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The role of uncertain forest data in a hierarchical forest planning setting with misaligned objectives

Patrik Ulvdal[a], **Karin Öhman**[a], **Mikael Rönnqvist**[b], **Göran Ståhl**[a], **Ljusk Ola Eriksson**[c], **Lars Sängstuvall**[a], **and Tomas Lämås**[a]

[a]Department of Forest Resource Management, Swedish University of Agricultural Sciences, Umeå SE-901 83, Sweden; [b]Département de génie mécanique et de génie industriel, Université Laval, Québec, Canada; [c]Department of Southern Swedish Forest Research Center, Swedish University of Agricultural Sciences, Alnarp SE-230 53, Sweden

Corresponding author: **Patrik Ulvdal** (email: patrik.ulvdal@slu.se)

Abstract

Forest planning is vital for ensuring objective fulfilment for decision-makers. Forest-owning companies often organise their planning in a hierarchy of separate stages (i.e., strategic, tactical, and operational planning). The objectives for the strategic stage are generally to maximise net present value and long-term harvest levels without threatening the environmental integrity of the forests. However, in the subsequent stages of the planning hierarchy, with a shorter-term focus, the objective is often to minimise costs due to budgetary constraints. These misaligned objectives introduce a dilemma, especially when considering that decisions are typically made using uncertain data. We examined the suboptimality caused by using low-quality forest data in a long-term harvesting planning problem and how this suboptimality is affected by misaligned objectives between the strategic and tactical planning stages. The low-quality forest data were simulated in a Monte Carlo simulation that maintained a real-world structure of errors. The results show that uncertainty in forest data impacts objective fulfilment more than the level of alignment of objectives. However, a high degree of objective alignment performs better than the opposite, regardless of the level of quality of data.

Key words: forest management, data uncertainty, Monte Carlo simulation, objective alignment, optimisation under uncertainty

Introduction

Forest planning organises forest management activities to achieve the objectives set by a decision-maker, such as a forest-owning company (Kangas et al. 2015). In large-scale forestry, this planning is typically structured into a three-tiered hierarchy: strategic, tactical, and operational planning (Nilsson et al. 2012).

The first stage involves planning of strategic importance that impacts a company's operations in the long run (Gunn 2007). Long-term assessments, such as optimised harvest evaluations over a full rotation period are conducted to determine sustainable yield levels and typically to maximise net present value (NPV) under constraints like maintaining an even flow of timber from final fellings (Ulvdal et al. 2023) and maintaining specified environmental values. To solve the planning problem at this stage, methods based on linear and mixed-integer programming are commonly used (Rönnqvist 2003).

Subsequent tactical and operational planning stages translate strategic harvest-level objectives into fine-scale, stand-level management actions with greater temporal and spatial detail (Flisberg et al. 2014; Ulvdal et al. 2023). If these stages do not align fully with the strategic objectives, the planning might be inefficient in reaching them. Having misaligned objectives throughout different hierarchical levels of a business is not beneficial (Joshi et al. 2003). Misalignment occurs when employees disagree on what is most important for the organisation to succeed (Boyer and McDermott 1999) or when the actual actions of employees do not contribute to the fulfilment of the stated objectives (Robinson et al. 1998 as cited by Joshi et al. 2003). Misalignment can also occur when what is measured (e.g., key performance indicators) does not fit the overall objective (Zapata et al. 2016).

In practice, the tactical and operational planning stages tend to prioritise cost minimisation (instead of NPV maximisation), thus reducing expenses related to road maintenance (e.g., Church et al. 2000), harvesting operations, and machinery logistics (e.g., Epstein et al. 2007) while fulfilling the strategic harvest-level objectives (e.g., Church 2007) and additional tactical constraints such as maximum clearcut areas, the availability of machines, and meeting delivery plans for assortments to industry (Mobtaker et al. 2018; Ahmadvand et al. 2021). This focus on cost reduction can lead to "cherry-picking", where easily harvested or high-value stands are preferentially targeted, potentially accumulating more costly, challenging operations for the future (McDill

Table 1. The data and objectives used to define each case.

Case	Data quality	Objective alignment	Strategic objective	Tactical objective
1-LQ-LA	Low	Low	Max. forest NPV	Min. total cost
2-LQ-HA	Low	High	Max. forest NPV	Max. total NPV
3-HQ-LA	High	Low	Max. forest NPV	Min. total cost
4-HQ-HA	High	High	Max. forest NPV	Max. total NPV
Reference	High	Integrated	Max. total NPV (integrated)	Not applicable

Note: The cases were constructed by varying the quality of input data (low-quality, LQ; high-quality, HQ) and the degree of alignment between strategic and tactical objectives (low alignment, LA; high alignment, HA). Max. is maximum, min. is minimum, and NPV is net present value.

2014). This is one example of the effect of not aligning objectives between the strategic and tactical/operational planning stages, i.e., that decisions made on the tactical stage are not optimal considering the objective on the strategic stage.

An additional source of suboptimality arises from uncertainty in forest inventory data used to predict the future development of a forest (e.g., Pasalodos-Tato et al. 2013; Ruotsalainen et al. 2021). The impact of forest data uncertainty is often analysed by comparing the outcome of forest management decisions based on erroneous data with data from the same forest assumed to be perfect (Duvemo and Lämås 2006). Such analyses frequently show that data uncertainty results in suboptimality losses in the range of 1%–10%. In practice, forestry uses data from multiple sources to inform planning (Ulvdal et al. 2023), such as forest attribute maps (Astrup et al. 2019), own field inventory (Lindgren 1984) or subjective assessments (Ståhl 1992), and compiles the data about all their stands in a stand database. The data will also be updated with estimated growth between data collection instances (Haara and Leskinen 2009). This variation in inventory methods produces heterogeneous data quality, where the structure and size of the uncertainty differ from stand to stand and attribute to attribute, given the type of data used to describe it, thus obscuring the overall reliability of forest data (Ståhl 1992). For example, predictions based on remote sensing will tend towards the mean, resulting in local bias that differs significantly between different sources (Ulvdal et al. 2025). Uncertainty in practically used datasets poses significant challenges for forest managers, especially those reliant on decision support systems (de Pellegrin Llorente et al. 2023).

While previous research has extensively examined how data uncertainty influences economic outcomes in forestry (e.g., Sprängare 1975; Eid 2000; Holmström et al. 2003; Duvemo and Lämås 2006; Holopainen et al. 2010; Kangas 2010; Pietilä et al. 2010; Mäkinen et al. 2012; Duvemo et al. 2014), the combined effects of uncertain forest data and misaligned hierarchical objectives in forest planning remain unstudied. Therefore, this study aims to address this gap by exploring the suboptimality of using low-quality forest data in a long-term harvesting planning problem and how this suboptimality is affected by misaligned objectives between the strategic and tactical planning stages. We hypothesise that combining uncertain data with misaligned objectives will perform worse than using either uncertain data or having misaligned objectives alone.

Materials and methods

Optimisation framework

We developed a two-phase optimisation model to investigate the effects of uncertainty in data combined with misaligned planning objectives. Mimicking a real-world planning process for a boreal industrial forest owner, the model emulated the strategic and tactical phases customary in forest planning. In the strategic phase, the model decided long-term harvest levels by maximising NPV over a 100-year planning horizon, subject to constraints ensuring non-declining harvest levels and compliance with legal and certification requirements (eqs. 1–17 in the optimisation model presented below). In the tactical phase of the model, management actions for individual stands were determined so that the harvest levels decided in the strategic phase were met. The tactical phase was solved using a rolling time horizon over five 20-year periods, with decisions made iteratively, subject to the restriction that decisions about forest management in later periods were consistent with those already made for earlier periods. This means that if the model decides that a certain stand should be thinned in year 8 (within the first 20-year period), the model will also be forced to decide to thin the stand in year 8 when management is decided for the second 20-year period, even if it could be more optimal to something else when 40 years of data are revealed instead of 20.

Four distinct planning cases were constructed (Table 1) by varying the quality of input data (low-quality, LQ; high-quality, HQ) and the degree of alignment between strategic and tactical objectives (low alignment, LA; high alignment, HA). These cases were compared to an integrated reference case that assumed perfect data and simultaneous decision-making of both harvest levels and management in individual stands without separate phases. The comparison was done by transferring the final tactical decisions for each case to the reference case model, thus calculating the objective function value for those decisions based on the reference model. The results from these evaluations were then compared with the solution of the reference case.

The low-quality data in the LQ cases were represented by discrete scenarios that describe uncertainty in the data about the initial state of the forest. How these scenarios were simulated is presented below.

In the strategic phases, all cases maximised NPV from forest management. For the tactical phases, objectives were either aligned with the corresponding strategic phase (max-

Table 2. The value for parameters α, γ, δ, the set of scenarios (*S*), and the set of periods (*P*) used for the different cases and phases in the optimisation model (eqs. 1–17).

Case	Phase	α	γ	δ	S	P
1-LQ-LA	Strategic	1	0	0	{1.100}	{0.20}
	Tactical	0	1	1	{1.100}	{0.5}, {0.10}, {0.15}, {0.20}
2-LQ-HA	Strategic	1	0	0	{1.100}	{0.20}
	Tactical	1	1	0	{1.100}	{0.5}, {0.10}, {0.15}, {0.20}
3-HQ-LA	Strategic	1	0	0	{0}	{0.20}
	Tactical	0	1	1	{0}	{0.5}, {0.10}, {0.15}, {0.20}
4-HQ-HA	Strategic	1	0	0	{0}	{0.20}
	Tactical	1	1	0	{0}	{0.5}, {0.10}, {0.15}, {0.20}
Reference	Integrated	1	1	0	{0}	{0.20}

Note: LQ is low-quality data, HQ is high-quality data, LA is low degree of objective alignment, and HA is high degree of objective alignment. See Table 1 for a description of the cases.

imising NPV, including discounted accessing costs) or misaligned (minimising total undiscounted costs from forest management and accessing harvest areas). The cost of accessing harvest areas was the primary tactical component of the optimisation model. It represented the cost of transporting harvest machinery between sites and increased the effort required by the model to cluster harvests geographically. The reason for using undiscounted costs in the misaligned cases was to more closely mimic the actions of forest managers in practice, which tend to minimise the cost each year (i.e., with no discounting). Irrespective of the tactical objective, the tactical phase enforced adherence to strategic harvest targets.

The optimisation model is presented equation-wise below. Note that the exact configuration of the model depended on the planning phase, data quality, and objective considered (see Table 2). The configuration was decided by certain parameters that take values depending on which case the model is used for.

$$\text{(1)}\quad \textit{maximise}\ Z = \alpha\sum_{s\in S}\sum_{i\in I}\sum_{j\in J_i} n_{sij}a_i x_{sij} - \alpha\gamma\sum_{s\in S}\sum_{p\in P} \times \sum_{h\in H}\sum_{k\in K}\frac{z_{sphk}b}{(1+d)^{5p-2.5}} - \gamma\delta\sum_{s\in S}\sum_{p\in P}\sum_{h\in H}\sum_{k\in K} z_{sphk}b - \gamma\delta\sum_{s\in S}\sum_{i\in I}\sum_{j\in J_i}\sum_{p\in P} a_i x_{sij}c_{sijp} - \sum_{s\in S}\sum_{p\in P}\sum_{r\in R} e_r\beta_{rsp}$$

Equation 1 is the objective function that maximises the NPV and/or minimises costs. The first term in eq. 1 is the total NPV from forest management and is active in the integrated case and all strategic phases of the other cases. The second term concerns the NPV of accessing costs and is active in the integrated case and the tactical phases of the HA cases. The third term considers the undiscounted accessing costs and is active in the tactical phases of the LA cases. The fourth term considers the undiscounted forest management costs and is active in the tactical phases of the LA cases. The fifth term is the sum of penalties for deviating from restrictions. It is active in all cases and phases. The parameters α, γ, and δ take the value 1 or 0 depending on which case the model is supposed to be used on (Table 2).

The sets defined in eq. 1 are the discrete uncertainty scenarios (*S*), stands (*I*), treatment programmes (TPs) for each stand (J_i), periods (*P*), harvest areas (*H*), harvesting machine systems (*K*), and restrictions (*R*). A TP is a fixed sequence of management activities spanning the whole planning horizon; thus, the model adheres to the model 1 formulation (Johnson and Scheurman 1977). The set of scenarios also differs between cases. For cases based on low-quality data, *S* contains simulated error scenarios 1–100; for cases based on high-quality data, *S* contains only scenario 0. Also, the set of periods changes, but it depends on the phase. For strategic phases, it contains all periods; for tactical phases, the first iteration only covers the first four periods (20 years). For each iteration, four more periods become available, while the management in the earlier periods is locked. The set harvest machines includes two machine types: thinning and final felling.

The main decision variable is x_{sij}, i.e., the proportion of stand *i* that in scenario *s* should be assigned TP *j*. The variable z_{sphk} is binary and takes the value 1 if the machine system *k* is used in scenario *s*, period *p*, and harvest area *h*, otherwise 0 (see eqs. 4, 7, 8, and 9). The variable β_{rsp} is the deviation from restriction *r* for scenario *s* and period *p*.

n_{sij} is a parameter that contains NPV for scenario *s*, stand *i*, TP *j*; a_i is the area of stand *i*; *b* is the accessing cost (50,000 SEK) per harvest area and period; *d* is the interest rate used for discounting; c_{sijp} is the cost of all management done in stand *i*, according to TP *j*, in scenario *s* and period *p* and; e_r is the cost of deviating one unit from restriction *r*. e_r for $r = \{2, 7\}$ is 500 SEK m^{-3} (approximately corresponding to the market price of wood in Sweden (Swedish Forest Agency 2025*a*)) and 1,000 SEK ha^{-1} (subjectively set after initial testing).

The objective function is subjected to the following restrictions (eqs. 2–17).

$$\text{(2)}\quad 0 \le x_{sij} \le 1 \qquad \forall s\in S, \forall i\in I, \forall j\in J_i$$

Equation 2 states that x_{sij} is a continuous variable between 0 and 1.

$$\text{(3)}\quad z_{sphk} \in \{0,1\} \qquad \forall s\in S, \forall p\in P, \forall h\in H, \forall k\in K$$

Equation 3 states that z_{sphk} is a binary variable.

$$\beta_{rsp} \geq 0 \quad \forall r \in R, \forall s \in S, \forall p \in P \tag{4}$$

Equation 4 states that β_{rsp} is a continuous variable larger or equal to 0.

$$y_{slp} \in \{0, 1\} \quad \forall s \in S, \forall l \in L, \forall p \in P \tag{5}$$

Equation 5 states that y_{slp} is a binary variable. y_{slp} helps in the calculation (see eqs. 8–10) of the allowable annual harvest area decided by Swedish law (12 a § SFS 2014:1027 Skogsvårdsförordningen n.d.). L is the set of area classes defined by Swedish law regarding the proportion of the forest that is older than a theoretical rotation age (see eqs. 8–10).

$$\sum_{j \in J_i} x_{sij} = 1 \quad \forall s \in S, \forall i \in I \tag{6}$$

Equation 6 ensures that the proportions of assigned TPs in each stand sum to 1.

$$\sum_{j \in J_i} f_{ij} x_{sij} \geq 0.1 \quad \forall s \in S, \forall i \in I \tag{7}$$

Equation 7 ensures that at least 10% of the area in each stand is set aside, which is in line with the actual level of area left as set-asides in harvests in Sweden (Swedish Forest Agency 2025*b*). Ti. f_{ij} is 1 in stand i with TP j if the stand is unmanaged in all periods, otherwise 0.

$$\sum_{l \in L} y_{slp} = 1 \quad \forall s \in S, \forall p \in P \tag{8}$$

Equation 8, together with eq. 5, makes sure that only one area class is used in eqs. 9–10 by forcing the sum of y_{slp} to be equal to 1 in each period and scenario.

$$\sum_{i \in I} \sum_{j \in J_i} g_{ijp} a_i x_{sij} \leq 5 \sum_{l \in L} m_s o_l y_{slp} \sum_{i \in I} a_i \quad \forall s \in S, \forall p \in P \setminus \{p_0\} \tag{9}$$

Equation 9 ensures that the final felled area does not exceed the largest allowable area according to Swedish law in all periods and scenarios. g_{ijp} is 1 in stand i with TP j if the stand is subjected to clear cut in period p, otherwise 0; m_s is an area factor from Swedish law, taking the value 0.014 in scenario s if the average site productivity of the forest holding is larger than 8 m^3 ha^{-1} year^{-1}, 0.011 if it is between 8 and 4 m^3 ha^{-1} year^{-1}, otherwise 0.009; and o_l is a correction factor from Swedish law, taking the value 1.4 for $l = 1$, 1.8 for $l = 2$, 2.2 for $l = 3$, 2.8 for $l = 4$. Note that the number 5 in eq. 9 transforms this annual value into a periodic total. p_0 is the first period in P.

$$y_{slp} t_l \sum_{i \in I} a_i \leq \sum_{i \in I} \sum_{j \in J_i} u_{sijp} a_i x_{sij} + \beta_{rsp} \quad \forall s \in S, \forall p \in P \setminus \{p_0\}, \ \forall l \in L, \ r = 1 \tag{10}$$

Equation 10 calculates y_{slp} for a given area proportion of forests older than a theoretical rotation age. t_l is an area class proportion from Swedish law taking the value 0 for $l = 1$, 0.26 for $l = 2$, 0.51 for $l = 3$, 0.76 for $l = 4$; u_{sijp} takes the value 1 in scenario s, in stand i with TP 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^3 ha^{-1} year^{-1}, 90 years if it is between 8 and 4 m^3 ha^{-1} year^{-1}, otherwise 110 years.

$$\sum_{i \in I} \sum_{j \in J_i} v_{sijp} a_i x_{sij} + \beta_{rsp} \geq \sum_{i \in I} \sum_{j \in J_i} v_{sij(p-1)} a_i x_{sij} \quad \forall s \in S, \forall p \in P \setminus \{p_0\}, r = 2 \tag{11}$$

Equation 11 enforces a non-declining harvest from final fellings in all periods and scenarios. v_{sijp} is the harvested volume from final fellings per hectare in scenario s, in stand i with TP j in period p.

Equations 12–14 are restrictions related to the FSC standard (FSC 2020).

$$\sum_{i \in I} \sum_{j \in J_i} w_{sijp} a_i x_{sij} \leq 0.5 \sum_{i \in I} a_i + \beta_{rsp} \quad \forall s \in S, \forall p \in P \setminus \{p_0\}, r = 3 \tag{12}$$

Equation 12 forces the area of forests under the age of 20 years to be less than 50% of the total area in all periods and scenarios (as stipulated by Swedish law). w_{sijp} is 1 in scenario s, in stand i with TP j in period p, if the age of the stand is <20 years, otherwise 0.

$$\sum_{i \in I} \sum_{j \in J_i} \varepsilon_{rsijp} a_i x_{sij} + \beta_{rsp} \geq \rho_r \sum_{i \in I} a_i \quad \forall s \in S, \forall p \in P \setminus \{p_0\}, r = \{4, 5\} \tag{13}$$

Equation 13 is a combined restriction that for $r = 4$ makes sure that all stands have a proportion of broadleaf trees higher than 10% in all periods and scenarios, and for $r = 5$ makes sure that the area of old forest makes up at least 2% of the total forest area in all periods and scenarios. ε_{rsijp} is 1 in scenario s, in stand i with TP j in period p for $r = 4$ if the proportion of broadleaf stems is higher than 0.1, otherwise 0, ε_{rsijp} is 1 in scenario s, in stand i with TP j in period p for $r = 5$ if the stand is older than 140, otherwise 0, ρ_r takes the value 1 for $r = 4$ and 0.02 for $r = 5$.

$$\sum_{i \in I} \sum_{j \in J_i} \sigma_{sijp} a_i x_{sij} + \beta_{rsp} \geq 0.05 \sum_{i \in I} a_i \varphi_i \quad \forall s \in S, \forall p \in P \setminus \{p_0\}, r = 6 \tag{14}$$

Equation 14 ensures that the area of broadleaf forest on mesic to moist soils makes up at least 5% of the total mesic to moist forest area. σ_{sijp} is 1 in scenario s, in stand i with TP j in period p if the stand is dominated by broadleaf trees and the soil is mesic to moist but not wet, otherwise 0 and φ_i is 1 in stand i if the soil in the stand is mesic to moist but not

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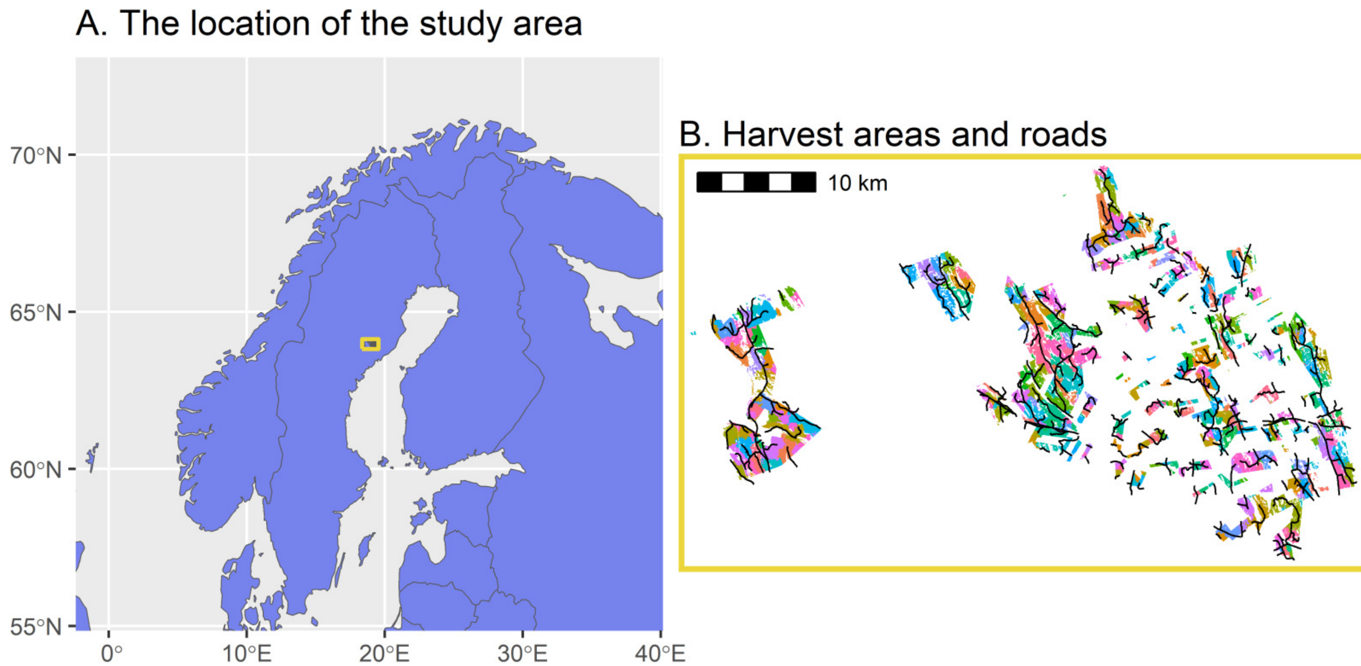
Fig. 1. Panel A: the location of the study area in northern Sweden, indicated by the yellow box. Panel B: an overview of the study area with the segments of road network (black lines) adjacent to stands and harvest areas (coloured polygons). The orange box in panel B corresponds to the orange box in panel A. The coloured polygons also show the extent of the productive forests included in the study. Map projection: plate carrée; Datum: WGS84; Sources: Country borders © naturalearthdata.com, Road map © Lantmäteriet, Stand map © Holmen Skog AB.



wet, otherwise 0.

$$\gamma \sum_{i \in I_h} \sum_{j \in J_i} \tau_{ijpk} x_{sij} \le M z_{sphk} \quad \forall s \in S, \forall p \in P, \ \forall h \in H, \ \forall k \in K \tag{15}$$

Equation 15 ensures that z_{sphk} take the value 1 if any harvest machine k is used in harvest area h according to x_{sij}. I_h is the set of stands belonging to harvest area h. τ_{ijpk} takes the value 1 if machine system k is used in stand i according to alternative j in period p and scenario s. The machine system is defined by whether the harvest is thinning or final felling. M is an arbitrarily large number that ensures that z_{sphk} takes the correct value. γ is only equal to 1 if the model is in the tactical phase (see Table 2).

$$\gamma = 1 \rightarrow \sum_{i \in I} \sum_{j \in J_i} v_{sijp} a_i x_{sij} = \vartheta_{sp} + \beta_{rsp} \quad \forall s \in S, \forall p \in P, r = 7 \tag{16}$$

Equation 16 ensures that the harvest levels from final fellings in the tactical phase match the corresponding harvest levels of the strategic phase. It is only active if $\gamma = 1$, i.e., if the model is in its tactical phase. ϑ_{sp} is the target levels from the strategic phase for final fellings in scenario s and period p. γ is only equal to 1 if the model is in the tactical phase (see Table 2).

$$\sum_{i \in I} \sum_{j \in J_i} \mu_{sijp} a_i x_{sij} = 0 + \beta_{rsp} \qquad \forall s \in S, \forall p \in P, r = 8 \tag{17}$$

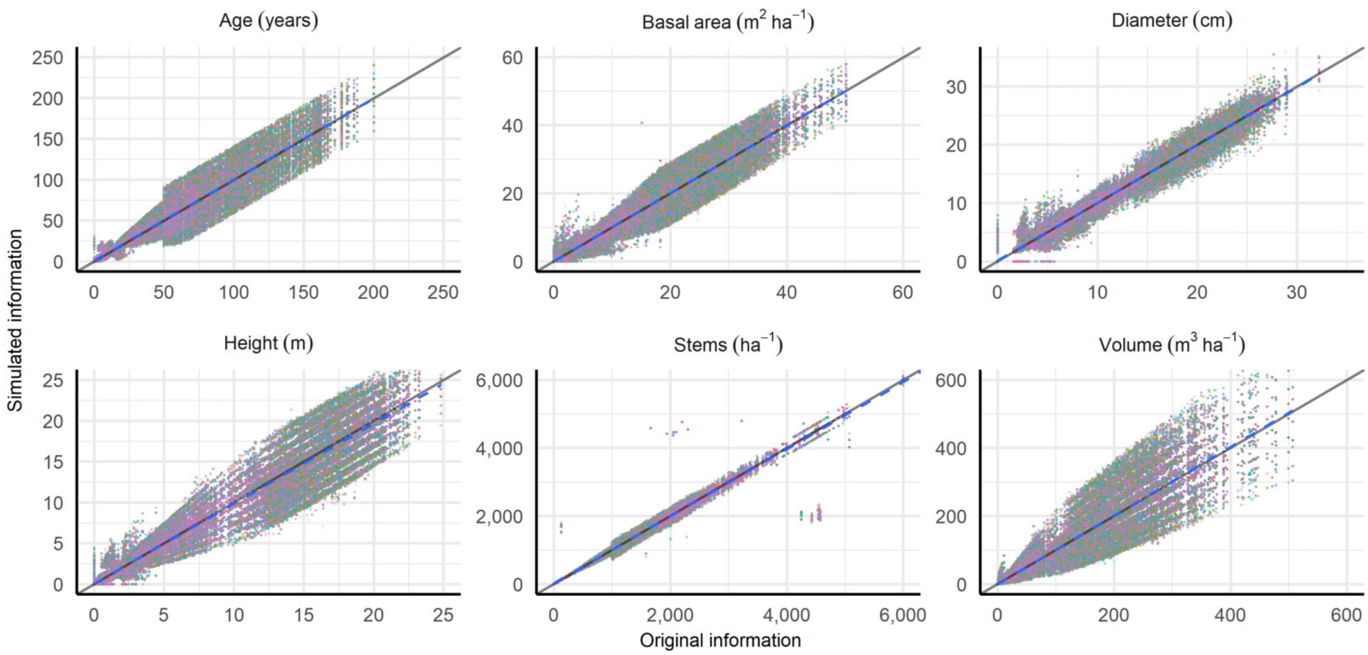
Equation 17 ensures that illegal harvests in stands that have not reached the legal age limit are not conducted. μ_{sijp} takes the value 1 if a final felling is conducted in stand i according to TP j in scenario s and period p and the age of that stand is lower than the lowest legal final age.

Study area and original forest data

The optimisation model was applied to a forest holding owned by an industrial forest company. The study area was located in northern Sweden and had a total area of 23,952 ha of productive forest land (see Fig. 1 for an overview of the holding's location and spatial configuration). We acquired a map and data about all 3,087 stands in the holding from the forest owner in the form of a forest stand database. The average standing volume in the forest was 102 m^3 ha^{-1}, consisting of 56% *Pinus sylvestris* L., 23% *Picea abies* (L.) H. Karst., 14% *Betula* spp. L., and 7% *Pinus contorta* Douglas ex Loudon. The mean stand age was 43 years.

The data about individual stands was collected by the forest owner using various methods over a long period of time. The oldest data were from the 1960s, primarily from manual interpretation of aerial photographs. However, most stands were inventoried with purposive methods in the field in the 1990s, i.e., quick and rough ocular estimates based on the surveyor's earlier experience. Since then, the data have been updated annually using simple growth models based on the forest management performed in each stand. After final felling, for example, the stand attributes were set to zero. In the years preceding this study, some stand attributes were updated

Fig. 2. The simulated attributes (average tree diameter, average tree height, number of stems, stand basal area, stand age, and site index) are shown with each point representing one realised value in a stand in one scenario. The colours represent each of the 100 simulated scenarios. The dashed blue line shows the linear relationship between the original and simulated data. The black line is the 1:1 line.



with predictions made with airborne laser scanning. Whatever the source of a stand's data, since the stand database has been in continuous operational use, individual forest officers could have made subjective changes to the data whenever they had a reason to do so. These changes were not tracked. This status of the data are a fair representation of similar forest stand databases in general (Ståhl 1992).

Simulation of low-quality forest data as uncertainty scenarios

To incorporate the effect of data uncertainty into our analyses, we performed a Monte Carlo simulation based on Cholesky-factorisation to produce 100 versions of our stand data representing 100 uncertain realisations (scenarios) of the forest stand database. The goal of the Monte Carlo procedure was to re-create the real-world multivariate error structure in the simulated values (Tucker 1962; Ross 2013). This methodology has been used in earlier studies (e.g., Holmström et al. 2003; Duvemo et al. 2014).

In summary, we examined how errors between the data in the stand database and reference data from an objective field inventory for a subset of stands covaried for the attributes average tree diameter (cm), average tree height (m), number of stems (ha^{-1}), stand basal area (m^2 ha^{-1}), stand age (years), and site index (m).

The reference data were collected in 2019 as standwise field plot inventories, following established protocols (Jonsson et al. 1993). Based on auxiliary data from the stand database, a two-phase sampling procedure was conducted. In the first phase, a stratified random sample of stands (541 in total) was selected. Stratification was achieved by clustering stands into classes based on standing volume per hectare and stand age. The survey of the sampled stands was conducted on a systematic grid of circular field plots. On these plots, individual tree information and stand properties were recorded (Lindgren 1984, 2000). For plots with average tree height above 4 m, all trees larger than 4 cm in diameter at breast height were calipered for diameter, and tree species were identified. A random number of trees was height-measured and age-determined by counting annual rings. On other plots, only main stems were height-measured. Each plot underwent detailed site characterisation, including descriptions of vegetation, climate, soil, terrain, and natural values. Averages for each stand were calculated across the plots and used to calculate covariances with the stand database data.

With these covariances as the basis, we simulated new populations of errors that maintained the same structure, in terms of average size, spread, and correlation, as the original error population. The simulated errors for any stand can be viewed as independent realisations of normally distributed and correlated error vectors for the included attributes. The original forest data (scenario 0) were considered to represent the accurate and error-free state of the forest. The results of the data simulation, compared to the original data are presented in Fig. 2. For more details about the data simulation, refer to Appendix A.

Assignment of stands to harvest areas by calculating shortest paths

To integrate spatial transport costs into the tactical model (eq. 15), each stand was allocated to a harvest area defined by proximity to the forest road network. All stands linked to one

Table 3. Relative weights representing the traversability of forest machines in different land-use types used in the cost-raster.

Land-use or characteristics	Weight (cost)
Buildings	255
Farmland	5
Nature conservation site	100
Power line	50
Railway tracks	255
Slope, under 6°	1
Slope, between 6° and 11°	2
Slope, between 11° and 18°	3
Slope, between 18° and 27°	25
Slope, over 27°	50
Wetlands, dryer	10
Wetlands, wetter	20
Forest land and roads	1
Open water and large streams	255
Small streams	50

Note: The weights were used to calculate the shortest terrain transport distance.

and the same road segment made up a specific harvest area. Road segments were delineated by splitting the network at intersections, limiting segment lengths to 1,000 m, and excluding segments shorter than 100 m.

Stands were assigned to the nearest road segment. Since a straight line from the stand to the nearest road would not result in realistic harvest areas, a simple heuristic was created to better mimic how forest machines traverse through terrain. A $5 \times 5\,\text{m}^2$ raster grid was generated based on openly available terrain data, where each grid cell was assigned a value depending on its characteristics from the terrain data. The values (Table 3) were assigned based on experiences from similar work (Färnstrand 2013) and initial testing to achieve probable terrain transportation paths. The terrain transportation paths were calculated using a shortest-path analysis with the raster grid as the cost raster, i.e., the shortest path from each stand to the nearest road that achieved the minimum total cost. Input datasets, including road networks, digital terrain models, and land-use classifications, were obtained from Lantmäteriet (The Swedish Mapping, Cadastral and Land Registration Authority). See Fig. 1, panel B and Fig. 3 for maps showing the aggregation of stands in harvest areas.

Generating treatment programs and forest development data for the optimisation model

Potential TPs for each stand were generated using the decision support system Heureka PlanWise, which contains models describing growth, mortality, and management of forest stands (Lämås et al. 2023). The generation assumed a certified commercial rotation forestry under even-aged management and intensive silviculture. Typically, final felling occurred when stands reached 65–100 years of age, followed by replanting with approximately 2,500 planted seedlings per hectare and subsequent cleaning and thinning operations. The forest management NPV for each TP was computed using a real interest rate of 3%, incorporating revenues from timber sales and costs from both harvest and silvicultural operations. On average, 13 TPs were generated per stand based on the original data. The treatment activities from these TPs were then re-applied to each simulated scenario, thus calculating what would happen if the treatments according to the original data were conducted on the forests described by simulated data.

Data processing

The optimisation model was solved using mixed-integer programming with a traditional branch and bound algorithm and a relative gap tolerance of 1% (Land and Doig 1960). All formulations and computations were performed with CPLEX Optimization Studio 22.1.1 on a workstation equipped with a 12-core 3.5 GHz Intel i9-10920X processor and 256 GB of RAM. Spatial computations were executed using FME and ArcGIS, while all further data processing and analyses were conducted in R (v4.4.1).

Results

The 4-HQ-HA case, i.e., the case with high data quality and high degree of objective alignment, achieved the highest objective function value (Z), followed by 3-HQ-LA, 2-LQ-HA, and 1-LQ-LA (Table 4). The ranking for area and volume penalties followed the same order as the ranking of Z. i.e., the 4-HQ-HA performed best followed by 3-HQ-LA and so on. The accessing costs were, however, lowest for the non-aligning cases, which explicitly minimised costs. Both forest management NPV and NPV including accessing costs for harvest areas, were higher for 4-HQ-HA than the reference case. The spread of forest management NPV was higher in 1-LQ-LA than in 2-LQ-HA (Fig. 4). For total NPV, the order was the opposite, i.e., 2-LQ-HA had a larger spread.

All cases' final felling harvest levels were generally quite similar to the reference case. Differences were most pronounced during the first 20 years, when levels were higher than the reference, and during years 20–40, when levels were lower (Fig. 5). During the later parts of the planning horizon, the harvest levels were somewhat higher in the uncertainty cases.

The optimisation model included constraints that aimed to fulfil certain area proportions of various forest types. An example of such a constraint was that all stands should have at least 10% broadleaf trees. In our cases, this target was almost reached in the reference case but not in the others (Fig. 6).

Additional figures for results for other indicators are presented in Appendix B.

Discussion

Our findings demonstrate that misaligned objectives and uncertainty in forest data impact the result of long-term forest planning. In comparing the reference case to other cases, the large variation in the objective function value Z (Table 4) confirms that planning with high-quality data and without a hierarchical separation of decision stages, or

Fig. 3. Panel A: Stands (delineated by thin black lines) grouped into harvest areas (coloured polygons) depending on the nearest road segment (thick black lines). Distance to the nearest road was calculated from the stand centroid over a cost raster. Panel B: The cost raster (background), where light yellow is easily traversable, and dark red is not as easily traversable. The shortest terrain transport distances are the grey dashed lines (from stand centroids to the nearest road). Map projection: plate carrée; Datum: WGS84; Sources: Road map © Lantmäteriet, Stand map © Holmen Skog AB.

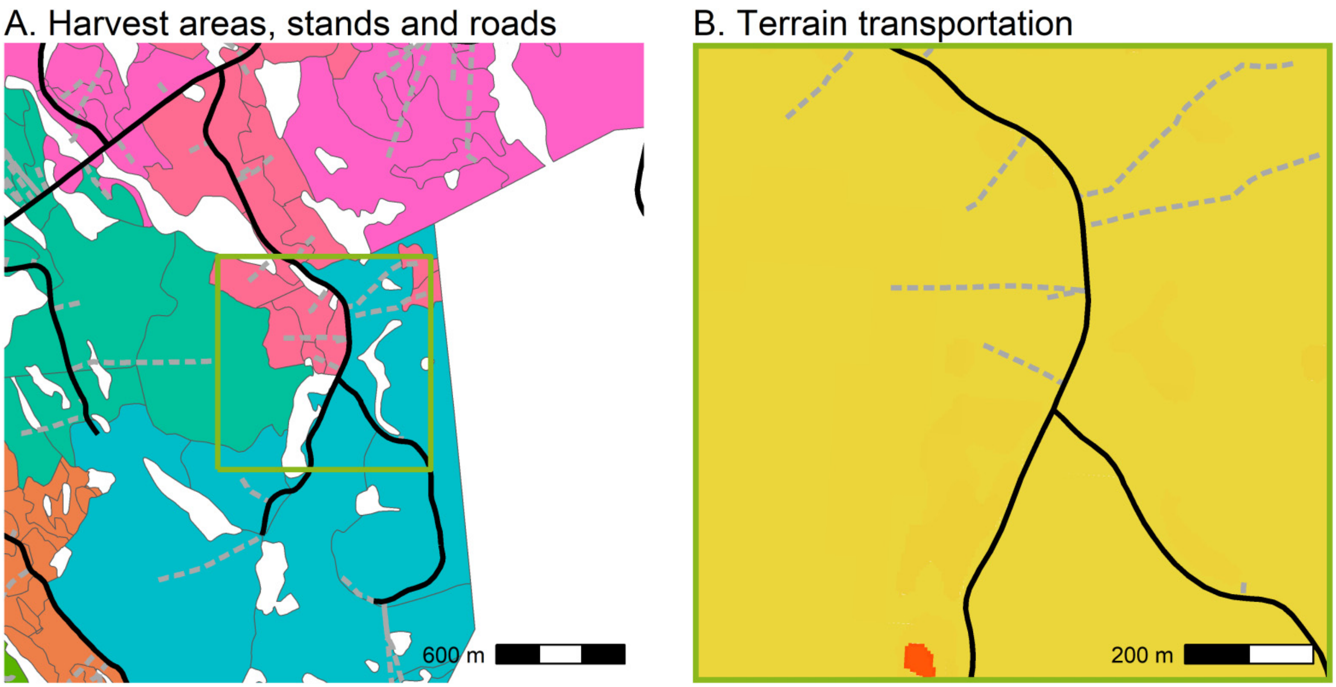


Table 4. The objective function value (Z) and its components for all cases.

Case	Z (ha^{-1})		Forest NPV (SEK ha^{-1})		Disc. accessing costs (SEK ha^{-1})		Total NPV (SEK ha^{-1})		Area penalty (SEK ha^{-1})		Volume penalty (SEK m^3)
1-LQ-LA	5,640	(−36.6%)	15,522	(−1.4%)	1,721	(+0.2%)	13,801	(−1.6%)	6,463	(+26.0%)	1,698
2-LQ-HA	6,096	(−31.5%)	15,728	(−0.1%)	1,832	(+6.6%)	13,896	(−0.9%)	6,272	(+23.3%)	1,527
3-HQ-LA	7,675	(−13.7%)	15,713	(−0.2%)	1,723	(+0.3%)	13,990	(−0.3%)	6,315	(+23.1%)	0
4-HQ-HA	8,125	(−8.7%)	15,952	(+1.3%)	1,796	(+4.5%)	14,156	(+0.9%)	6,031	(+17.6%)	0
Reference	8,898		15,746		1,718		14,028		5,129		0

Note: Forest NPV is NPV from forest management. Disc. is discounted. Total NPV is the NPV from both forest management and harvest area accessing costs. The area penalty is the cost of all area missing due to area-based restrictions. The volume penalty is the cost due to volume-based restrictions. LQ is low-quality data, HQ is high-quality data, LA is low degree of objective alignment, and HA is high degree of objective alignment. The percentages are relative changes compared to the reference. See Table 1 for a description of the cases.

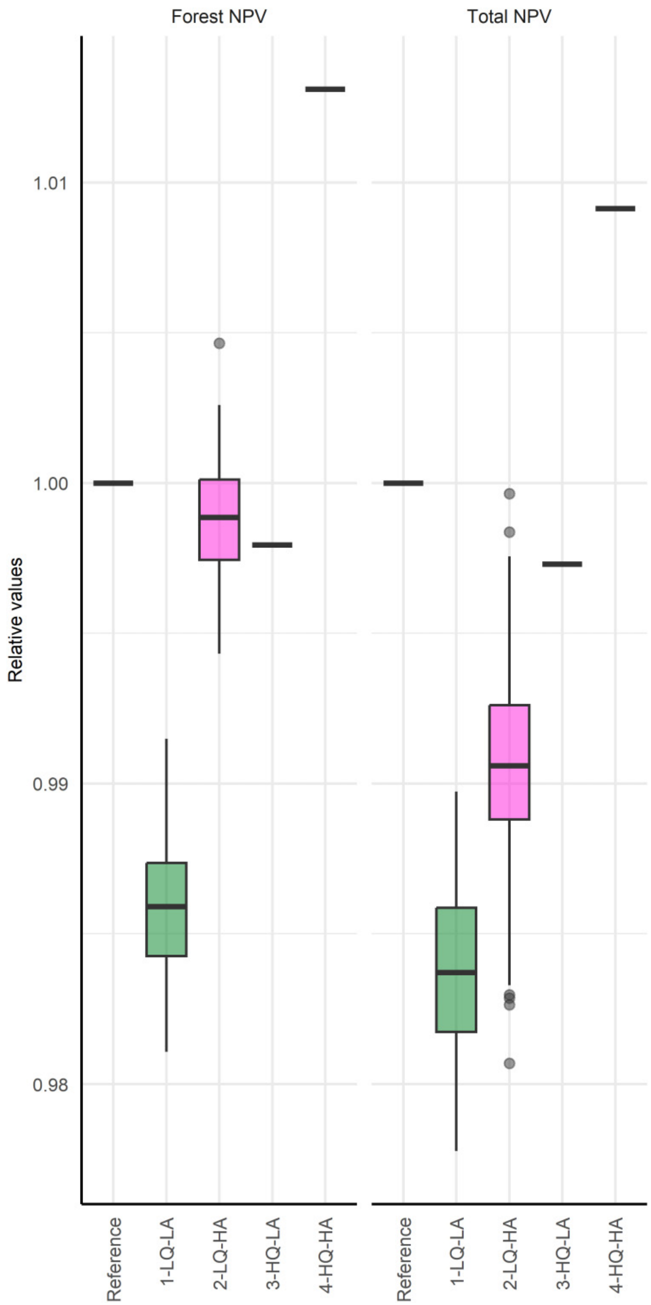
at least maintaining the same objective between planning stages, yields superior overall performance. Although the integrated method produced the best overall objective function value (Z), the 4-HQ-HA case achieved a higher NPV. This divergence likely arises from two factors. First, the inclusion of area and volume penalty components in the objective function may shift the balance in favour of NPV and associated access costs under certain conditions; the markedly lower area penalty in the reference case supports this interpretation. Second, the 1% mixed-integer programming gap tolerance used in our analyses had the same magnitude as the observed NPV differences, potentially masking some trade-offs.

Consistent with our expectations, cases that employed high-quality data and aligned objectives outperformed those using lower-quality data and misaligned objectives. This finding reinforces the broader body of evidence on the value of data in managing uncertainty (e.g., Duvemo et al. 2014; Eyvindson and Kangas 2014; Eyvindson and Cheng 2016; Nahorna et al. 2024). In practice, given that some uncertainty is inevitable in practically available data, ensuring alignment within the planning hierarchy is a critical step towards improving forest planning results.

While our model incorporated aspects of road maintenance, machinery transport, and machine availability indirectly via harvest area access costs, future research could benefit from an explicit representation of these tactical elements (Church et al. 2000; Epstein et al. 2007; Mobtaker et al. 2018; Ahmadvand et al. 2021). Such an approach might reveal even greater impacts of misaligned objectives, particularly where tactical decisions play a significant role.

The number of uncertainty scenarios was 100, which should be sufficient to describe normally distributed random

Fig. 4. The relative net present value (NPV) from forest management (forest NPV) and NPV including accessing costs (total NPV) for the cases independendtly compared to the reference case (1). The horizontal bars show the median. The boxes and whiskers show the spread of the cases with uncertainty. The points are extreme values. See Table 1 for a description of the cases.



errors for the set of attributes included in the study. One hundred scenarios are well within the suggested scenario set size for similar cases (Eyvindson and Kangas 2016). Anyhow, uncertainties other than initial forest data uncertainty, for example, the variance of growth models, should be included in future studies.

The objectives we say are misaligned could be seen as two sides of the same coin. Minimising costs in the tactical phase,

Fig. 5. The average final felling harvest levels over the planning horizon for the different cases. Case 1-LQ-LA is the brown line and area on the bottom right. Case 2-LQ-HA is purple line and area on the bottom left. Case 3-HQ-LA is green line on the top right. Case 4-HQ-HA is the red line on the top left. The reference case is the grey line present in all panels. See Table 1 for a description of the cases.

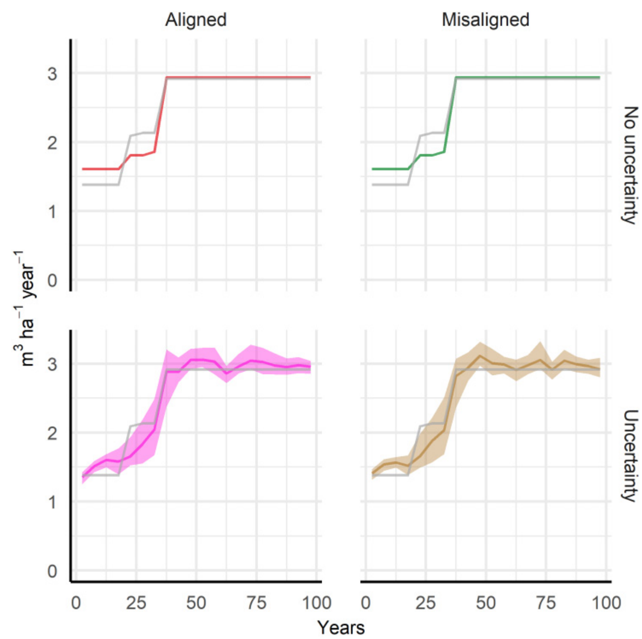
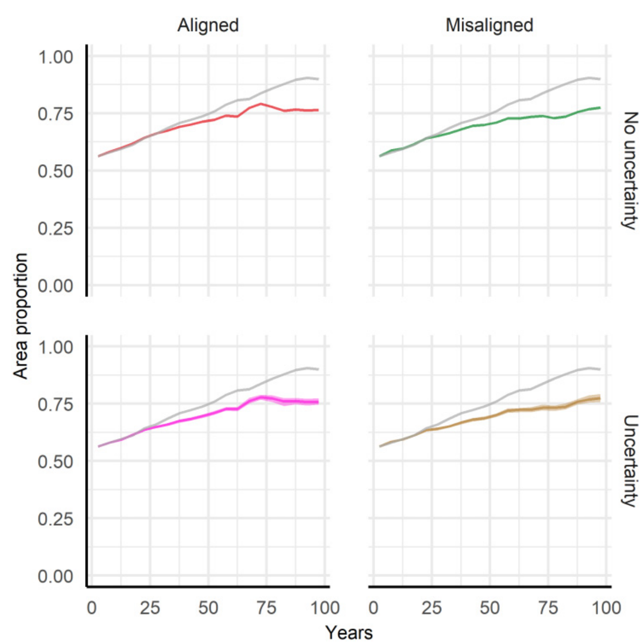


Fig. 6. The area proportion of stands with >10% broadleaf trees over the planning horizon for the different cases. Case 1-LQ-LA is the brown line and area on the bottom right. Case 2-LQ-HA is purple line and area on the bottom left. Case 3-HQ-LA is green line on the top right. Case 4-HQ-HA is the red line on the top left. The reference case is the grey line present in all panels. See Table 1 for a description of the cases.



given the restriction of reaching the harvest levels decided in the strategic phase by maximising NPV, could yield similar results as maximising NPV in the first place. Minimising costs and maximising NPV do not contradict each other as much as some other potential objectives, e.g., planning for considerations of biodiversity values. Another aspect that could make the misaligned objectives more different is if the scope of the objective were to change completely. If other utilities from forests, such as CO_2 emissions (e.g., Raymer et al. 2009), biodiversity values (e.g., Marshalek et al. 2014) or recreational values (e.g., Pukkala et al. 1995), had been included in our objective function, the differences could have been even larger. For example, concerns about biodiversity have a strong trade-off against the financial value of forestry (Eggers et al. 2022). Thus, having financial value as the strategic objective and biodiversity value as the tactical objective would probably increase supoptimality drastically.

Lastly, our analysis shows that the penalties associated with the area restrictions, like having 10% broadleaf trees in all stands (Fig. 6), comprised a significant share of the objective function. This shows that much of the results come down to the weights and costs of the objective function. Although the cost of missed harvested volume (500 SEK m^{-3}) aligns with current market conditions in Sweden (Swedish Forest Agency 2025*a*), the subjectively set values for missing area (1,000 SEK ha^{-1}) and harvest area access cost (50,000 SEK per period) likely influenced the results. It is reasonable to believe that different decision-makers with different subjective values on the costs of deviating from restrictions would assign different costs.

Conclusions

Ultimately, our results underscore that hierarchical planning procedures can incur significant losses in optimal objective function value and achieve non-optimal harvest levels relative to integrated approaches, particularly when affected by uncertain data and misaligned planning objectives. Our recommendation to a decision-maker involved in real-world decisions, for whom the theoretical comparison of objective function values (Z) between cases might be less important than the confidence in the plan, is to strive towards using higher-quality data in planning. However, if that would decrease the value of information due to high inventory costs, it is also the case that efforts to align objectives are efforts well spent.

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Data availability

Data generated or analysed during this study are not available since the data belongs to a third party (Holmen Skog AB) and may have financial implications. However, the data processing scripts (in R) are available from the corresponding author upon reasonable request.

Author information

Author ORCIDs

Patrik Ulvdal https://orcid.org/0000-0002-7755-9406

Author notes

Present adress for Lars Sängstuvall is Bergvik Skog Öst AB, Gävle, SE-801 39, Sweden.

Author contributions

Conceptualization: PU, KÖ, LOE, TL
Data curation: PU
Formal analysis: PU, KÖ, MR, GS, LOE, LS, TL
Funding acquisition: KÖ, TL
Methodology: PU, MR, LS, TL
Project administration: PU
Software: PU, LS
Supervision: KÖ, TL
Visualization: PU
Writing – original draft: PU
Writing – review & editing: PU, KÖ, MR, GS, LOE, LS, TL

Competing interests

During the work with this study, Patrik Ulvdal was affiliated part-time with Holmen Skog AB, the company that provided data and our problem formulation. Holmen also funded part of the study. The other authors declare no competing interests.

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Appendix A: Simulation of uncertain data

We generated multiple simulated populations of forest stands by treating errors in selected attributes as realisations of a multivariate random process. In principle, if a forest inventory is performed using one method and a subset of stands is re-measured with a second method, the resulting paired estimates can be used to characterise the relationship between the two methods. This relationship is then exploited to simulate alternative populations described by one of the methods. Our approach relies on constructing a covariance matrix and its Cholesky decomposition.

The covariance matrix, $\boldsymbol{C}$, used for generating multivariate errors, was calculated as

$$\text{(A1)} \quad \boldsymbol{C} = \boldsymbol{q}^T\boldsymbol{q}\frac{1}{n-1}$$

where

$$\text{(A2)} \quad \boldsymbol{q} = \boldsymbol{M} - 1_n 1_n{}^T\boldsymbol{M}\frac{1}{n}$$

and n was the number of rows (one per objectively inventoried stand, in our case 541) in the matrix $\boldsymbol{M}$ consisting of differences between m (in our case 6) measured attributes on plots in stands and estimates of the same attribute and stand in the operational stand inventory, one stand per row, and $\mathbf{1}_n$ is a size n vector of 1 s. From the covariance matrix $\boldsymbol{C}$, the Cholesky decomposition as a lower triangular matrix $\boldsymbol{L}$ was computed such that

$$\text{(A3)} \quad \boldsymbol{C} = \boldsymbol{L}\boldsymbol{L}^T$$

where $\boldsymbol{L}^T$ is the transpose of $\boldsymbol{L}$. The simulation of multivariate errors for i stands was performed by generating 100 independent versions of the error matrix $\boldsymbol{E}_s$, one for each scenario in the set $s = \{1,\ 2,\ \ldots, S = 100\}$ such that

$$\text{(A4)} \quad \boldsymbol{E}_s = \left\{\boldsymbol{L}\boldsymbol{Z}_{1j}, \ldots, \boldsymbol{L}\boldsymbol{Z}_{ij}\right\}$$

where $\boldsymbol{E}_s$ was a matrix of a set of i row vectors resulting from the vector multiplication of $\boldsymbol{L}$ by $\boldsymbol{Z}_{ij}$. Each row i in $\boldsymbol{Z}_{ij}$ was uniformly sampled from a set of $j = \{1,\ 2,\ \ldots, J = 10\}$ vectors, each in the form of

$$\text{(A5)} \quad \boldsymbol{Z}_{ij} = (z_1, \ldots, z_m)$$

where each z_m was a normally distributed independent random variable with m elements, $z_m \sim N(0,1)$, truncated between σ_{1j} and σ_{2j}, where $\alpha = 2$ and

$$\text{(A6)} \quad \sigma_{1j} = -\alpha + \frac{2\alpha}{J}(j-1)$$

and

$$\text{(A7)} \quad \sigma_{2j} = -\alpha + \frac{2\alpha}{J}j,$$

and stored as the mth element of $\boldsymbol{Z}_{ij}$. The reason for using a normal distribution truncated between $\sigma = \pm 2$ and divided into 10 steps, was to ensure that the simulated errors were not too large and that each simulated scenario could have representations of errors for all parts of the distribution. The uniform sampling was done proportionally to the probability mass between σ_{1j} and σ_{2j}.

The final set of simulated deviations $\boldsymbol{R}_s$ was generated by taking the stand inventory data $\boldsymbol{D}$ of the m attributes for i stands and adding it to each of the 100 $\boldsymbol{E}_s$. Thus, let

$$\text{(A8)} \quad \boldsymbol{R}_s = \boldsymbol{D} + \boldsymbol{E}$$

Table A1. The relative covariances between the attributes used to simulate errors.

	Diameter	Height	Stems	Basal area	Age	Site index
Diameter (cm)	0.027	0.018	– 0.03	0.01	0.011	0.001
Height (m)		0.024	– 0.021	0.013	0.008	0.001
Stems (ha^{-1})			0.134	0.051	– 0.017	– 0.003
Basal area (m^2 ha^{-1})				0.113	– 0.006	0.002
Age (years)					0.054	– 0.003
Site index (m)						0.014

Table A2. The absolute covariances between the attributes used to simulate errors.

	Diameter	Height	Stems	Basal area	Age	Site index
Diameter (cm)	8.2	3.0	– 684	2.4	82	0.34
Height (m)		3.2	– 323	1.8	37	0.37
Stems (ha^{-1})			287,227	1231	–753	–63
Basal area (m^2 ha^{-1})				26	– 17	1.2
Age (years)					331	– 6.3
Site index (m)						5.9

This procedure was repeated twice for each scenario—one for absolute errors (above), and one for relative errors, where $\boldsymbol{R}_s$ instead was calculated as

$$\text{(A9)} \quad \boldsymbol{R}_{s,\text{relative}} = \boldsymbol{D} + \boldsymbol{E}_{s,\text{relative}} \circ \boldsymbol{D}$$

Note that $\circ$ is the element-wise multiplication (Hadamard product).

The final dataset with attributes constructed from simulated errors was a matrix where each element was chosen from each $\boldsymbol{R}_{s,\text{ relative}}$ or $\boldsymbol{R}_{s,\text{ absolute}}$, based on rules from similar works (Holmström et al. 2003). Relative errors were chosen (depending on the original value in $\boldsymbol{D}$) if the volume was under 150 m^3 ha^{-1}, the diameter at 1.3 m was under 10 cm, Lorey's mean height was under 12 m, the number of stems was under 1000 ha^{-1}, the basal area was under 18 m^2 ha^{-1}, the mean age was under 50 years, and if the site index was under 25 m.

The covariance matrices used in the Monte Carlo simulation are presented in Tables A1 and A2.

Appendix B: Additional results

Figure B1 shows the average cost from forest management per m^3 of harvested wood. Figure B2 shows the area share of old forests. Figure B3 shows the average final felling age. Figure B4 shows the standing volume. Figure B5 shows area share of young forests. Figure B6 shows the average diameter in final fellings.

Fig. B1. The average cost in SEK per m^3 of harvested wood over the planning horizon for the different cases. Case 1-LQ-LA is the brown line and area on the bottom right. Case 2-LQ-HA is purple line and area on the bottom left. Case 3-HQ-LA is green line on the top right. Case 4-HQ-HA is the red line on the top left. The reference case is the grey line present in all panels. See Table 1 for a description of the cases.

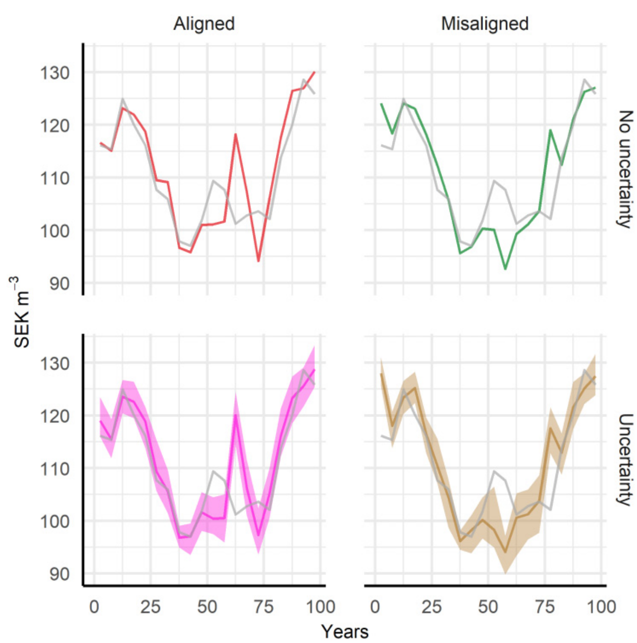

Fig. B2. The area proportion of stands older than 140 years over the planning horizon for the different cases. Case 1-LQ-LA is the brown line and area on the bottom right. Case 2-LQ-HA is purple line and area on the bottom left. Case 3-HQ-LA is green line on the top right. Case 4-HQ-HA is the red line on the top left. The reference case is the grey line present in all panels. See Table 1 for a description of the cases.

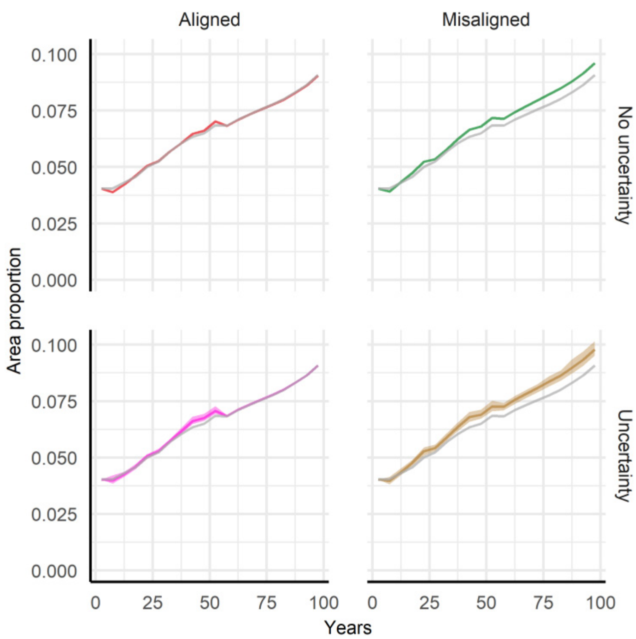

Fig. B3. The average volume-weighted final felling age over the planning horizon for the different cases. Case 1-LQ-LA is the brown line and area on the bottom right. Case 2-LQ-HA is purple line and area on the bottom left. Case 3-HQ-LA is green line on the top right. Case 4-HQ-HA is the red line on the top left. The reference case is the grey line present in all panels. See Table 1 for a description of the cases.

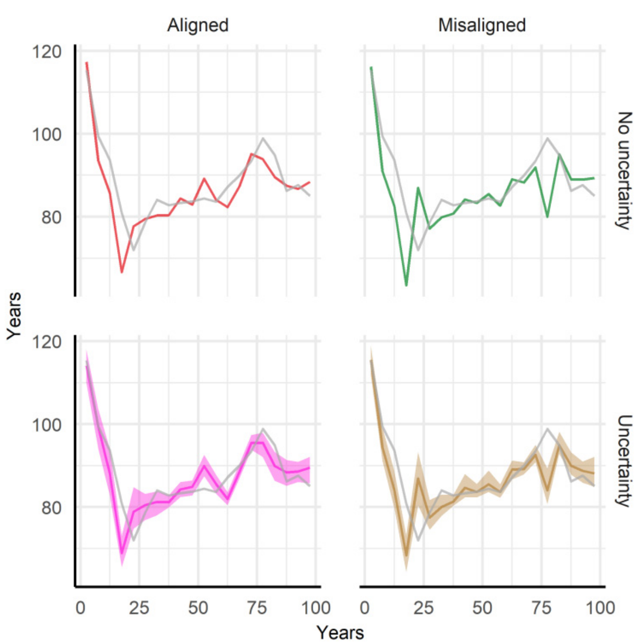

Fig. B4. The average standing volume over the planning horizon for the different cases. Case 1-LQ-LA is the brown line and area on the bottom right. Case 2-LQ-HA is purple line and area on the bottom left. Case 3-HQ-LA is green line on the top right. Case 4-HQ-HA is the red line on the top left. The reference case is the grey line present in all panels. See Table 1 for a description of the cases.

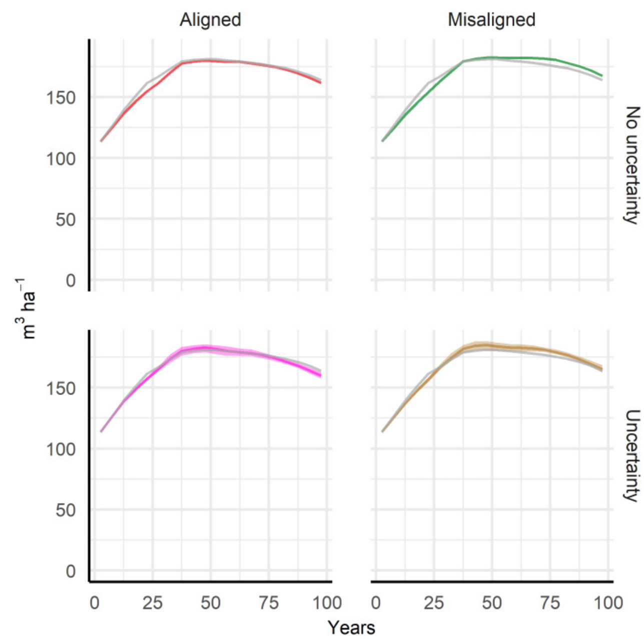

Fig. B5. The area proportion of forests < 20 years over the planning horizon for the different cases. Case 1-LQ-LA is the brown line and area on the bottom right. Case 2-LQ-HA is purple line and area on the bottom left. Case 3-HQ-LA is green line on the top right. Case 4-HQ-HA is the red line on the top left. The reference case is the grey line present in all panels. See Table 1 for a description of the cases.

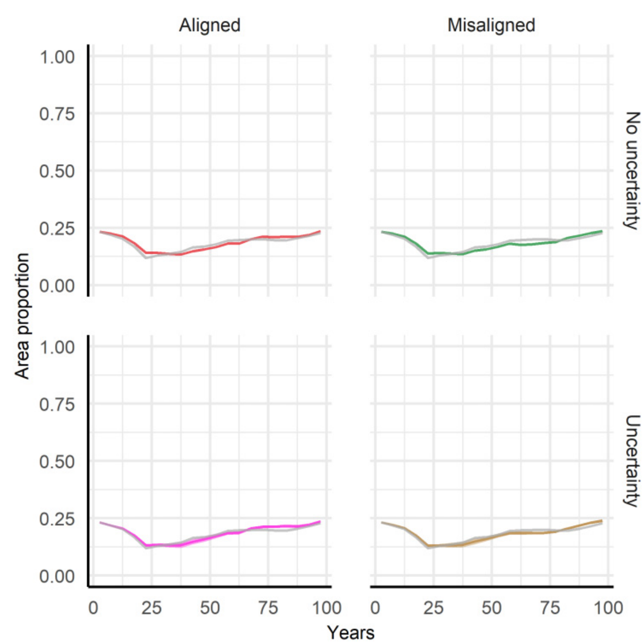

Fig. B6. The average volume-weighted diameter in final fellings over the planning horizon for the different cases. Case 1 is the brown line and area on the bottom right. Case 1-LQ-LA is the brown line and area on the bottom right. Case 2-LQ-HA is purple line and area on the bottom left. Case 3-HQ-LA is green line on the top right. Case 4-HQ-HA is the red line on the top left. The reference case is the grey line present in all panels. See Table 1 for a description of the cases.