2016).

Climate scenarios (HIST, RCP4.5, RCP8.5) and climate models (10 per RCP) introduced additional uncertainty that increased for most indicators with simulation time. This aligns with previous studies identifying climate models as a major source of uncertainty in forest simulations (Snell et al., 2018; Huber et al., 2021). Our results similarly demonstrated that climate-related uncertainty becomes increasingly relevant for certain BES indicators in long-term projections (Fig. 6). Indicator-specific assumptions, such as temperature sensitivity in deadwood decomposition models (Schumacher et al., 2006), may further explain differences in the relative importance of uncertainty sources.

Interestingly, inter-model variability contributed a larger fraction of variance than differences between climate scenarios. Although HIST represents fundamentally different climatic conditions than under future RCPs, variability among individual climate models within each RCP exceeded the variance between scenarios themselves. This finding is consistent with Djahangard et al. (2024). Consequently, the use of multi-model ensembles is essential to derive robust mean projections and capture inter-model variability (Snell et al., 2018; Djahangard et al., 2024; Yousefpour and Hanewinkel, 2016). However, ensemble averaging may suppress localized extreme events present in individual climate models (CH2018, 2018; Lindner et al., 2014). Improving climate model development and evaluation therefore remains crucial for forest models and DSS applications.

Beyond uncertainty attribution, our results indicated a general decline in BES provision under future climate scenarios, especially for C-seq and timber production (see Fig. 5). This reinforces the challenge of sustaining BES under climate change (Winkel et al., 2022; Mina et al., 2017; Thrippleton et al., 2021).

4.3. Methodological considerations

The reference forest inventory was derived from high-resolution LiDAR. DBH and tree positions were verified using point cloud density rasters and manual comparisons (see Supplementary Material S2.1). Tree species, however, could not be fully validated using manual field inventory data and were only assessed by a general expert assessment. Additional inaccuracies stemmed from the tree segmentation process, which led to missing trees, particularly in dense forest areas, due to reduced detection rates (Xiang et al., 2024) (see Supplementary Material S2.3). These inventory uncertainties propagated through the DSS pipeline and likely influenced observed sensitivity patterns. Furthermore, reference data were compared against only one low-cost ULS system (Table 1); results are therefore not directly transferable to other ULS platforms (e.g., DJI L3 or Riegl VUX120).

Several limitations also arise from the sampling design. First, the analysis was restricted to a single forest stand, so the results cannot be extrapolated to determine a minimum sample size for multiple forest stands (see Section 4.1). Second, the farthest-point sampling approach tended to select patches near stand edges, potentially introducing edge effects. Although basal area densities were adjusted for intersecting patches (see Supplementary Material S2.4), inner stand boundaries may still have contributed to underestimation of tree density. A comparison with and without the basal area adjustment showed no considerable effect on model results.

Furthermore, limitations are related to the experimental design. Replication of sampling variants provided controlled conditions but underestimated within-stand stochasticity. In a non-replicated setup, high spatial heterogeneity may delay convergence beyond the observed 70-year horizon. Additionally, for some indicators, such as species diversity, alternative ecological methods (e.g., species accumulation curves) would typically be used to address incomplete sampling. Variance component analysis results also depend on the chosen parameter space; alternative designs (e.g., inclusion of RCP2.6 or higher minimum sample sizes) may yield different variance partitioning. Finally, future work could extend the analysis to different ForClim parameterizations (Huber et al., 2018), particularly given the sensitivity of establishment processes (Huber et al., 2018; Käber et al., 2024; Díaz-Yáñez et al., 2024).

Additional uncertainty arises from utilized climate projections, model limitations and the BES indicators. While ensemble approaches address some uncertainty (Lindner et al., 2014; CH2018, 2018), they rely on assumptions that may not capture climate tipping points (e.g., van Westen et al., 2024). Moreover, ForClim v. 4.1 may overestimate drought-induced mortality (Fischer et al., 2025) and does not account for disturbances such as bark beetle outbreaks or windthrow (Marano et al., 2025). Incorporating multiple forest models (Bugmann and Seidl, 2022) and/or model versions could further broaden uncertainty assessments (Huber et al., 2020). The BES indicators are proxies derived from simulated indices for forest structure and composition, and may therefore differ from the actual provision of BES. Furthermore, their aggregation into BES groups relies on predefined weights (λ_i in Table 2), which may not reflect the true contribution of each indicator to the corresponding BES group.

4.4. Operational implications and recommendations

Increasing demands for multifunctional forest management under climate change and disturbance risks intensify the need for holistic DSSs capable of projecting forest developments (Blattert et al., 2024; Mutterer et al., 2025). However, DSS initialization introduces substantial uncertainty, particularly due to forest inventory data quality (Mina et al., 2025; Temperli et al., 2013). While previous ForClim-based studies have focused on qualitative thresholds using representative stand types (e.g., Bircher, 2015; Huber et al., 2021), this study provides a quantitative assessment of sensitivity to inventory sample size.

Our results demonstrate that the required inventory sample size depends on planning horizon and management objectives. Forest management inherently operates over long planning horizons, making explicit consideration of climate change and corresponding uncertainties at all management stages necessary. Projected declines in BES provision under severe climate scenarios for lower elevated temperate forests are consistent with recent findings (e.g., Mina et al., 2017; Thrippleton et al., 2021).

Small sample sizes or inaccurate initial data introduce an additional source of uncertainty that can obscure initialization sensitivity in decision support. This uncertainty compounds with climate-related uncertainty over time. Importantly, the interaction between these uncertainty sources has distinct temporal implications: while climate uncertainty dominates long-term projections, inventory data quality is critical for short- to medium-term planning horizons (e.g., 20–50 years), when management actions must be explicitly defined. This aligns with the perspectives of forest professionals, who identify inventory data uncertainty as one of the most critical uncertainty sources for short-term planning (de Pellegrin Llorente et al., 2023). Precise inventory data becomes especially relevant when balancing competing economic management objectives (Nahorna et al., 2024). These findings support an adaptive management approach, in which periodic re-inventorying (potentially every 10–20 years) using close-range remote sensing methods could effectively reduce initialization uncertainty in DSSs. While uncertainty in future climate trajectories cannot be eliminated, the quality of forest inventory data is a controllable factor.

Comprehensive and reliable forest inventories derived from close-range remote sensing methods therefore offer a practical means of reducing uncertainty and improving DSS reliability. However, improvements in time efficiency and labor costs are required to enable scaling to larger forest areas. Platforms such as 3Dtrees.earth offer promising solutions by enabling extraction of single-tree attributes without the need for local computational infrastructure (3Dtrees.earth, 2026). In this study, terrestrial laser scanning remained necessary to resolve complex tree structures with sufficient precision. To balance accuracy with operational efficiency, mobile laser scanning (MLS) systems based on LiDAR (e.g., Liang et al., 2016) or photogrammetry (e.g., Hristova et al., 2025) may offer scalable alternatives, combining the detailed perspective of terrestrial approaches with faster data collection.

At present, the DSS applied in this study requires further development to fully exploit the detailed information provided by close-range remote sensing. High-resolution LiDAR data enable precise estimates of tree volume (Antonarakis et al., 2011), crown extent (Irwin et al., 2025), regeneration (Witzmann et al., 2025), and fine-scale tree structure (Maeda et al., 2025). Integrating these attributes into DSS would allow more accurate assessments of current forest status and its implications for specific management decisions, such as improved representation of regeneration processes in forest simulations (Díaz-Yáñez et al., 2024), or derivation of competition indices for thinning interventions (Irwin et al., 2025; Ronoud et al., 2022). In addition, close-range remote sensing-derived metrics could support analyses of economic indicators at the single-tree level, for instance veneer standing volume (Larysch et al., 2025). As close-range remote sensing methods continue to improve in efficiency, repeated measurements will become increasingly feasible, enabling near-real-time monitoring and more robust evaluation of forest development under uncertainty.

5. Conclusion

This study demonstrated the integration of forest inventory data derived from high-resolution LiDAR into a DSS framework to assess the sensitivity of BES indicators and aggregated BES groups to inventory sample size. It provides a structured and transparent assessment of how uncertainty arising from sample size propagates through a DSS framework, quantifying the relevance of forest composition and structure for long-term BES projections under varying management strategies and climate scenarios. The results show that, for the investigated forest stand, accurate inventory data are particularly important for short-term planning under no to low management intensity. Over longer simulation periods, deviations in initial inventory data were partially compensated by model dynamics, while uncertainty arising from climate change became increasingly dominant.

Although future climate development entails unavoidable uncertainty, high-resolution LiDAR systems offer substantial potential to improve DSS initialization through more comprehensive and precise inventory data. Capturing detailed structural information at the single-tree level enables a shift from stand-level averages toward tree-level precision. Future research should therefore focus on fully leveraging high-resolution LiDAR data to extract additional information on forest composition and state, thereby strengthening decision support for long-term forest planning under profound uncertainty and increasing demands for BES provision.

CRediT authorship contribution statement

Justus Nögel: Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Clemens Blattert:** Writing – review & editing, Methodology, Data curation, Conceptualization. **Simon Mutterer:** Writing – review & editing, Writing – original draft, Methodology, Conceptualization. **Markus Karppinen:** Writing – review & editing, Software, Data curation. **Ulrike Hiltner:** Writing – review & editing, Software. **Julian Frey:** Writing – review & editing, Software. **Sunni Kanta Prasad Kushwaha:** Writing – review & editing, Data curation. **Cédric de Crousaz:** Writing – review & editing, Data curation. **Raphael Zürcher:** Writing – review & editing, Data curation. **Iga Pepek:** Writing – review & editing, Data curation. **Thomas Seifert:** Writing – review & editing, Conceptualization. **Janine Schweier:** Writing – review & editing, Supervision, Project administration, Funding acquisition, Data curation, Conceptualization.

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

During the preparation of this work the author(s) used Claude (Anthropic) in order to check grammar and spelling and to improve the clarity of the text. After using this tool, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

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Declaration of competing interest

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

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.ecoinf.2026.103896.

Data availability

The data and code supporting the sensitivity analysis are openly available on EnviDat (https://doi.org/10.16904/envidat.784). The ForClim model (v. 4.1) is openly available from the ETH Zurich Institute of Terrestrial Ecosystems (https://ites-fe.ethz.ch/openaccess/products/forclim, accessed 27 May 2026)

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