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Incentives and strategies

Patrik Ulvdal

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Patrik Ulvdal
Faculty of Forest Sciences
Department of Forest Resource Management
Umeå

SLU
SWEDISH UNIVERSITY
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Cover: A forester pondering the future management of a forest, knowing that decisions can lead to uncertain outcomes. Drawing by Dr. Martin Goude.

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Swedish University of Agricultural Sciences, Department of Forest Resource Management, Umeå, Sweden

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Recognising information uncertainties in forest planning: Incentives and strategies

Abstract

This thesis addresses uncertainty in information about the state of forests and the implications of this uncertainty for long-term forest planning. This is done by examining how forestry manages forest information uncertainty, including the effects of ignoring it. It also proposes a methodology to explicitly address this uncertainty using an optimisation approach. The primary motivation of this thesis is to enhance decision-making in forestry, which is why emphasis is placed on practical relevance. Paper I explores existing strategies for addressing forest information uncertainty at large forest companies. Notably, the use of analytical methods, such as optimisation, for planning under uncertainty was found to be rare. The effects of ignoring forest information uncertainty are analysed in Papers II and III. Paper II examines whether mismatches between strategic and tactical objectives lead to suboptimal decisions and how information uncertainty affects planning results in this context. Paper III examines how errors in remote sensing predictions, which stem largely from regression towards the mean, affect planning results. Here, regression towards the mean is the tendency to underestimate large true values and overestimate small ones. The results of Papers II and III show that objective fulfilment decreases when uncertainty is not addressed. Finally, Paper IV evaluates a stochastic programming model that explicitly incorporates uncertainty into long-term planning. The model was integrated into a forest decision support system and tested in a case study to assess the value of accounting for multiple uncertainty scenarios simultaneously. Feedback from users provided managerial insights, supporting further refinement and application of the model, including decision support system development. In conclusion, this thesis provides a deeper understanding of what strategies forestry currently employs to address information uncertainty. Furthermore, the thesis provides clear incentives why information uncertainty should be recognised and proposes a method to consider this uncertainty explicitly to improve the objective fulfilment of forest planning.

Keywords: errors, forest decision support systems, forest information uncertainty, forest inventory, forest management, optimisation, remote sensing, stochastic programming

Beaktandet av osäker information i skoglig planering: drivkrafter och strategier

Sammanfattning

Denna avhandling behandlar osäkerhet i information som beskriver skogars tillstånd och vad denna osäkerhet har för konsekvenser för långsiktig skoglig planering. Detta görs genom att undersöka hur skogsbruket hanterar denna osäkerhet och vad effekterna blir av att ignorera den. Även en optimeringsmetodik för hur denna osäkerhet kan hanteras föreslås. Det övergripande syftet är att möjliggöra bättre beslutsfattande inom skogsbruk, varför tonvikten ligger på praktisk relevans. Studie I utforskar befintliga strategier hos skogsföretag för att hantera osäker skoglig information i sin planering. Ett viktigt resultat är att användningen av avancerade beräkningstekniker, såsom optimering, för planering under osäkerhet är ovanlig. Effekterna av att inte hantera osäkerhet i skoglig information analyseras i studierna II och III. Studie II undersöker om skillnad i målsättning mellan strategisk och taktisk planering leder till suboptimala beslut och hur informationsosäkerhet påverkar detta. Studie III undersöker hur fel i fjärranalysbaserade prediktioner, som ofta har fel som beror på dragning till mitten, påverkar planeringsresultatet. Dragning mot mitten innebär att höga sanna värden underskattas medan låga sanna värden överskattas. Resultaten från studierna II och III visar att måluppfyllelsen minskar om osäkerhet ej beaktas. Slutligen utvärderar studie IV en modell baserad på stokastisk programmering som explicit integrerar osäkerhet i långsiktig planering. Modellen implementerades i ett skogligt beslutsstödsystem och testades i en fallstudie för att bedöma värdet av att samtidigt beakta flera osäkerhetsscenarier. Feedback från användare gav viktiga insikter för vidareutveckling och tillämpning av modellen, inklusive beslutsstödsystemet. Sammanfattningsvis ger denna avhandling en fördjupad förståelse för vilka strategier skogsbruket i dag använder för att hantera informationsosäkerhet. Vidare visar avhandlingen tydliga incitament till varför informationsosäkerhet bör beaktas samt föreslår en metod som explicit hanterar osäkerhet för att förbättra måluppfyllelsen i skoglig planering.

Nyckelord: fel, fjärranalys, optimering, osäkerhet i skoglig information, skogliga beslutsstödsystem, skogshushållning, skogsinventering, stokastisk programmering

Dedication

To *Anders och Måns*, for your never-ending search for knowledge and facts. You inspire us to keep on asking questions and to answer them one by one. Sometimes, the answer may be *lite fel*, but that is an integral part of science. Because next time, the answer will probably get *lite mindre fel*.

Contents

List of publications

This thesis is based on the work contained in the following papers, referred to by Roman numerals in the text:

I. Ulvdal, P.*, Öhman, K., Eriksson, L.O., Wästerlund, D.S. & Lämås, T. (2023). Handling uncertainties in forest information: the hierarchical forest planning process and its use of information at large forest companies. Forestry: An International Journal of Forest Research, 96(1), 62-75. https://doi.org/10.1093/forestry/cpac028

II. Ulvdal, P.*, Öhman, K., Rönnqvist, M., Ståhl, G., Eriksson, L.O., Sängstuvall, L., & Lämås, T. (2025). The role of uncertain forest data in a hierarchical forest planning setting with misaligned objectives. Canadian Journal of Forest Research. Advance online publication. https://doi.org/10.1139/cjfr-2025-0118

III. Ulvdal, P.*, Ståhl, G., Sängstuvall, L., Eriksson, L.O. & Öhman, K. (2025) Long-term strategic forest planning based on biased remote sensing predictions. Forests Monitor, 2(1), 138-175. https://doi.org/10.62320/fm.v2i1.25

IV. Ulvdal, P., Rönnqvist, M., Ståhl, G., Eriksson, L.O., Sängstuvall, L., & Öhman, K. Enabling stochastic programming for improved forest planning under uncertainty: moving from theory to practice (manuscript)

 * Indicates the corresponding author.

The contribution of Patrik Ulvdal to the papers included in this thesis was as follows:

I. Planned the study, developed the methodology (interview-guide, planning process mapping), performed the interviews, conducted the analyses, made the figures, interpreted the results, drafted the manuscript, and revised it after feedback from co-authors.

II. Co-developed the research question, planned the study, acquired the data, developed the methodology (wrote the code and developed the optimisation models), conducted the analyses, made the figures, interpreted the results, drafted the manuscript, and revised it after feedback from co-authors.

III. Co-developed the research question, planned the study, acquired the data, developed the methodology (wrote the code and developed the optimisation models), conducted the analyses, made the figures, interpreted the results, drafted the manuscript, and revised it after feedback from co-authors.

IV. Developed the research question, planned the study, acquired the data, developed the methodology (wrote the code and developed the optimisation models), conducted the analyses, made the figures, interpreted the results, drafted the manuscript, and revised it after feedback from co-authors.

1. Introduction

Forests host biodiversity and provide ecosystem services vital for life on Earth (Brockerhoff et al. 2017). The photosynthesis of the world's forests accounts for 49% of the global gross primary production of terrestrial biomes (Beer et al. 2010). Forests are also the primary habitat for many species (Pillay et al. 2022). Human society depends on biodiversity and on these services (Brockerhoff et al. 2017). One obvious example is the provision of goods such as timber and game meat (FAO 2020b; Needham et al. 2023). However, regulating services, such as stabilising the climate and mitigating soil erosion, should also be acknowledged (Li et al. 2015; Bullock et al. 2016). Forests are also crucial for human well-being and recreation (Oh et al. 2017; Derks et al. 2020).

The numerous values associated with forests must be considered when utilising their resources, especially in light of climate change (Başkent 2018; Felton et al. 2024). Forest planning (i.e., defining the objective of a forest's management and proposing the best actions to achieve that objective) provides tools and processes to consider these values, thereby contributing to sustainable forest management. Since forests and forestry are impacted by much uncertainty, these tools and processes should preferably be able to consider that uncertainty.

Uncertainty can be viewed as a spectrum ranging from determinism to complete uncertainty (Walker et al. 2003). In a deterministic system, one has complete knowledge of all objects' states and movements, as well as how all processes function both historically and in the future. However, knowledge like this never exists. Thus, all systems and decisions regarding them should be considered to exist under some uncertainty.

The uncertainty affecting forests and forestry stems from many sources. On the ecological side, there is the natural randomness of ecosystems, ranging from the molecular level to interactions between organisms and communities (Buiatti & Longo 2013; Messier et al. 2016). Biotic disturbances in managed forests, such as damage from pests or browsing, should be included here (Canelles et al. 2021). Related to the ecosystem, there are abiotic uncertainties associated with the physical world, the atmosphere, and the weather, including storms, rainfall, lightning-induced fires, and drought (Seidl et al. 2011). These uncertainties are, of course, interlinked; for example, drought increases trees' susceptibility to insect damage (Gely et al. 2020). All the above factors affect the growth of trees in various ways (Fox et al. 2001). Uncertainty is also present on the socio-economic side of forests and forestry. For example, market prices for wood fluctuate (Hildebrandt & Knoke 2011) due to changes and uncertainties in wood supply and demand (Carlsson et al. 2009). Policy changes are also a source of uncertainty (Hyde & Olmos 2024). From a decision-making perspective, there is usually great uncertainty about decision-makers' preferences (Eyvindson et al. 2018a). The different uncertainties have been categorised by Pasalodos-Tato et al. (2013):

1. Uncertainty due to forest inventory errors
2. Uncertainty from growth models
3. Uncertainty in market conditions
4. Uncertainty in the preferences of decision-makers
5. Uncertainty from natural hazards

The scope of this thesis is uncertainty[1] in forest planning. More precisely, it examines how forest information uncertainty, i.e., uncertainty in the description of forests (point 1 in the list above), is addressed in contemporary long-term forest planning and how current practices, which largely overlook this uncertainty, impact objective fulfilment. Lastly, it evaluates and suggests a method for explicitly dealing with forest information uncertainty in forest planning models. A special focus is given to large forest-owning organisations with formalised planning routines. Uncertainty connected to points 2-5 according to Pasalodos-Tato et al. (2013) is important, but is not explicitly considered here.

[1] Connected to uncertainty is the concept of risk. Sometimes, risk is referred to as a state of quantifiable uncertainty, i.e., it is possible to estimate the probability of an event (Knight 1921). The risk preference, i.e. how willing one is to gamble with the potential (negative and positive) outcomes of a decision, is an important characteristic of decision-makers (Weber 2010). However, in this thesis, a decision-maker is generally considered risk-neutral.

1.1 Forest planning in practice: dealing with an uncertain future

Long-term forest planning has evolved over the centuries in response to the need for sustainability in society's use of forests and forests' ecosystem services (Kangas et al. 2015). In fact, as the sections below will show, forest planning emerged from the need to minimise the uncertainty of future wood supply.

1.1.1 Early planning of wood production

The first ideas about conserving forests systematically for future wood supply stem from the late medieval period or the early Renaissance (Warde 2011, 2018). The earliest example of forest planning with a scientific approach was made by von Carlowitz (1713). When managing the declining forest resources used by Saxony's mines, he concluded that the harvesting rate should not be higher than the rate at which the forests could be regenerated. With his stipulation, he is often considered the first person to have framed the concept of sustainability (Morgenstern 2007). His work was continued by Hartig (1795) and Cotta (1804), who both proposed measures to achieve a steady supply of harvestable forests, i.e. a sustained yield, by dividing the forest into equally large parts according to standing volume or area in what can be called a framework pattern (Hagberg 1943; Lundmark 2020). The number of such areas should correspond to the number of years needed for an entire forest rotation; i.e., from planting to final felling. Hartig's and Cotta's systems are early cases of scientifically based forest management, as they were based on assessments from inventories and considered the future need for forest resources. In principle, one could say that these systems were developed to control and minimise the uncertainty of future wood-supply.

Hartig and Cotta are two examples of early *calculating foresters,* a new type of forester who drew inspiration from the Central European movement towards a cameral science, by introducing data-driven rationality to the use of forests (Lowood 1990). Cameral science, which aimed to establish economic order in the governance of states and nations, significantly influenced the new *Forstwissenschaft* (forest science) developed by these calculating foresters. In essence, the need to plan the use of forests was one of the main reasons for developing forest science as a scientific field of enquiry.

A general principle governing most forest planning and general forest science literature in the 19th century is the idea of a normal forest (Reed 1986). A normal forest is the hypothetical state of a forest in which the area for all age classes for each site class is equal (Eklund 1979). A normal forest will, in theory and per definition, result in sustained yield and is the natural consequence and long-term steady state of harvesting systems like those suggested by the early German foresters (Hartig 1795; Cotta 1804). With no other aides to ensure sustained yield, most early planning instructions aimed to transform any forest into a normal one, as this structure seemed the easiest to manage (Reed 1986). A normal forest is a simple (idea-wise, at least) way of managing the uncertainty of future harvests. The rigid division of forests into the same number of stands (all equally sized) as the number of years in the rotation period, will, at least in theory, and without any external actions, lead to reduced variation over time in the outcomes of ecosystem services if one stand is harvested per year (Petrini 1948).

The Industrial Revolution in the 1800s led to a significant increase in the demand for wood, while most of continental Europe at the time lacked the necessary forest resources to meet this demand (Lotz 2015; McGrath et al. 2015). The focus of new harvesting campaigns was on the sparsely populated and previously largely untouched boreal forests in the Nordic countries (Östlund 1995). The forestry that came to be practised in these areas was initially exploitative. However, concerns soon emerged regarding the long-term wood supply when it became evident that the exploited forests were not regenerating as rapidly as had been anticipated (e.g. Ström 1860). In response to this concern, numerous European countries enacted legislation during the late 19th and early 20th centuries to address declining forest resources (Luzzi 2001; Richards 2003; Nylund 2009). With that process, legal and policy-oriented rationales for forest planning also emerged, further confirming the general objective of reaching sustainable use of forest resources.

With the increasing demand for planning the utilisation of forest resources and the availability of forest inventory methods, the concept of a forest management plan emerged. According to Obbarius, a German forester active in Sweden during the 1800s, a forest management plan must be long-term; i.e., covering at least one rotation period (Obbarius 1847). Furthermore, he stated that a plan should consist of a map showing borders between forest stands, including descriptions of every stand, planned management operations, and estimates of future harvest levels based on these operations. For Obbarius, it was also obvious that a plan must aim to reach the maximum forest yield while remaining comprehensive and easily understandable.

Forest planning remained very stable, both in terms of objectives (highest possible yield) and what methods (normal-forest-oriented) were used through the first half of the 20th century (Föreningen för skogsvård i Norrland 1914; Norrlands skogsvårdsförbund 1918, 1923, 1941). The underlying information to describe forests also remained similar over time. Throughout history, the main source of forest information has been field-based surveys. First, they were rudimentary, mostly subjective and coarse, but as mathematics, statistics, and forest science developed, so did forest inventory and sampling (Warde 2018). The earliest example of a forest survey method with an objective approach was the tallying of all trees in a forest while assigning them to diameter classes, as explained by Beckmann in the 1750s (Lowood 1990). The total enumeration of trees was unrealistic for large-scale inventories, which soon led to the development of other inventory designs. Surveys on strips, i.e., walking in a straight line and counting or measuring all trees within the strips, were probably the most common during the 19th century and the first decades of the 20th century. This survey technique was employed in many of the first national forest inventories, including in Sweden (Fridman et al. 2014). To avoid spatial autocorrelation, i.e., that forests close to each other are more similar than those farther away (Matérn 1960), the strip survey evolved into the plot survey, which has remained one of the most dominant methods for objective field surveys of forests since then (Fridman et al. 2014). Purposive sampling methods have been employed in parallel to the development of probability-based survey methods (Ståhl 1992). They are based on ocular and subjective estimates and rely heavily on the surveyor's experience and expertise.

During the 1950s, the increased availability of aerial photography made it possible to assess forests in ways other than by visiting them in the field (Norrlands skogsvårdsförbund 1956). The art of aerial reconnaissance based on stereoscopy was first developed during World War I (Ives 1920). Like many new technologies, it was later applied to forestry, providing the first remote-sensing estimates of forests (e.g. Hesselman 1939).

1.1.2 Computers and mathematical programming

During and after the Second World War, considerable effort was devoted to the development of computational science and electronic computers (Rosen 1969). Simultaneously, these new machines proved to be of great use in the emerging field of operations research (Rau 2005), which is the field of development and application of analytical methods for problem-solving and decision-making. In operations research, solving optimisation problems with mathematical programming (e.g., linear programming) has become the cornerstone of many analyses, thanks to new computers and their ever-increasing power, along with the introduction of the Simplex algorithm by Dantzig in 1947 (Dantzig 1990). The Simplex algorithm provides a fast and efficient method for solving linear programming problems. Soon after its creation, the algorithm was implemented on an electronic computer (Hoffman et al. 1953). Since then, the original implementation of the Simplex algorithm has been further developed and optimised, leading to shorter solution times (Bixby 2012).

Together with computers, linear programming and other mathematical programming approaches have been used to solve forest planning problems since the 1950s (Lindgren & Näslund 1968; Ware 1968; Bettinger & Chung 2004). In Sweden, the first documented application of linear programming in long-term forest planning was performed by Stridsberg (1959). He wanted to examine the usability and applicability of linear programming for the Swedish case. He concluded that linear programming was promising overall but found that the computationally demanding method for simulating alternatives needed to be expanded. He also acknowledged the uncertainty of the plan and stated that the forest information used for the calculations needed to be sufficient.

In Swedish forestry, computers were first used during the 1960s to store and process forest information for all stands in a forest holding (Hagner 2005). By the end of the 1960s, the Swedish forest industry faced economically harsh times, which is why some of the largest forest companies turned to computerisation and linear programming to increase profit by lowering forest management costs. As a result, the forest company SCA (Svenska Cellulosa Aktiebolaget) had a working system for conducting holding-wide analyses based on optimisation at the beginning of the 1970s. The system was also used for national analyses in 1973 (Hagner 2001). Also, internationally, linear programming was used early on in forest planning.

According to a travel report from 1969, multiple companies in North America, such as Columbia Cellulose Co. Ltd. and Weyerhaeuser Co., used linear programming for forest planning, while even more had installed computers for other purposes (Lönner et al. 1969). Since then, linear programming has become standard in forest planning (Rönnqvist 2003).

1.1.3 Introduction of decision support systems and multiple objective forestry

Efficient solution techniques and improved computing power and storage were combined into decision support systems[2] in the late 1960s and early 1970s (e.g. Turban 1967; Andersson 1971). By the 1980s, the use of decision support systems had become integral to forest planning (Vacik & Lexer 2014). Initially, the scope of the decision support system development was quite narrow. If we take Sweden as an example, HUGIN and the Forest Management Planning Package were two early examples of decision support systems, both developed in the 1970s and 1980s (Jonsson et al. 1993; Lundström & Söderberg 1996). Both systems were designed to improve the financial value of forestry by, for example, finding maximum timber yields. Other values of forests were not considered.

However, towards the end of the 20th century, a new type of forestry emerged: multi-objective, or multiple-use forestry. A forerunner in the transition to this new forestry was the United States Forest Service, with its regulations to consider values other than wood production on federal land (Lämås & Fries 1995; Lämås 1996). Following the development in the United States, Sweden and the other Nordic countries adopted a broader view on forest resources (Angelstam et al. 2011). With the introduction of a new national forest policy in 1993 and increasing conservation demands from voluntary certifications, forest planning has also evolved to consider more than just wood production (Lämås 1996). For example, large forest companies use ecological landscape plans (Elbakidze et al. 2013), which highlight areas for conservation or nature-oriented management. Increased time is also invested in finding natural values on potential harvest sites (Willén & Andersson 2015). Additionally, the social aspects of planning evolved as efforts devoted to co-planning or consultation with the reindeer

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[2] For a definition and more background, refer to section 1.2.4.

husbandry increased during the 20th century and accelerated further with the introduction of voluntary certifications at the beginning of the 21st century (Widmark 2006).

The growing complexity of forestry objectives spurred new decision support system development. The need to consider more than one objective was a strong argument for employing more structured problem-solving approaches, leading the way for new solution techniques being used, such as multi-objective optimisation and multi-criteria decision analysis (e.g. Öhman & Lämås 2003; Mendoza & Martins 2006). In response, the Heureka system was developed in Sweden, expanding the scope of what could be considered in forest planning to, for example, species habitat, carbon storage, and the amount of dead wood (Lämås et al. 2023).

1.1.4 Forests and forest planning in Sweden today

Sweden is a forested country, with 68% of its land area covered by forests (Nilsson et al. 2025). Even though most Swedish forests are boreal (Ahti et al. 1968), Swedish forestry has relatively high wood production rates considering the country's small size (FAO 2020a; b). This productivity can be explained by the long-standing focus of many actors in forestry on high wood production through intensive rotation forestry, combined with a large and developed forest industry (Lindahl et al. 2017). Other important aspects include the long tradition of using decision support systems for forest planning (Stridsberg 1959; Jonsson et al. 1993; Lämås et al. 2023) and the high share of productive forest land belonging to forest companies, which is approximately 37% (Nilsson et al. 2025).

Large forest-owning companies have significant incentives to employ a formal planning process due to their size and economic focus. This planning process is commonly assumed to adhere to the planning hierarchy paradigm (Weintraub & Cholaky 1991; Martell et al. 1998; Sessions & Bettinger 2001; Tittler et al. 2001; Andersson 2005; Ogden & Innes 2007; Eriksson 2008; Nilsson et al. 2012; Duvemo et al. 2014; Lämås et al. 2014; Gautam et al. 2015, 2017; Kangas et al. 2015:160). According to the paradigm, the forest planning process is divided into three stages that are organised hierarchically. The three stages are strategic, tactical, and operational planning, where each stage addresses different aspects of the decision-making problem in forest planning. The strategic stage primarily addresses long-term and high-impact issues, such as determining sustainable harvest levels over extended time periods. The operational stage comprises the day-to-day scheduling of harvests to meet short-term industry demand. The tactical stage bridges the other two and primarily deals with medium-term planning on what stands should be harvested in which year to fulfil the strategically decided harvest levels. Traditionally, the tactical stage is also considered to facilitate the planning of road construction and maintenance. Some investigations on how the forest planning process is structured in practice have been conducted implicitly (Nilsson et al. 2012), but explicit analyses are lacking to a large extent.

1.2 Forest planning in theory

As we have seen, forest planning in practice has, throughout history, evolved both in scope (wood production → multiple objectives), underlying information (rudimentary estimations → probability-based field surveys → remote sensing predictions), and decision support (normal forest state → optimisation → decision support systems). This section will provide an overview of the current state of the scientific theory used in this thesis.

This section, as well as section 3, will introduce equations and other mathematical statements. The notation is context-based and not very strict. Some symbols are reused between, for example, utility functions and optimisation models. In those cases, the symbols should represent either the same thing or something very similar. In other cases where symbols are reused but do not represent the same thing, this should be clear given the context.

1.2.1 Decision-making and planning

Simon (1960) presented a conceptual decision-making model consisting of three steps: 1) intelligence, 2) design, and 3) choice. The first step involves the search for reasons to make a decision. The second step involves the mapping of alternative actions. The last step is the process of actually choosing an alternative. According to Simon, these steps can be intertwined and may call back to each other. However, to a large extent, decision-making should follow that order of business. Keeny (1982) presented a decision-making model sharing many similarities with Simon's model. Keeny's model involves four steps: 1) structuring the problem by defining objectives and alternative actions; 2) evaluating the impact of the alternative actions, including their probabilities; 3) describing decision-maker preferences; and finally, 4) comparing alternatives to each other to facilitate a decision (Figure 1). The main difference is probably Keeny's emphasis on decision-maker preferences and objectives, which are only implicitly covered by Simon's model.

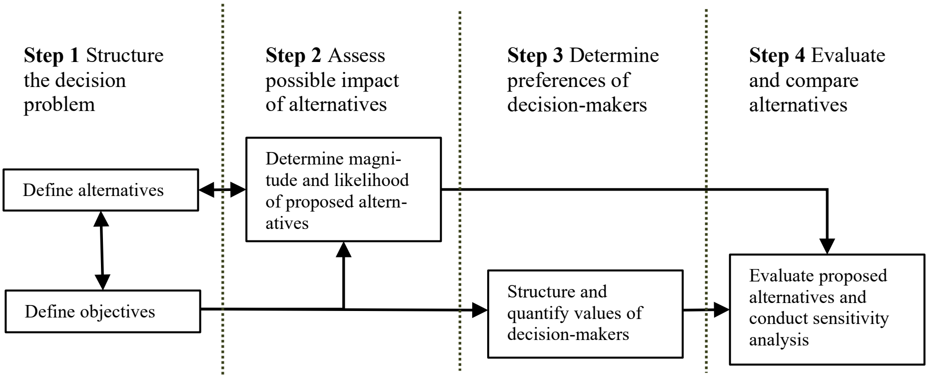

Figure 1. The structure and process of decision making according to Keeny (1982).

Planning is connected to decision-making in the sense that planning facilitates the entire decision-making process in a structured manner, i.e., it organises the problem, provides rational alternative actions, and forms the basis for the final choice. (Kangas et al. 2015). However, in contrast to decision-making, planning involves linking different decisions to each other into a system to accomplish an expected or desired outcome, i.e., to create a plan (Eliasson 1976). Another difference is that planning mostly deals with the future; otherwise, the two fields are closely interlinked. Based on Eliasson (1976), one can develop a definition of planning as an "*ex-ante rehearsal of the decision-making process*", which means that planning lets a decision-maker test a particular combination of decisions before implementing them. However, more simply put, planning can be described by the components needed to create a plan: 1) an objective, 2) activities that can be used to reach the objective, and 3) methods to combine these two components (Stålhandske 1974). These planning components are very similar to those in the decision-making process in Figure 1. However, defining the decision-maker's objective is only implicitly included in the way that an objective has already been given.

Forest planning, in principle, does not differ from any other planning. However, some practical differences should be noted. Forest planning stands out due to its long time horizons, the intricate production systems subject to natural randomness, and the complex decision-making process involving many stakeholders with contrasting objectives (e.g. Kangas et al. 2015). These differences pose challenges for practitioners and researchers, but thanks to information acquisition methods, forest development models, and advanced solution techniques implemented in decision support systems, forest management plans are made continuously.

A concrete result of forest planning can be a forest management plan, which is a document that describes the future management and development of a forest, together with the forecasted output (resulting products and services given stated actions). The decisions involved in creating such a plan should consider the interlinked relations between management today and in the future. Morgenstern (2007) concluded that the information included in a forest management plan should be at least a general description of the forest and of the inventory methods used; a list of all stands and relevant attributes for each; an outline of the proposed management, including regeneration; a list of previous management; and the expected harvest volumes. This suggested content can likely be viewed as standard and is common throughout practice (e.g. Bettinger et al. 2010; Brukas & Sallnäs 2012; McDill 2014).

1.2.2 Formulating the planning problem

Theoretically, it is often assumed that a decision-maker is rational and has a utility function that can be described mathematically (von Neumann & Morgenstern 2004). Based on such a utility function, it is possible to rank alternative actions according to which alternative provides maximum utility. From the utility function of a decision-maker, an optimisation model can be developed to solve the posed planning problem; i.e., find the optimal way of reaching the stated objective. Any optimisation model is a mathematical program that consists of an objective function, decision variables, and a set of constraints that restrict the values of the decision variables (Lundgren et al. 2010). The objective function describes what the model should optimise, for example, to minimise cost or maximise profit. The decision variables, which can be either discrete (taking on a fixed set of values) or continuous (taking any real value in an interval), are the levers that the decision-maker can use to affect the objective function. The constraints limit what values the variables are allowed to take.

Let us say that a decision-maker has the utility function, which for a certain action x has the utility

(1) $$U = f(x)$$

If there are alternative actions, say x_1, x_2 up to x_j and that the utility provided we choose a specific action j can be described as $f(x_j) = n_j x_j$, where n is some quantity that has a linear relationship between the decision x and utility U (the relationship can be non-linear, but for simplicity's sake we will only cover the linear case here), then we want to maximise the sum of all potential actions, like

(2) $$\max U = \sum_{j \in J} n_j x_j.$$

Thus, we look for the values of x_j that provide the largest sum, i.e.,

(3) $$x_j = \underset{x}{\operatorname{argmax}}\, U$$

It is easy to see that if x_j represents a yes or no to alternative j, we need to include some bounds for what values x_j can take. In a binary situation where only one alternative can be chosen, these bounds can be stated as

(4) $$x_j \in \{0,1\}\, \forall j$$

(5) $$\sum_{j \in J} x_j = 1.$$

Eq. (4) indicates that we can only assign 0 or 1, i.e., no or yes, to any alternative. Eq. (5) indicates that we can only choose one alternative. We now have a utility function that can be used to rank alternative actions and determine the best option for this specific decision-maker.

The quantity n_j in the utility function can denote whatever the decision-maker wants to maximise. In many cases of forest planning, the quantity used to describe utility is the net present value, i.e., the present value of future cash flows (Pearse 1967; Knoke et al. 2020). The net present value for rotational forestry can be calculated as

(6) $$n = \sum_{t=0}^{S} \frac{R_t}{(1+r)^t} + \frac{(1+r)^{-S}}{1-(1+r)^{-T}} \sum_{t=S}^{T} \frac{R_t}{(1+r)^t}$$

where n is the net present value, R_t is the net revenue at year t, and r is the real interest rate (Faustmann 1849, 1995). The first term of Eq. (6) sums all discounted net revenue for an ongoing forest generation up to the time for final felling (S) back to year 0. The second term refers to the soil expectation value and is the net present value of the next full forest generation up to the year for (the next) final felling (T) repeated to infinity by multiplying it in a geometric series represented by $(1-(1+r)^{-T})^{-1}$. Calculating net present value for non-rotational forestry is somewhat more complex, but essentially the same (Haight & Getz 1987).

Even if maximising net present value is standard in forest planning, other objectives can be used. A decision-maker concerned with biodiversity might, for example, try to maximise the number of species or habitats in a forest (e.g. Kangas & Kuusipalo 1993; Marshalek et al. 2014). Other possible objectives include decreasing carbon emissions (e.g. Raymer et al. 2009), increasing recreational values (e.g. Pukkala et al. 1995), decreasing fire hazards (e.g. González-Olabarria & Pukkala 2011), and many others. Practices have also evolved to consider multiple objectives simultaneously (Steiguer et al. 2003; Mendoza & Martins 2006). It is also possible to translate other objectives and their indicators to financial terms and thus include them in the net present value calculation (Brander et al. 2024). In practice, however, many forest companies strive for maximum sustained yield (Elbakidze et al. 2013) since wood production is what provides financial value (Chudy et al. 2020). This is an old idea; as Hartig stated in 1803, "*always deliver the greatest possible constant volume of wood*" should be the overall objective of forestry (Hartig 1803:64 as cited by Lowood 1990).

1.2.3 Solving the planning problem

One of the most common mathematical programming techniques for solving optimisation problems is linear programming. A linear programming model is a special case of an optimisation problem where the objective function and constraints are expressed as linear equations or inequalities, together with continuous variables. This technique is frequently used in forest planning applications (Rönnqvist et al. 2023).

Let us use the problem of maximising the total profit from conducting a harvest in a forest during a year as an example for a standard linear programming model. If $\boldsymbol{c}$ is a column vector where each element is the profit per hectare for harvesting a stand in the forest, then $\boldsymbol{x}$ is the column vector with the area of each stand that will be harvested. The objective of the decision-maker is then to

(7) $$max\ \boldsymbol{c}^T\boldsymbol{x}\ ,$$

i.e., the decision-maker wants to find the vector $\boldsymbol{x}$ that provides the largest product $\boldsymbol{c}^T\boldsymbol{x}$. However, the decision-maker should acknowledge that the stands do not have infinite areas. Thus, we need to introduce a symmetric matrix $\boldsymbol{A}$, in which the diagonal elements are the total area of each stand and the off-diagonal elements are 0, and the vector $\boldsymbol{b}$, which, in this example, also contains the total area of each stand. This means that the maximisation is subject to

(8) $$\boldsymbol{Ax} \leq \boldsymbol{b}\ ,$$

i.e., the total area harvested in each stand should not be larger than the total available area in that stand. Furthermore, it is natural in this case that $\boldsymbol{x}$ needs to be positive, as it is not possible to harvest negative areas. Thus, the maximisation should also be subject to

(9) $$\boldsymbol{x} \geq 0.$$

By utilising linear programming, the decision-maker can solve the problem and thus create a plan for harvesting operations that maximises profit while keeping the plan within the reasonable natural boundaries of the problem. However, this plan is not sustainable, since the future harvest supply is not considered (in fact, the decision will naturally be to harvest the whole forest). If the decision-maker wants to include some considerations towards sustainability, it is possible to add multiple rows in $\boldsymbol{A}$ and $\boldsymbol{b}$ that account for this.

Since the aforementioned standard formulation of linear programming is not very pedagogical, we will reformulate it more extensively and adapt it to a forestry context as

(10) $$\max U = \sum_{i \in I} \sum_{j \in J_i} n_{ij} a_i x_{ij}$$

subjected to

(11) $$0 \leq x_{ij} \leq 1 \qquad \forall i \in I, \forall j \in J_i$$

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

In this formulation, Eq. (10) is the objective function that maximises the sum of the product between the net present value per hectare (n_{ij}), the area of stand i (a_i), and the proportion x_{ij} of stand i that should be treated with the alternative j over all stands in the set I and all alternatives for every stand in the set J_i. The alternatives are different ways of managing the forest. Eq. (11) states that x_{ij} is a number between 0 and 1 for all stands and alternatives. Eq. (12) states that the whole area of each stand i should be assigned an alternative j. To make the resulting plan sustainable in relation to future harvest levels in terms of non-declining yield, a third restriction could be added as

$$(13) \qquad \sum_{i \in I} \sum_{j \in J_i} v_{ijp} a_i x_{ij} \leq \sum_{i \in I} \sum_{j \in J_i} v_{ijp+1} a_i x_{ij} \qquad \forall p \in P \setminus \{p_0\}$$

where v_{ijp} denotes the harvested volume per hectare in period p for stand i that is treated with the alternative j. The restriction is active for every p except the first (p_0) in the set of periods (P) and ensures that harvest levels do not decline over time. This sustained yield restriction can also be expressed in terms of, for example, the maximum allowed fluctuation in harvest volumes between periods or in terms of a minimum ending inventory of standing timber.

A development of the linear programming formulation is the mixed-integer program, which introduces binary or integer variables. The problem described in Eq. (10) and onwards could easily be subject to the constraint that only one alternative should be assigned to each stand. This is, for example, relevant in a spatial case, where whole stands, rather than proportions of stands, should be planned (Başkent et al. 2024). To change the above model accordingly, Eq. (11) should be modified to

$$(14) \qquad x_{ij} \in \{0,1\} \qquad \forall i \in I, \forall j \in J_i$$

where x_{ij} is defined to be either 0 or 1. A mixed integer programming model is much harder to solve than its corresponding linear programming relaxation, since there exist no algorithms that can solve it as efficiently as the Simplex method can solve a standard linear programming model (Garey & Johnson 1990); even so, the performance of algorithms for solving mixed integer programming problems is steadily increasing (Bixby & Rothberg 2007; Klotz & Newman 2013). Linear programming and mixed-integer programming models, as described above, play a crucial role in this thesis.

1.2.4 Decision support systems and forest planning

Commonly, the definition of what a decision support system is, usually revolves around it being a software based on models that includes a database used to store initial forest information and results, a system for solving problems based on the information, and a user interface that lets users interact with the decision support system and its outputs (Burstein & Holsapple 2008; Eriksson & Borges 2014; Lämås et al. 2023). Thus, a decision support system requires information about the forest, models that describe the forest's development under different management strategies, and methods that enable users to pose questions about the forest's management or development and receive answers. All these components must be packaged so that sub-systems and sub-models can communicate within the system and users can interact with the system as a whole.

How decision support systems are structured varies greatly (Segura et al. 2014). Broadly, it is possible to distinguish two main categories of decision support systems: simulating and optimising systems (von Malmborg 1971). The first category comprises systems that forecast forest development primarily based on rules, such as what management will be applied in a forest at a certain age. Such systems are mainly used to analyse what will or could happen in a forest if set rules are followed, i.e., they help in answering questions in the form of *what if* (Nobre et al. 2016). They are particularly suitable for descriptive or exploratory analyses of new management strategies, like how changes in harvest residue extraction intensity affect soil carbon (Ortiz et al. 2014) or how changes in rotation lengths impact carbon accumulation in forests (Ericsson 2003).

However, a planner typically seeks the most efficient way to achieve one's objective. For that purpose, optimising decision support systems have been developed. These systems also use rules to simulate forest development, but instead of only one future development, multiple alternative developments within the limits defined by the rules are generated to allow for optimisation. Optimising decision support systems can be used to answer questions in normative analyses like *how to* do something most efficiently, like optimising the wood supply chain (Pekka et al. 2020) or finding the financially best harvesting plan given certain demands of the spatial configuration and amount of species habitat (Öhman et al. 2011).

The core of any forest decision support system is the models describing forest dynamics. Of these, tree growth models have probably been considered the most important, as tree growth is the resource utilised in traditional forest management. Tree growth models can be divided into two broad categories: empirical growth-and-yield models and climate-sensitive process-based models (Mendoza & Vanclay 2008). Empirical growth models build upon observed growth and therefore forecast growth based on historical conditions, such as climate, species mix, and management. Process-based models will instead predict the ecophysiological response to actual conditions, providing possibilities to explore what will happen if conditions, such as the climate, change. Between these two concepts, hybrid growth modelling has emerged that mixes these approaches to make use of the empirical rigour of traditional models and the climate responsiveness of process-based models (e.g. Goude et al. 2022). Apart from pure growth models, forest decision support systems require mortality models (e.g. Fridman & Ståhl 2001), models for the establishment of new trees (e.g. Holmström et al. 2017), and models for management responses (e.g. Jonsson 1995). Furthermore, all these models must be interconnected to capture the dynamics of the forest ecosystem. Apart from the core models related to the growth of trees, other models that describe various aspects of forests and forest management are also necessary. Common examples include economic models such as machine productivity functions (e.g. Eriksson & Lindroos 2014) and tree-bucking models (e.g. Sessions et al. 1989), biodiversity models, like habitat suitability models (e.g. Edenius & Mikusiński 2006), and models describing social values, like recreational values (e.g. Eggers et al. 2018).

1.2.5 Area-based vs. strata-based forest planning

Different approaches to forest planning can be employed depending on the type of information available or collected (Öhman et al. 2020). If the information about the forest is wall-to-wall, i.e. geographically comprehensive, planning can be area-based (e.g. Nelson et al. 1991; Murray 1999). Here, *area-based* indicates that the entire area of the forest is explicitly and directly considered for planning purposes, commonly by utilising wall-to-wall remote sensing maps or information from stand inventory databases. Note that area-based planning, per se, does not require a map. As long as the entire forest area is explicitly included, area-based planning is possible. If we take the model presented in Eq. (10) and onwards (page 24) as an example, the set I contains all stands in the forest. Spatial planning is a continuation of the area-based approach, which includes considerations regarding individual stands' positions relative to neighbouring stands, the shapes of stands, and other spatial properties (Başkent & Keles 2005).

Since the area-based approach requires information about all stands in the forest, and all these stands must be represented in the planning model, the need for computational power increases (Liittschwager & Tcheng 1967). Another problem is that inventories covering all stands in a large forest holding often use coarse methods and purposive sampling, resulting in the information having unknown or low quality (Duvemo et al. 2014). The need for computational power can be reduced by aggregating information about similar stands within strata (Daust & Nelson 1993; Church et al. 2000), and the quality and detail of the information can be improved or controlled by selecting a stratified sample of stands for field surveys (Jonsson et al. 1993). Modelling forest development based on such information is the basis of the strata-based planning approach.

With the strata-based approach, the forest is represented by either aggregated stands in the form of strata or sampled stands that represent more stands than themselves. Thus, with this approach, the decision x_{ij} (see Eqs. (10) and onwards on page 24) does not refer to the proportion of a stand per se; instead, since the set I represents a set of strata or representative stands (or plots), x_{ij} is the proportion of that stratum or all stands of the same type as the one included. Strata-based planning has been the standard approach for strategic planning in Sweden for a long time (Jonsson et al. 1993).

1.3 Forest information and information acquisition methods

In this thesis, forest information is defined as structured data about forest resources; i.e., attributes that describe the state of forests (definition based on Ackoff 1989). The distinction between data and information is, in part, a philosophical one. However, a common view in the literature is that when data has been given structure and meaning, it turns into information (Rowley 2007). Thus, data are only the raw data points; i.e., the numbers.

Forest companies require information about their forest resources to plan and execute operations (Nilsson et al. 2012; Kangas et al. 2018). Forest information has traditionally been mainly related to the forest as a resource (even though other uses are common). Thus, most of the focus has been on information about the tree layer and its potential for harvest, such as total tree volume, tree species, and tree age, in combination with the attributes needed to calculate volume, including basal area and average tree height (e.g. Brandel 1990; Johansson 2005). However, information has also been needed to estimate economic returns from planned harvests, which is why attributes such as average tree diameter and the number of trees per hectare have been collected (Eriksson & Lindroos 2014). Additionally, information about the terrain's traversability and accessibility for harvest machines has become important since forestry was mechanised during the second half of the 20th century (Reisinger & Davis 1986). Information regarding site characteristics, such as soil moisture, vegetation type, and slope aspect, is important for forecasting tree growth based on site productivity and can be used to estimate site index (Hägglund & Lundmark 1977). This thesis primarily focuses on the attributes presented above, which describe the forest as an economic resource. However, one also needs to acknowledge forest information describing other values of forests, such as biodiversity and the ecological values of forests, e.g., information about species, substrates, and habitat abundance (Hekkala et al. 2023).

Forest information can be collected, measured, or estimated in various ways (Maltamo et al. 2021). Each method, or group of methods, has its pros and cons (Bergstrand 1983). Furthermore, each method represents a trade-off between the quality of the collected information and its cost (Burkhart et al. 1978).

1.3.1 Field-based inventory

Traditionally, field-based inventory has been the only source of forest information collected with any scientific or statistical rigour. The field-based methods can be categorised as either probability-based or based on purposive sampling (Maltamo et al. 2021).

Probability-based inventories

The first category encompasses randomly (often on a systematic grid) sampled inventories, which are often based on circular field plots (Lindgren 2000).

Sweden has a long tradition of probability-based inventories, both within the scope of the national forest inventory (Fridman et al. 2014) and forest management-oriented inventories (Jonsson et al. 1993; Maltamo et al. 2021). From the beginning, both utilised landscape-wide systematic approaches, where the positions of individual inventory plots were systematically sampled across whole landscapes without considering forest stand boundaries. For planning purposes, this kind of representation is somewhat problematic, since stands are the units managed in reality, not individual plots (Hägglund 1982). Therefore, a system of two-phase sampling of forest stands and plots was developed during the 1970s (Jonsson et al. 1993). According to this system, a sample of stands represents the whole forest holding (typically based on stratified sampling, i.e., sample stands selected within strata, often with probability proportional to stand area), and the information for each stand is collected on systematically sampled field plots within the sampled stand. This system combines the advantages of sampling only parts of the forest holding and the use of whole stands that are assumed to be management units.

Purposive sampling

In comparison to probability-based sampling, the purposive approach has no scientific foundation that informs about the quality of any gathered information (Ståhl 1992). Even so, purposive sampling has provided substantial value for forestry and forest planning. In forest conditions where stands can be assumed to be uniform, it might be economically sound to select fewer sampling points that the surveyor deems representative, especially in cases when the quality of the information is not particularly important to know. Commonly, purposive sampling is coupled with ocular methods, i.e., the surveyor, based on previous knowledge and experience, estimates the attributes without measurements, sometimes referred to as '*guesstimation*'.

1.3.2 Remote sensing inventory and wall-to-wall information

Remote sensing is the process of gathering information about an object without physical interaction using sensors in the electromagnetic spectrum located on mobile platforms (Fussell et al. 1986). Remote sensing has its roots in air reconnaissance, which dates back to the invention of hot air balloons in the 18th century (Kotar & Gessler 2011). However, it gained greater usability and spread with the development of aeroplanes. The first applications were probably wartime mapping (Ives 1920).

Remote sensing can be categorised by the sensor used and the location from which it is used. The first sensors worked in the visible spectrum of light; i.e., cameras for optical imagery. If two photographs are taken simultaneously but with a physical distance approximately the same as that between human eyes, it is possible to join those photographs in an optical illusion (stereography) that shows the photograph in three dimensions (King 2013). If these photographs are taken from above a forest, it is possible to construct instruments that allow a person to measure attributes in the photograph, such as tree heights (Ives 1920; Moessner 1953; Åge 1985). If stereography is expanded with multiple photographs of objects from multiple angles, it is possible to produce real three-dimensional information about those objects (Goodbody et al. 2019). This method, known as photogrammetry, has demonstrated promising value for mapping certain forest attributes (Bohlin et al. 2017). Optical images can also be captured from satellites in space, providing relatively inexpensive and timely images with global coverage (White et al. 2016). These images can be used to describe a wide range of forest attributes (Falkowski et al. 2009).

Optical sensors have a major weakness, as they are passive; i.e., they require an external source (mostly the sun) to emit light onto the object to record information about the object from the reflection. Active sensors instead emit their own electromagnetic waves and can therefore measure distances and directions of objects that are hit by the waves. For example, radar (radio detection and ranging), mounted on either aircraft or spacecraft, can be applied to forest inventory (Sinha et al. 2015). Radar can, for example, be used to predict above-ground biomass. One major advantage of radar is that it can penetrate clouds, providing more timely data for clouded areas.

However, the sensors that have proven to be probably the most valuable for forest inventory are lidar (light detection and ranging) sensors used for airborne laser scanning (Lim et al. 2003). In comparison to radar and normal light, lidar emits focused and monochromatic beams of energy at a single wavelength, making it possible to distinguish the return of individual beams (Næsset et al. 2004). This enables the accurate definition of high-density point clouds delineating objects in three-dimensional space. Based on the point clouds, secondary metrics can be computed for a two-dimensional grid and related to ground-truth information collected on field plots (Næsset 2002). Such predictions have been used widely to produce forest attribute maps.

To produce forest attribute maps, models are constructed, describing the relationship between some ground truth and corresponding remote sensing metrics (e.g. Nilsson et al. 2017). The models can be non-parametric, like k-nearest neighbour matching (e.g. Reese et al. 2002), or parametric, like least squares regression (Næsset et al. 2005).

Forest attribute maps have been produced for large areas (e.g. Reese et al. 2003; Hansen & Loveland 2012; Kotivuori et al. 2016; Nilsson et al. 2017; Astrup et al. 2019). These maps introduced a groundbreaking change to forest planning, which, until recently, lacked high-quality, wall-to-wall information. The maps can be used to update already collected information (Lindgren et al. 2022), or to directly form the basis for forest planning (Wilhelmsson et al. 2025).

1.3.3 Stand inventory databases

A business system is a computer-based system that supports the planning and execution of business within a company (Snoeck et al. 2000). Forestry is a business that revolves around the harvesting of wood in various stands spread over a larger area. Large forest organisations, such as forest-owning companies, utilise business systems to organise their operations and facilitate communication between departments. One key component of such systems in forestry is the stand inventory database, which stores forest information for all stands belonging to the company (Nilsson et al. 2012).

Historically, the forest information in this database has been collected from various sources, including field survey campaigns or aerial photo interpretation (Ståhl 1992; Koivuniemi & Korhonen 2006; Maltamo et al. 2021). Today, most forests have also been surveyed using remote sensing methods (Næsset 2014; Nilsson et al. 2017). Direct feedback from harvesting machines is also used (Möller et al. 2017). The contents of the stand inventory database are continuously updated using growth models, resulting in declining quality over time (Haara & Leskinen 2009).

1.4 Decision-making and planning under uncertainty

From a decision-maker's point of view, uncertainty can be included in the utility function to increase rationality (Kangas 2010). The function in Eq. (1) on page 22 can be expanded so that the action x is dependent on some observed state q as

$$U = f(x(q)) \tag{15}$$

If the observation is uncertain, the observed state q can be viewed as a random variable from some probability distribution. The width of the distribution corresponds to how certain we believe our observation is. If we are more certain that the observed state q actually is the true state, the width of the distribution is narrower, and vice versa.

The distribution of the observed state q may be discretised into a finite number of plausible scenarios (S). Thus, assume that the observed state q has $|S|$ potential scenarios for the quantity n due to uncertainty, linked with probabilities π_s, then we can alter the utility function in Eq. (2) on page 22 to consider the expected utility across all scenarios in S given the decision x as

$$\max \mathbb{E}(U) = \sum_{s \in S} \sum_{j \in J} \pi_s n_{sj} x_j. \tag{16}$$

n_{sj} in Eq. (16) is a realisation from the probability distribution of the observed state q in Eq. (15).

If we assume that the distribution is normal $n \sim N(\mu, \sigma^2)$, then the variance indicates how certain we are that the observed state q is the same as the mean of the distribution (μ). The variance can be described as a function $g(.)$, so that $\sigma^2 = g(m)$, where m is a measure of how much effort is spent to provide the information on which we base the decision x. If m is larger, then σ in most cases should be smaller, returning a narrower probability distribution and, thus, a higher expected utility. It is possible that another effort, say m', costs less but returns the same σ and utility. When deciding between doing m and m', choosing m' would be more rational, since the cost is lower, but the yielded utility is the same. The total utility, considering the cost of the information acquisition effort and the utility of the decided action, would be larger.

1.4.1 The value of information

The value of information can be defined as the change in the total value of a decision situation resulting from the presentation of new, better information to the decision-maker (Hirshleifer & Riley 1979; Kangas 2010). If the value of information depends on the observed state q it is more fitting to talk about the expected value of information. It can be calculated as

$$\mathbb{E}(VOI) = f\big(x'(q')\big) - f\big(x(q)\big) \quad (17)$$

where the functions in Eq. (15) are used to describe the utility of the decision x, which is dependent on the state q to the utility of making another decision x' based on information about the state with lower uncertainty (q'). If the information about q' is collected with effort m' which carries some cost, it is rational to collect the new information if $\mathbb{E}(VOI)$ is larger than that cost. If the new information about the state (q') does not yield any change in the outcome of the decision, $\mathbb{E}(VOI)$ is, per definition, 0.

A concept related to the calculation of the value of information is the cost-plus-loss analysis (Duvemo 2009). In such an analysis, the value of a particular information acquisition method is compared to the case of the optimal action given perfect information, thereby including the distance to optimality (see Figure 2). The expected cost-plus-loss ($\mathbb{E}(C + L)$) can be calculated as

$$\mathbb{E}(C + L) = m' + f\big(x^*(q^*)\big) - f\big(x'(q')\big) \quad (18)$$

where q^* is the state q described with perfect information (i.e., '*true*') and x^* is the optimal action given that state. A cost-plus-loss analysis is useful for comparing information acquisition methods, while the value-of-information approach provides knowledge on whether any method is profitable and thus rational. However, minimising $\mathbb{E}(C + L)$ and maximising $\mathbb{E}(VOI)$ should lead to the same decision regarding what information acquisition method to choose.

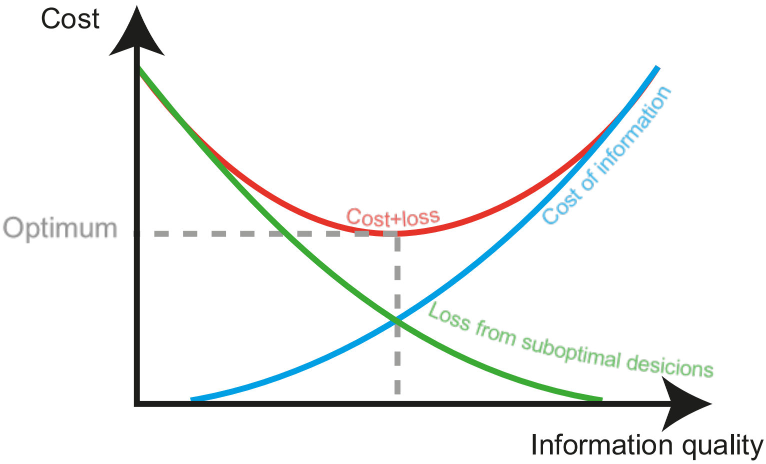

Figure 2. The conceptual relation between the cost of information, the loss from suboptimal decisions and their sum (cost+loss) with increasing information quality.

1.4.2 Forest information uncertainty

The information describing the observed state q in Eq. (15) does not have to be information describing the initial state of a forest to be modelled in a forest planning process; it can be any information that, in general terms, describes some state in nature, now or in the future. However, seeing it as information describing the initial state of a forest is suitable for the work in this thesis.

If we see the initial information about some unit i as some observed value (q_i) being a combination of the true unobservable value (y_i) and an error (ε_i), this relationship can simply be described as

$$q_i = y_i + \varepsilon_\mathrm{i} \tag{19}$$

The error component ε_i can be further subdivided into random (η) and systematic error (b_i), where it is often assumed that the random error belongs to a normal distribution, $\eta \sim \mathrm{N}(0, \sigma^2)$, with mean 0 and variance σ^2. The full description of the observed value would, therefore, be

$$q_i = y_i + \eta + \mathrm{b_i} \tag{20}$$

Errors exist for many reasons. They can stem from faulty measurement tools, biased sampling, or flawed modelling. They can also result from natural randomness. The random errors (η) have a variance (σ^2) that can describe their probable size.

In a practical sense, it is easiest to see uncertainty in forest information as some vagueness in our knowledge about the true state of a certain forest. For example, we may have some prior understanding of the size of the growing stock in a stand for which we have collected information. After the final felling, we know with greater certainty what the growing stock was, since all trees have been individually measured. The difference between these two figures is an example of real uncertainty affecting real forestry. If the harvested volume is less than expected, problems may arise due to a higher demand than supply, and vice versa. Coming back to the concept of the value of information, it might be a rational choice to spend more money on getting a more certain figure on the growing stock if the cost of the consequences of erroneous information is more severe than the cost of getting the information. The size of random errors can be improved by using better equipment or making a greater effort; e.g., taking a larger sample or repeating the sample multiple times. The systematic error or bias can be estimated by comparing, for example, the estimated population mean obtained using one inventory procedure with the estimated population mean obtained using a more accurate and unbiased inventory method. Knowing the bias makes it possible to calibrate the less accurate method to remove some of that error.

A special type of bias commonly found in remote sensing predictions is regression towards the mean (Ståhl et al. 2024). This bias arises when using models generated from covariates that have a relatively low correlation between the quantity to be predicted and the true values. The resulting predictions tend to overestimate small true values and underestimate large true values (e.g. Gilichinsky et al. 2012). This effect reduces the variance among the predicted values compared to the true ones. In comparison to classical errors, errors due to regression towards the mean (also known as Berkson-type errors) correlate with the true values rather than the predicted ones (Carroll et al. 2006; Kangas et al. 2023).

1.4.3 Risk

A decision-maker can be either risk-averse, risk-neutral or risk-seeking (Weber 2010). A risk-averse decision-maker will make decisions that minimise the likelihood of unwanted outcomes. Such a decision-maker would choose a concave $f(.)$ as utility function in Eq. (15) so that reducing σ increases the expected utility $\mathbb{E}(f(x(q)))$ even if μ remains the same. A risk-seeking decision-maker will instead make risky decisions, i.e., decisions that potentially can lead to very positive outcomes (e.g., jackpots) but also naturally have some probability of failure. Such a decision-maker would choose a convex $f(.)$ as utility function so that a wider distribution (larger σ) increases the expected utility $\mathbb{E}(f(x(q)))$ even if μ remains the same, since some low-probability scenarios yield very large utility. A risk-neutral decision-maker will make the decision that leads to the maximum degree of objective fulfilment. Such a decision-maker would choose a linear $f(.)$ so that expected utility $\mathbb{E}(f(x(q)))$ increases with increasing μ.

1.4.4 Methods to acknowledge information uncertainty in forest planning

An early attempt to acknowledge information uncertainty in forest planning was Sprängare (1975). He used Monte Carlo simulation to generate an uncertainty scenario of forest information for a forest holding and then solved the same linear programming problem for both the original and generated forests. He then compared the solutions to investigate the effect of the information uncertainty. He found that 30-40% of harvesting decisions would be different if better data were available. By doing so, he conducted a sensitivity analysis. It is considered good practice to conduct sensitivity analyses when proposing models of any kind, especially optimisation models (Janová et al. 2024). However, many sensitivity analyses reported for new models can be referred to as uncertainty analyses (Saltelli et al. 2019). An uncertainty analysis is conducted by varying input factors and recording the possible ranges of the output. The purpose of a sensitivity analysis is to take the process one step further by pointing out each input factor's contribution to the output uncertainty.

Others have conducted investigations into how uncertainty in forest information affects optimality in forest planning. As in the case of Sprängare (1975), many have used simulation techniques to explore this area (refer to Duvemo & Lämås 2006 for an overview). In such analyses, the aim is often to assess the value of information from some suggested inventory method in a certain decision setting. The standard procedure is to compare decisions based on new information with decisions based on the currently available information (value of information analysis) or to compare decisions based on information from a specific method (e.g., new) with decisions based on information considered to be without uncertainty (cost-plus-loss analysis). Results from these analyses provide insight into how much decisions can be improved by enhancing the quality of information. Common suboptimality losses in terms of net present value from inventory errors reported in the literature range from 1% to 7% (Duvemo & Lämås 2006).

The aforementioned methods mostly deal with assessing the potential effects of uncertainty posterior to the actual solution. However, there also exist methods that involve considerations of uncertainty when solving a problem by optimisation (Näslund 1965; Pasalodos-Tato et al. 2013). An early attempt was the mean value process, where a linear programming model is adapted so that, for example, the expected area of burned forests in each period is treated as bare land in the next (e.g. Reed & Errico 1986). The mean value process is thus rather simplistic. Another possibility is to use what is called chance-constrained programming. It can be used when the right-hand side of the constraints in a linear programming model (i.e., the vector $\boldsymbol{b}$ in Eq. (8) on page 24) has an uncertainty that can be described with a closed-form cumulative distribution function (e.g. Hof & Pickens 1991). In that case, a decision-maker can set restrictions on the tolerated probability of infeasible solutions dependent on $\boldsymbol{b}$, like, for example, *"in 95% of the cases, the supply should meet the demand"*. A somewhat similar approach is to let elements in the objective function and constraints (i.e., the vectors $\boldsymbol{c}$ in Eq. (7) and $\boldsymbol{b}$ in Eq. (8) on page 24) belong to fuzzy sets according to some membership functions (e.g. Mendoza & Sprouse 1989). Another method, especially suitable for large, non-linear problems of great dimensions with interlinked decisions (e.g., in spatial forest planning) some heuristics can be applied instead of exact solution methods (e.g. Meilby et al. 2001). The large dimensions of such problems with interlinked decisions have spurred the use of graph-based Markov decision processes, which organise the interconnection between management and uncertainty but lack exact solution methods (e.g. Forsell et al. 2011). Similarly, stochastic dynamic programming can be used (van Kooten et al. 1992). Another possibility is to use stochastic programming.

Stochastic programming

Stochastic programming[3] is an optimisation approach that assumes that data in the optimisation model belong to probability distributions instead of being single values. In essence, stochastic programming provides the solution that,

[3] Note: not stochastic dynamic programming.

on average, is the best given the uncertain parameters. The common approach to stochastic programming is to model decisions that must be made without realising the uncertainty and what the optimal decision would be following the realisation of uncertainty. Generally, this is done in two stages, but one or multiple stages are also possible.

A two-stage stochastic program analogous to the linear program presented in Eq. (7) and onwards (page 24) can be stated as

$$\max \boldsymbol{c}^T \boldsymbol{x} + \mathbb{E}(Q(\boldsymbol{x}, \xi)) \tag{21}$$

Subjected to

$$\boldsymbol{Ax} \leq \boldsymbol{b} \tag{22}$$

$$\boldsymbol{x} \geq 0 \tag{23}$$

where $Q(\boldsymbol{x}, \xi)$ is the optimal value for $\boldsymbol{x}$ in the second-stage problem, given the realisation of the uncertain data ξ belonging to some probability distribution. Eq. (21) states that we want to maximise the return of the decision vector $\boldsymbol{x}$ (first-stage) including the expected return of the same decision vector when the uncertainty ξ has been realised (second stage).

A general stochastic program with parameters belonging to continuous distributions is not solvable with available methods. Therefore, it is standard practice to develop its deterministic equivalent. The following example is the same as provided in Eqs. (10) and onwards (page 24), with uncertainty considered in the outcome of harvested volume and net present value. First, one has to assume that the uncertain data belong to a known distribution. Let us say that the net present value (n) is explained by the distribution of probable harvest volume per hectare ($n = f(v)$) and that $v \sim N(\mu, \sigma^2)$. In some process, the distribution is discretised for a set of scenarios (S). If so, the formulation of the stochastic program can be stated as

$$\max U = \sum_{s \in S} \sum_{i \in I} \sum_{j \in J_i} \pi_s n_{sij} a_i x_{ij} \tag{24}$$

subjected to

$$0 \leq x_{ij} \leq 1 \qquad \forall i \in I, \forall j \in J_i \tag{25}$$

$$\sum_{j \in J_i} x_{ij} = 1 \qquad \forall i \in I \tag{26}$$

(27) $$\sum_{i\in I}\sum_{j\in J_i} v_{sijp}a_ix_{ij} \leq \sum_{i\in I}\sum_{j\in J_i} v_{sijp+1}a_ix_{ij} \qquad \forall s \in S,\ \forall p \in P \setminus \{p_0\}$$

What is new in Eq. (24) compared to Eq. (10) is the probability π_s for each scenario s in S, given $\sum_{s\in S}\pi_s = 1$. Net present value (n_{sij}) is also indexed by s, since it is an indirect realisation of the distribution of v. Also v_{sijp} in Eq. (27) has been indexed over S. Note that $x_{ij}$is not indexed over S, which means that a decision of what alternative to be applied in a stand must be the same over all scenarios. The first-stage problem would correspond to finding the highest expected net present value across all scenarios. In this formulation, there are no second-stage decisions. However, they probably need to be introduced due to feasibility concerns. Changing the formulation only in Eqs. (24) and (27) would encompass that:

(28) $$\max U = \sum_{s\in S}\sum_{i\in I}\sum_{j\in J_i} \pi_s n_{sij}a_ix_{ij} - \sum_{s\in S}\sum_{p\in P}\pi_s\beta_{sp}$$

subjected to

(29) $$0 \leq x_{ij} \leq 1 \qquad \forall i \in I, \forall j \in J_i$$

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

(31) $$\sum_{i\in I}\sum_{j\in J_i} v_{sijp}a_ix_{ij} \leq \sum_{i\in I}\sum_{j\in J_i} v_{sijp+1}a_ix_{ij} + \beta_{sp} \qquad \forall s \in S,\ \forall p \in P \setminus \{p_0\}$$

The new term ($\sum_{s\in S}\sum_{p\in P}\pi_s\beta_{sp}$) in the objective function (Eq. (28)) minimises the sum of the deviations from reaching the restriction on harvest levels in Eq. (31). The first-stage problem will still be to find the highest expected net present value. The second stage will be to consider those decisions in light of the realised deviations from the desired harvest levels. Note that the two stages are solved for simultaneously, not separately.

The discretisation of continuous probability distributions can be achieved using Monte Carlo simulation. In essence, Monte Carlo simulations utilise the law of large numbers, which, simply put, states that if you draw enough random samples from a distribution, the mean among those samples will converge to the true expected value of the distribution, or

(32) $$\overline{X_n} \rightarrow \mathbb{E}(X)\ when\ n \rightarrow \infty$$

where $\overline{X_n}$ is the average of n random samples from the random variable X.

Stochastic programming has been used for forest planning applications since the 1980s (Gassmann 1989). Applications have ranged from considering the risk of wildfires or storms (Gassmann 1989; Boychuk & Martell 1996; Eyvindson et al. 2024) to considering uncertainty in growth (Eriksson 2006) and future wood prices (Álvarez-Miranda et al. 2019). Stochastic programming has also been used to produce forest management plans under forest information uncertainty (Eyvindson & Kangas 2014; Kangas et al. 2014; Eyvindson et al. 2017; Nahorna et al. 2024).

2. Motivation and aims

What is striking about the uncertainty handling methods described in section 1.4.4 is that most of them are probably rather difficult and non-intuitive to use, especially for non-experts. If ordinary linear programming models are a stretch for many to grasp and use, how could a graph-based Markov decision process with all its complexity ever be implemented and made available in an easy-to-use decision support system? That is one of the probable reasons why there exist very few decision support systems that have methods for considering uncertainty (Pasalodos-Tato et al. 2013; de Pellegrin Llorente et al. 2023). Even fewer, if any, specifically deal with information uncertainty.

It is probably first when methods to consider uncertainty are available in decision support systems that forestry will begin to use them to any large extent. However, since these systems are widely used in forestry (Eriksson & Borges 2014; Segura et al. 2014), any implementation could potentially reach a large user base quickly (e.g., see the nationwide use of Heureka in Lämås et al. 2023). However, an implementation of a new method must consider the experiences and needs of end-users (Schulz 2021). Not much value will be added if a new uncertainty-dealing method is too difficult to use.

No available decision support system lets users easily set up stochastic programming formulations to solve planning problems under uncertainty (Pasalodos-Tato et al. 2013; de Pellegrin Llorente et al. 2023). Even so, stochastic programming could be a viable method to consider. It may seem technically complicated at first, but upon examining the deterministic equivalent of a stochastic programming problem, it is not much different from a standard linear programming formulation. As long as one can describe the underlying uncertainty in discrete scenarios, the only necessary change compared to the linear programming formulation is to introduce the index s for those parameters and variables that are dependent on each scenario (compare Eq. (24) with Eq. (10)). Stochastic programming models can, of course, be made as increasingly complicated as one wish them to be, however, even with the simplest applications (one-stage problems), the decisions will be made to provide the maximum or minimum expected value across all scenarios. Having the possibility to make such analyses would likely improve forest managers' decision-making processes and increase their objective fulfilment, as they would shift from deterministic ignorance of point values to accessing knowledge on probable distributions of results.

2.1 Aims

This thesis aims to examine how forest information uncertainty is addressed in contemporary long-term forest planning and how current practices and uncertainty levels impact decision makers' objective fulfilment. Furthermore, the aim is to showcase a forest planning approach that explicitly deals with forest information uncertainty and to evaluate its performance, implementability, and usability in a practical context.

These aims have been addressed in the four separate chapters (papers) of this thesis in the following way:

- **Paper I** examines how forest information uncertainty is handled in contemporary practice.
- **Paper II** analyses the combined effects of using uncertain forest information while having misaligned objectives throughout the planning process.
- **Paper III** examines how the use of biased remote sensing information impacts the objective fulfilment of long-term forest planning.
- **Paper IV** analyses the benefits of implementing stochastic programming for solving forest planning problems under forest information uncertainty in a state-of-the-art decision support system.

The primary motivation of this thesis is to enhance decision-making in forestry, which is why emphasis is placed on practical relevance.

3. Materials and methods

This thesis utilised a mixed-methods approach. Paper I was fully qualitative, with interviews as the only data collection method. Paper IV used both qualitative and quantitative approaches in an interdisciplinary fashion (Nuijten 2011). Papers II-III were fully quantitative. Refer to Table 1 for an overview of the methods and datasets used in the underlying papers.

Table 1. The primary methodologies and datasets used in each paper are presented.

Paper	Research mode	Primary methodologies	Primary datasets
I	Qualitative	Semi-structured interviews with forest planning experts at major forest companies.	Recordings and transcripts of interviews, as well as planning process maps created during the interviews.
II	Quantitative	Monte Carlo simulation based on Cholesky decomposition, treatment programme generation with Heureka PlanWise, and mixed integer programming (area-based).	A stand inventory database, a road net-work, and a field plot survey
III	Quantitative	Treatment programme generation with Heureka PlanWise, and mixed integer programming (strata-based).	A stand inventory database, a field plot survey, optical satellite predictions, and airborne laser scanning predictions.
IV	Mixed	Monte Carlo simulation based on Cholesky decomposition, treatment programme generation with Heureka PlanWise, stochastic programming (area-based), and a semi-structured focus group interview.	A stand inventory database, a field plot survey, and the recording of focus group interviews.

3.1 Qualitative methods and data

The qualitative methods employed in this thesis primarily involve semi-structured interviews (Knott et al. 2022). Paper I involved individual semi-structured interviews, while Paper IV involved an interview with a focus group.

3.1.1 Paper I

Paper I was conducted as a qualitative study based on semi-structured interviews. To guide the study, four research questions were identified:

1. Is the hierarchical forest planning paradigm implemented in large forest-owning companies? If so, how?
2. What forest information is used by large forest-owning companies, and how?
3. What level of uncertainty does this forest information have?
4. What strategies do large forest-owning companies employ to handle or control the effects of forest information uncertainty?

The respondents were representatives from six major forest companies in Sweden. They were chosen by inviting all forest companies that own or manage at least 200,000 hectares of productive land in Sweden, with the rationale that these large companies should have a formal planning process (Eriksson 2008). All invited companies agreed to participate in the study and nominated one representative each. The representatives were planning experts working with long-term forest planning. The six companies included in the study represented approximately 34% (7.8 million hectares) of Sweden's total productive forest land.

The interviews were conducted in person or online via video call (due to COVID-19 restrictions) during spring 2020. The interviews were recorded and then professionally transcribed. The length of the interviews was, on average, 177 minutes and 24,192 words. An interview guide aided the interviews. It was based on the research questions and preliminary written materials, such as internal documents, provided by three of the companies. Since the interviews were semi-structured, questions not included in the guide were asked if necessary. This approach fitted the exploratory scope of the interviews.

Parallel to the interview, each respondent, together with the aid of the interviewer, co-created a process map that covered all actions and decisions made, as well as all supporting systems and information used, before a forest stand could be harvested. Also, the quality of the information used in the planning was mapped. Furthermore, all actions were marked as belonging to either the strategic, tactical or operational planning stages.

All qualitative data collected during the study were stored in computer-assisted qualitative data analysis software. The analysis focused on identifying common patterns and differences among the participating companies.

3.1.2 Paper IV

In Paper IV, major forest companies were invited to participate in a workshop (focus group) to evaluate the benefits and drawbacks of transitioning to stochastic programming in forest planning, with the implementation of stochastic programming in a decision support system as an example. The rationale for organising the data collection as a focus group was the possibility of obtaining individual responses and feedback, as well as group consensus during the same session (Cyr 2016).

The same sampling criterion as in Paper I was used, i.e., companies owning or managing more than 200,000 ha of productive forest land were invited. The two smallest companies declined, resulting in 7.3 million hectares of productive forest land being represented in the final sample. The representatives were nominated on the same premises as in Paper I and had titles such as forest planning specialist or analyst.

During the workshop, the participants and the authors of Paper IV engaged in a discussion divided into two principal parts. In the first part, a paper-based mock-up illustrating how a forest planning problem is conventionally solved with deterministic optimisation in a decision support system was used to guide the discussions. In the second part, another, but similar, paper mock-up was used. The mock-up had been altered to show how to solve the same problem as described in the first part of the workshop, but with stochastic programming instead of standard deterministic optimisation. During the second part, discussions focused on the benefits and drawbacks of altering Heureka PlanWise to enable stochastic programming.

The workshop discussions were digitally recorded to aid the analysis, which focused on highlighting how uncertainty affects companies' planning today, how usable the decision support system is and should be (with and without stochastic programming), how results are and should be presented, and how enabling stochastic programming will impact the value of using the decision support system.

3.2 Quantitative methods and data

3.2.1 Forest information

Four types of forest information were used in Papers II-IV:

- Forest information in stand inventory databases (Papers II and IV)
- Field plot surveys of sampled stands (Papers II-IV)
- Predictions of forest information based on airborne laser scanning (Paper III)
- Predictions of forest information based on satellite imagery (Paper III)

Information in stand inventory databases

Operational wall-to-wall information from the stand inventory database belonging to the forest company Holmen Skog AB was used in Papers II and IV. In Paper II, the stand inventory database was related to a field plot survey to produce simulated errors. In the final analysis of Paper II, the stand inventory database information represented the true state of the forest. In Paper IV, the same error-generating procedure as in Paper II was used. However, in the analyses of Paper IV, the stand inventory database information represented a scenario very close to the expected value scenario, but not the true state.

Field plot surveys of sampled stands

In Papers II-IV, stand-wise field plot inventories were used as reference information in different ways. This reference information originated from two independent inventories conducted during the summer of 2010 (used in Paper III) and 2019 (used in Papers II-IV) to describe Holmen Skog's forests (approximately one million hectares of productive forest land). The inventory method followed established protocols for data collection developed for the predecessor of Heureka PlanWise[4], the Forest Management Planning Package (Jonsson et al. 1993). According to this protocol, stands belonging to the forest holding in question should first be described extensively using a cheaper data collection method if no stand inventory database already exists. Based on this auxiliary information, a two-phase sampling procedure should be conducted.

The first phase is the stratified sampling of a number of representative stands selected randomly with the probability of selection proportional to the stand area. Stratification is achieved by clustering stands into classes based on two of the most important attributes for forest planning: standing volume per hectare and stand age. By doing so, the sample will, at least in theory, better represent the true distributions of age and volume. In 2010, 1070 stands were sampled for field survey. The corresponding number for 2019 was 800. The survey of the sampled stands was conducted on a systematic grid of circular field plots, with radii ranging from 3-10m, depending on the tree height of the particular stand (smaller radii for stands with low tree heights and vice versa). On these plots, individual tree information and stand properties were recorded to provide unbiased stand-level estimations (Lindgren 1984, 2000). For plots with average tree height >4m, all trees >4cm in diameter at breast height (1.3m above ground) were calipered for diameter, and tree species were identified. A random number of these trees was height-measured with a hypsometer and age-determined by counting annual rings on bored increment cores. Dominant tree height was also measured for site index estimation. On sapling-dominated plots, only the main stems were height-measured, and no trees were calipered. Whatever the average tree height, each plot underwent detailed site characterisation, including descriptions of vegetation, climate, soil, terrain, and natural values. Information about the individual trees was stored in a tree-list. The plot survey information was used to represent the true state of the forest in the error simulations in Papers II and IV. In Paper III, it acted as a reference for evaluating management decisions based on remote sensing predictions.

Remote sensing information

The remote sensing sources used in Paper III were the SLU Forest Map and the Forest Attribute Map from the Swedish Forest Agency. The SLU Forest

[4] Heureka PlanWise is further explained in section 3.2.3.

Map was based on optical satellite imagery and included predictions for volume, Lorey's mean height, mean age, and proportion, presented on 25 × 25m raster elements covering all of Sweden. The map was produced by k-nearest neighbour imputation of national forest inventory plots to images from Landsat 7 Enhanced Thematic Mapper (Reese et al. 2003). The map covers a set of years, but only predictions for the year 2010 were used in the analysis. The Forest Attribute Map, produced by the Swedish Forest Agency, was created based on regression analyses between metrics from point clouds collected using airborne laser scanning in 2019 and national forest inventory information. The map had a resolution of 12.5 × 12.5m and included predictions of standing volume, Lorey's mean height, average diameter at breast height (D_{bh}), and stand basal area. For details, see Nilsson (2017). The version of the airborne laser scanning-based map used in Paper III had not undergone any data filtering (removal of predictions for tree heights >3m), which is usually done with the public version.

Additional data

In Paper II, the stands in the stand inventory database were assigned to harvest areas. The harvest area allocation was defined by the shortest or most cost-effective terrain transport path from each stand to the roadside, over a cost-raster describing the relative ease of traversability for forest machines.

3.2.2 Scenario generation

In Papers II and IV, Monte Carlo simulation was used to generate a plausible discretisation of a continuous distribution describing multivariate errors in contemporary forest information used operationally by forest companies. In principle, the same method used by Sprängare (1975) was employed, where the relation between two types of inventory methods applied to the same population was mimicked in a simulated population (Figure 3). Thus, in the case of Papers II and IV, errors were calculated as the differences between what was recorded in the stand inventory database and what a field plot survey of the same stand showed, with the latter representing the assumed true unbiased state. This procedure has become standard in the field (e.g. Jacobsson 1986; Larsson 1994; Holmström et al. 2003; Holopainen et al. 2010; Mäkinen et al. 2010).

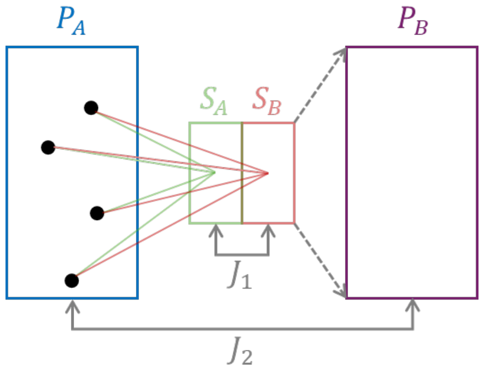

Figure 3. The population of stands described with method A is denoted P_A and is illustrated with the left rectangle in the figure. From P_A the sample S is selected and described with a different method B. Thus S_A is the sample described with method A, and S_B with method B. The simulation uses the relationship between S_A and S_B (denoted J_1) to project P_B from P_A (whose relationship is J_2). From Sprängare (1975).

In Papers II and IV, any covariance matrix ($\boldsymbol{C}$) between errors for the set of attributes was calculated as

(33) $$\boldsymbol{C} = \frac{1}{n-1}\boldsymbol{q}^T\boldsymbol{q}\text{ , where}$$

(34) $$\boldsymbol{q} = \left(\boldsymbol{I}_n - \frac{1}{n}\,\mathbf{1}_n\mathbf{1}_n^T\right)\boldsymbol{M}\text{, and}$$

n was the number of rows (one per plot-surveyed stand) in the matrix $\boldsymbol{M} \in \mathbb{R}^{n\times m}$ consisting of errors calculated for m attributes as differences between field surveys in stands and recorded data of the same attribute and stand in the operational stand inventory database, with one stand per row and $\mathbf{1}_n \in \mathbb{R}^n$ was a size n vector of 1s and ${\mathbf{1}_n}^T$ was its transpose.

Cholesky decomposition was then used in a Monte Carlo simulation to maintain a plausible covariance structure in the simulated information (Benoit 1924; Kroese et al. 2014). For the symmetric and positive semi-definite covariance matrix $\boldsymbol{C}$, the unique Cholesky decomposition as a lower triangular matrix $\boldsymbol{L}$ was computed such that,

(35) $$\boldsymbol{C} = \boldsymbol{L}\boldsymbol{L}^T\text{ where}$$

(36) $$\boldsymbol{L} \in \mathbb{R}^{m\times m}$$

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 $s = \{1, 2, \dots, 100\}$ such that

(37) $$\boldsymbol{E}_s = \{\boldsymbol{LZ}_{1j}, \dots, \boldsymbol{LZ}_{ij}\}, \text{ where}$$

$\boldsymbol{E}_s$ 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 $j = \{1, 2, \dots, J = 10\}$ vectors, each in the form of

(38) $$\boldsymbol{Z}_{ij} = (z_1, \dots, z_m), \text{ where}$$

each z_m was a normally distributed independent random variable with m elements, $z_m \sim N(0,1)$, iteratively $(j = \{1, 2, \dots, J = 10\})$ truncated between σ_{1j} and σ_{2j}, where $\alpha = 2$ and

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

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

and stored as the m:th element of $\boldsymbol{Z}_{ij}$. The reason for using a standard normal distribution truncated between $\sigma = \pm 2$ and divided into 10 steps, was to ensure that the generated errors were not too large and that each generated scenario could have representations of errors for all parts of the distribution. The uniform sampling was taken 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 database information $\boldsymbol{D}$ of the m attributes for i stands and adding it to each of the 100 $\boldsymbol{E}_s$. Thus, let

(41) $$\boldsymbol{R}_s = \boldsymbol{D} + \boldsymbol{E}.$$

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

(42) $$\boldsymbol{R}_{s,relative} = \boldsymbol{D} + \boldsymbol{E}_{s,relative} \circ \boldsymbol{D}.$$

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 $\boldsymbol{R}_{s,relative}$ or $\boldsymbol{R}_{s,absolute}$, 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

150m^{3}ha^{-1}, the diameter at 1.3m was under 10cm, Lorey's mean height was under 12m, the number of stems was under 1000 ha^{-1}, the basal area was under 18m^{2}ha^{-1}, the mean age was under 50 years, and if the site index was under 25m.

The finalised covariance matrices (one for absolute and one for relative errors) are presented in Table 2 and Table 3.

Table 2. The relative variances and covariances between the attributes used to simulate deviations.

	Diameter	**Height**	**Stems**	**Basal area**	**Age**	**Site index**
Diameter	0.027	0.018	-0.03	0.01	0.011	0.001
Height		0.024	-0.021	0.013	0.008	0.001
Stems			0.134	0.051	-0.017	-0.003
Basal area				0.113	-0.006	0.002
Age					0.054	-0.003
Site index						0.014

Table 3. The absolute variances and covariances between the attributes used to simulate deviations.

	Diameter	**Height**	**Stems**	**Basal area**	**Age**	**Site index**
Diameter (cm)	8.2	3.0	-684	2.4	8.2	0.34
Height (m)		3.2	-323	1.8	3.7	0.37
Stems (ha^{-1})			287,227	1231	-753	-63
Basal area (m^{2}ha^{-1})				26	-1.7	1.2
Age (years)					331	-6.3
Site index (m)						5.9

3.2.3 Generation of treatment programmes with Heureka PlanWise

The decision support system Heureka PlanWise was used to project possible forest development trajectories for each stand and scenario/dataset in Papers II-IV. Heureka PlanWise includes a core of functions that project forests based on the initial state, while varying the timing and configurations of forest management activities within frames specified by the user (Lämås et al. 2023). Within these frames, PlanWise generates multiple alternative treatment programmes per stand over a user-set planning horizon. This set of treatment programmes can then be used as alternatives in an optimisation model. The forecasts are done in five-year increments, with management assumed to be implemented 2.5 years into the period. Since each treatment programme explicitly covers the whole planning horizon, the treatment programme generation adheres to the Model I formulation for optimisation in forest planning (Johnson & Scheurman 1977).

For Papers II and IV, a preliminary set of treatment programmes was first generated based on the original information in the stand inventory database. The generation aimed to mimic certified business-as-usual forestry, focusing on high yields through rotational forestry while also considering the impact on biodiversity. The management activities in the preliminary treatment programmes were then extracted and applied to each scenario for the corresponding stand. For Paper III, treatment programmes were generated for each of the three datasets independently; i.e., the field survey, the airborne laser scanning-based map and the satellite-based map. After selecting the optimal treatment programme in a set of planning problems (see section 3.2.4), the management activities decided based on the remote sensing information were extracted and applied to the field survey information for the corresponding stand.

3.2.4 Optimisation

Optimisation was used in Papers II-IV. More precisely, mixed-integer programming was used in Papers II and III to solve the respective planning problems. In Paper IV, stochastic programming, with mixed-integer programming as a basis, was employed instead. The models in Papers II and IV were solved using CPLEX. The models in Paper III were solved in the optimisation module of Heureka PlanWise with Gurobi as solver.

Paper II

In Paper II, a series of planning problems was solved to mimic the hierarchical approach to planning in forestry. The problems were also solved in parallel for a set of cases and uncertainty scenarios. The cases investigated in Paper II were defined based on the level of objective alignment between strategic and tactical planning stages and the quality of the information used (Table 4). The uncertainty scenarios represented a discrete realisation of uncertain information about the initial state of the forest (see section 3.2.2).

Table 4. The cases investigated in Paper II. Max. is maximum, min. is minimum, and NPV is net present value. LQ is low-quality information, HQ is high-quality information, LA is low degree of objective alignment, and HA is high degree of objective alignment.

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

First, a strategic problem of finding the solution that provided the highest net present value, given a sustained yield, was solved for each case and scenario. The objective function for this problem was stated as:

$$maximise\ Z = \sum_{s \in S} \sum_{i \in I} \sum_{j \in J_i} n_{sij}\, a_i\, x_{sij} - \sum_{s \in S} \sum_{p \in P} \sum_{r \in R} e_r\, \beta_{rsp} \tag{43}$$

The objective function in Eq. (43) maximises the sum of net present value minus the sum of penalties over the sets of scenarios (S), stands (I), treatment programmes for each stand (J_i), periods (P) , and restrictions (R). x_{sij} is a variable that represent the proportion of stand i, that in scenario s should be assigned treatment programme j. The variable β_{rsp} is the deviation from restriction r for scenario s and period p. The parameter n_{sij} is the net present value per hectare for scenario s, stand i, and treatment programme j calculated with the interest rate 3%; a_i is the area of stand i; and e_r is the cost of deviating one unit from restriction r (500 SEK m^{-3} and 1000 SEK ha^{-1}). The objective function was also subject to a set of restrictions that described the problem in more detail and bound it to reality. An example is the restriction governing the sustained yield. It was stated as:

$$\sum_{i \in I} \sum_{j \in J_i} v_{sijp}\, a_i\, x_{sij} + \beta_{rsp} \geq \sum_{i \in I} \sum_{j \in J_i} v_{sij(p-1)}\, a_i\, x_{sij} \qquad \forall s \in S, \forall p \in P \setminus \{p_0\},\ r = r' \tag{44}$$

Eq. (44) sets the restriction that the sum of harvest from final fellings in one period should not decline compared to the previous period. v_{sijp} is the harvested volume from final fellings per hectare in scenario s, in stand i with treatment programme j in period p. r'indicates that the number of that restriction is only relevant when presenting the full problem (see Paper II). p_0 is the first period in the set P, which is avoided to not include elements outside the range of P.

The harvest levels per period, as decided in the strategic problem, were then independently passed on to a tactical model for each case and scenario. The tactical models were solved iteratively with a rolling time horizon by letting the model plan over a subset of the periods that increased by five periods after each iteration. A restriction ensured that management decisions for later periods were consistent with those made for earlier periods.

For cases 1-LQ-LA and 3-HQ-LA (see Table 4); i.e., planning with a low level of objective alignment, the tactical objective function was

$$minimise\ Z = \sum_{s\in S}\sum_{p\in P}\sum_{h\in H}\sum_{k\in K} z_{sphk}b + \sum_{s\in S}\sum_{i\in I}\sum_{j\in J_i}\sum_{p\in P} a_i x_{sij} c_{sijp} + \sum_{s\in S}\sum_{p\in P}\sum_{r\in R} e_r\, \beta_{rsp} \tag{45}$$

The objective function in Eq. (45) minimises the undiscounted costs of forest management and accessing harvest areas. The first term sums up the costs of accessing harvest areas with harvest machines (suitable for either thinning or final felling). Additional sets, compared to Eq. (43), are harvest areas (H) and harvesting machine systems (K). The variable z_{sphk} is a binary variable that takes the value 1 if the machine system k is used in scenario s, period p, and harvest area h; otherwise it is assigned 0. b is the accessing cost (set to 50,000 SEK) per harvest area and period. The second term of Eq. (45) is the sum of forest management costs. The parameter c_{sijp} is the cost of all management done in stand i, according to treatment programme j, in scenario s and period p. The third term is the same as in Eq. (43).

For cases 2-LQ-HA and 4-HQ-HA, i.e. planning with a high level of objective alignment, the tactical objective function was

$$maximise\ Z = \sum_{s\in S}\sum_{i\in I}\sum_{j\in J_i} n_{sij} a_i x_{sij} - \sum_{s\in S}\sum_{p\in P}\sum_{h\in H}\sum_{k\in K} \frac{z_{sphk}b}{(1+d)^{5p-2.5}} - \sum_{s\in S}\sum_{p\in P}\sum_{r\in R} e_r\, \beta_{rsp} \tag{46}$$

Eq. (46) maximises the net present value of forest management minus the discounted costs for accessing harvest areas. The first term sums the net present value. The second term sums up the discounted costs of accessing harvest areas. The parameter d is the interest rate (3%). The third term is the same as in Eq. (43).

For all cases, the tactical model included various restrictions, for example,

$$\sum_{i \in I} \sum_{j \in J_i} v_{sijp} a_i x_{sij} = \vartheta_{sp} + \beta_{rsp} \qquad \forall s \in S, \forall p \in P, r = r' \tag{47}$$

Eq. (47) ensures that the harvest levels from final fellings in the tactical phase match the corresponding harvest levels of the strategic phase. ϑ_{sp} is the target levels from the strategic phase for final fellings in scenario s and period p. Note that the set of scenarios (S) and periods (P) varied between models and cases. Their configuration is presented in (Table 5).

The decisions of x_{sij} from the tactical phase of each case and scenario were transferred to the reference model, which represents an integrated case where stand-level management decisions and harvest levels are made simultaneously in one step without uncertainty. The objective function for the reference case is the same as Eq. (46), but it considers all periods, not just five at a time (Table 5).

Table 5. The set of scenarios (S) and the set of periods (P) used for the different cases and phases used in the optimisation models in Paper II. LQ is low-quality information, HQ is high-quality information, LA is low degree of objective alignment, and HA is high degree of objective alignment. S is the set of scenarios.

Case	**Phase**	***S***	***P***
1-LQ-LA	Strategic	{1..100}	{0..20}
	Tactical	{1..100}	{0..5},{0..10},{0..15},{0..20}
2-LQ-HA	Strategic	{1..100}	{0..20}
	Tactical	{1..100}	{0..5},{0..10},{0..15},{0..20}
3-HQ-LA	Strategic	{0}	{0..20}
	Tactical	{0}	{0..5},{0..10},{0..15},{0..20}
4-HQ-HA	Strategic	{0}	{0..20}
	Tactical	{0}	{0..5},{0..10},{0..15},{0..20}
Reference	Integrated	{0}	{0..20}

Paper III

In Paper III, optimisation was used to emulate the decision-making of two types of decision-makers as they plan their forest management for 100 years. The first decision-maker (denoted HARVEST) wants to maximise net present value from forest management while ensuring compliance with laws and maintaining a sustained harvest from final fellings. The second (BIO-CARBON) wants to do the same thing but also wants to ensure that the forest's total carbon stock does not decline and that various nature values do not decrease. A similar optimisation model to the one used in Paper II was used to emulate these decision-maker behaviours. However, it only concerned the maximum net present value and did not encompass any scenarios. Its objective function was defined as

$$maximise\ Z = \sum_{i \in I} \sum_{j \in J_i} n_{ij} a_i x_{ij} \tag{48}$$

Note that Eq. (48) is defined with the same parameters and variables as in Eq. (43), apart from the set S and the index s. The set of restrictions in the model varied depending on the decision-makers. For HARVEST, only restrictions connected to the production of wood were included. For BIO-CARBON, also restrictions like

$$\sum_{i \in I} \sum_{j \in J_i} g_{ijpr}\, a_i\, x_{ij} \geq \sum_{i \in I} \sum_{j \in J_i} g_{ij(p-1)r}\, a_i\, x_{ij} \qquad \forall p \in P \setminus \{p_0\},\ \forall r \in R \tag{49}$$

were introduced, where g_{ijpr} is the indicator included in restriction r. The restrictions described in Eq. (49) ensured non-decline of the carbon stock of living trees per hectare, the area of forests older than 120 years in the boreal-nemoral to nemoral zones or 140 years in the boreal zone, the area of forests where at least 25% of the basal area is broad-leaf and the stand is older than 60 years in the boreal-nemoral to nemoral zones or 80 years in the boreal zone, and the area of forests with more than 60 large trees per hectare.

The optimisation models in Paper III were solved in four cases with forest information from either satellite or airborne laser scanning predictions (Table 6). The results from these solutions represent what a decision-maker would expect from using either dataset; thus, these results can be denoted as EXPECTATION. The same models were solved in two corresponding reference cases based on field-measured ground truth information for comparison (Table 6). These results can be denoted REFERENCE. To estimate the effect of decision-making based on remote sensing information, the decisions regarding management, i.e., according to x_{ij} from EXPECTATION were transferred to the reference dataset. The resulting solution can be denoted REALISATION.

Table 6. The definition of the cases in Paper III. Satellite refers to optical satellite imagery, ALS to airborne laser scanning, and Field to field-measured ground truth.

Case	**Information used**	**Decision-maker**
1	Satellite	HARVEST
2	Satellite	BIO-CARBON
3	ALS	HARVEST
4	ALS	BIO-CARBON
Reference 1	Field	HARVEST
Reference 2	Field	BIO-CARBON

Paper IV

In Paper IV, optimisation was used to demonstrate the impact of planning based on uncertain information about the initial state of the forest and how that impact could be addressed explicitly. Stochastic programming was employed to achieve this. The objective function was defined as

$$(50) \qquad maximise\ Z^{SP} = \frac{1}{|S|}\left(\sum_{s\in S}\sum_{i\in I}\sum_{j\in J_i} n_{sij}\, a_i\, x_{ij} - \sum_{s\in S}\sum_{p\in P}\sum_{r\in R} e_r\, \beta_{rsp}\right)$$

Eq. (50) is almost identical to Eq. (43), except that x_{ij} is not defined over the set of S and the whole objective function is divided by the number of elements in S; i.e., the number of scenarios. The first term of Eq. (50) within the parentheses ensures that the same decision is made for management in each stand across all scenarios. The second term is the second stage decision variable; i.e., the penalty that will result from a solution for x_{ij} and provides a recourse to ensure the optimal solution given the realised uncertainty in n_{sij}. Analogous to Eq. (44) used in Paper II, the stochastic programming model in Paper IV also strived for sustained yield with a restriction defined as

$$(51) \qquad \sum_{i\in I}\sum_{j\in J_i} v_{sijp}\, a_i\, x_{ij} + \beta_{rsp} \geq \sum_{i\in I}\sum_{j\in J_i} v_{sij(p-1)}\, a_i\, x_{ij} \qquad \forall s \in S, \forall p \in P \setminus \{p_0\}, r = r'$$

To emulate problem-solving without consideration towards uncertainty, it is standard to develop what is called the expected value (EV) problem. In essence, the EV problem is similar to the stochastic programming problem, but all parameters are instead averages (i.e., the expected values) over the scenarios. The objective function for the EV problem was defined as

$$maximise\ Z^{EV} = \sum_{i \in I} \sum_{j \in J_i} \frac{\sum_{s \in S} n_{sij}}{|S|} a_i\ x_{ij} - \sum_{p \in P} \sum_{r \in R} e_r \beta_{rp} \tag{52}$$

Note that the variable β_{rp} lacks the index s, since it is not defined over the set of scenarios in the EV-problem. The objective function in Eq. (52) had accompanying restrictions, similar in form to those connected to Eq. (50). An example of such is the restriction of non-declining harvest levels from final fellings

$$\sum_{i \in I} \sum_{j \in J_i} \frac{\sum_{s \in S} v_{sijp}}{|S|} a_i\, x_{ij} + \beta_{rp} \geq \sum_{i \in I} \sum_{j \in J_i} \frac{\sum_{s \in S} v_{sij(p-1)}}{|S|} a_i\, x_{ij} \qquad p \in P \setminus \{p_0\}, r = r' \tag{53}$$

In principle, all parameters in the EV model are averages (i.e., expected values) of the corresponding parameters in the stochastic programming model. However, in the implementation in Paper IV, the parameters that were binary indicators were assigned based on the average of the attribute from which they were originally defined, rather than using averages of indicators. Thus, the indicator of old forests, for example, was defined in the EV problem based on the average stand age across all scenarios instead of the average of the indicators. After solving the EV problem, the solution for x_{ij} was transferred to the stochastic programming model. The resulting calculation can be denoted as the expectation of the expected value (EEV) problem. EEV consists of the same objective function as the stochastic programming model, except that $x_{ij}^* = x_{ij}$ from the solution to the EV problem. Thus, the objective function is defined as

$$Z^{EEV} = \frac{1}{|S|} \left(\sum_{s \in S} \sum_{i \in I} \sum_{j \in J_i} n_{sij}\, a_i\, x_{ij}^* - \sum_{s \in S} \sum_{p \in P} \sum_{r \in R} e_r\, \beta_{rsp} \right) \tag{54}$$

4. Results

4.1 How forestry handles forest information uncertainty (Paper I)

Paper I examined the planning process at large forest companies in Sweden, aiming to map its structure, the use of forest information, the quality of that information, and the strategies employed to address uncertainty. The results connected to each research question in the paper are reported below and summarised in Figure 4 and Table 7.

Is the hierarchical forest planning paradigm implemented in large forest-owning companies? If so, how?

The traditional planning paradigm, with its hierarchical subdivision of the planning process, remains valid, at least for large forest companies in Sweden. The strategic stage sets the overall objectives for the subsequent stages and revolves primarily around the long-term harvest levels. The tactical stage determines when individual stands should be harvested while aiming to fulfil the strategic harvest levels. Implicitly, the tactical stage determines the latest date for performing harvest area planning in individual stands. This harvest area planning is an intermediate stage between the tactical and operational stages, and it is difficult to categorise it in either. It focuses on producing detailed harvest instructions for the individual stands (now grouped as harvest areas). It is the last visit before the actual harvest, thus verifying the feasibility of the planned harvest in terms of technical attributes and natural values. Once the harvesting instructions are completed, the harvest area is available for production planners to schedule harvesting during the operational stage.

What forest information is used by large forest-owning companies, and how?

In long-term strategic planning, all companies in the study relied on Heureka PlanWise. Their information sources varied: most used the traditional strata-based approach (a stratified field survey of sample stands), some adopted an area-based method (a comprehensive stand inventory database), and others combined both. Regardless of origin, plans were evaluated using optimisation, primarily linear programming, to determine sustainable harvest levels.

Beyond strategic planning, decision-support systems saw little use. Planners typically relied on internal tools without advanced solution techniques. In tactical planning, the planners "*pointed and clicked*" in a GIS application to assemble an acceptable plan. This limited uptake reflects a widespread mistrust of optimisation: "*An optimising tool tends to optimise only the thing you ask for and leave the rest unanswered. To really benefit from an optimisation, the description of the reality needs to be sufficiently good".*

The stand inventory database was the primary information source outside strategic planning. It pairs tabular information, such as stand volume, height, diameter, basal area, age, site index, and management history, with maps showing stand boundaries. The information had originally been collected through large-scale field surveys in the late 20th century and had been continuously updated by forest officers, harvest machine data, growth models, and government airborne laser scanning mapping (see Nilsson et al. 2017 for a description of the map). The same system granted access to auxiliary map layers like wetness, nature values, elevation, roads, etc., which were used in tactical and harvest-area planning. For operational planning, planners use the harvest-area database (individual harvesting instructions), short-term weather forecasts, and industry demand.

What level of uncertainty does this forest information have?

Most respondents felt the planning information was of low quality but still usable. As one noted, *"It depends on what you mean by large uncertainties. Suppose one discussed that with a chemist; he or she would think that all we have [in forestry] are large uncertainties. However, the deviations combine in such a way that when looking at the complete picture, it works."*

For strategic planning, most companies preferred strata-based surveys for their known, unbiased precision (standard errors around 2%), while those using the stand inventory database typically performed extra sampling to gain knowledge of its accuracy. The respondents viewed the stand inventory database as the most central information source, but also reflected upon the fact that minimal effort is put into improving its quality. They did, however, believe that the planned updates based on airborne laser scanning methods would significantly improve the information quality. Notably, no automatic error detection protocols are included by default in the most commonly used stand inventory database system.

The biggest problems arose from missing or poor information on natural values (e.g., endangered species and habitats). Combined with errors in volumes and ages, this created serious challenges: the late discovery of high-value conservation areas forced companies to alter or abandon parts of their harvest strategy, jeopardising their long-term targets. This was exemplified by one of the respondents: *"We are currently harvesting the last remains of the older forests (...), and we are doing it with the support of a stand inventory database that contains errors (...). Proportionally, there are more errors in the small share of remaining semi-natural forests"*.

What strategies do large forest-owning companies employ to handle or control the effects of forest information uncertainty?

Six main strategies for handling information uncertainty were identified.

1. locking the future by deciding on a plan that should be followed to mask uncertainty from the business.

By *locking the future,* companies commit to a fixed plan and follow it at almost any cost. For example, they pursue harvest levels even if information errors might have rendered them unsustainably high, thus prioritising operational stability and administrative simplicity. As one respondent put it: *"It feels safe, and the reason is that we want [...] some kind of momentary truth, from which we will not deviate. This is the world, this is how it looks, and we will manage it in this way. And then we use that truth for a couple of years until we realise that the world has changed compared to the models and that we have to create a new starting point."*

2. utilising a buffer of available stands for harvest to tackle unknown discrepancies between the plan and reality.

Companies use buffers at every planning stage to absorb unexpected variations and ensure wood supply targets are met. As one respondent noted: "*If we have enough slack in the system, we can cope with quite large errors"*.

3. controlling or updating forest information.

Throughout all planning stages, companies actively verify and update their information. Good examples include running sensitivity analyses to test the robustness of long-term plans and conducting field checks during harvest-area planning to gather fresh information. One of the respondents described the situation: "*When talking about uncertainties, it is so fascinating that we, in fact, judge all the information we utilise to be of such an insufficient quality that we have to verify everything out in the forest. This means that everything we do before we've been to the forest to gather information in the harvest area planning is very much a guessing game*".

4. adaptive re-planning.

Adaptive planning involves replanning when the plan deviates significantly from reality. This happens frequently in the operational stage, where much uncertainty, which has not been acknowledged in earlier stages, is finally realised. For example, if there are significant uncertainties in the harvest area database, such as road quality, soil wetness, or soil bearing capacity, production planners will have a challenging time during wet seasons or thawing periods.

5. planning based on previous outcomes.

Strategy 5 (looking backwards) utilises knowledge about the outcome of earlier plans to plan ahead. A notable example is that some companies plan the procurement of harvesting machine resources based on earlier outcomes rather than the actual harvesting plan.

6. ignoring the uncertainty, either intentionally or unintentionally.

For many reasons, uncertainty is often ignored (strategy 6). It is not a mitigating strategy, per se – rather a coping strategy – as it might be good practice to ignore uncertainties that can be dealt with at low costs when realised.

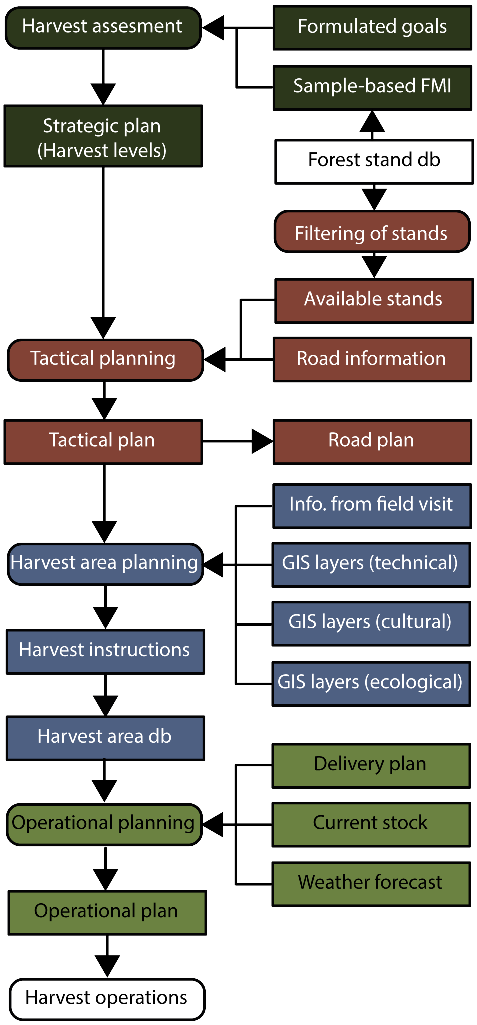

Figure 4. A generalised and simplified example of the process maps created during the interviews. The colours of the boxes indicate the planning stage: dark green for strategic planning, brown for tactical planning, blue for harvest area planning (part of the operational planning), and light green for operational planning. Rounded boxes are activities, while those with sharp corners are data used for these activities. The figure and its caption were originally published in Ulvdal et al. (2023).

Table 7. A summary of the most important results from Paper I. A version of the table was originally published in Ulvdal et al. (2023). DSS refers to decision support system.

Planning stage	**Strategic**	**Tactical**	**Harvest area planning**	**Operational**
Problems addressed	Long-term harvest levels	When to harvest specific stands	How specific harvests should be conducted	Decision on harvesting date and what machines to use
Time considered	100 years	3–10 years	One year	Months
Area considered	Whole company	Regional	A small group of neighbouring stands	District level
Part of the organisation	Specialists and managers at the main office	Local planners	Local planners	Local production planners
Information used	Field plot survey or stand inventory database	Stand inventory database and road networks	Stand inventory database, geographical information on natural, technical, and cultural values	Harvest area database, stand inventory database, delivery plan and weather forecasts
Main output	Harvest levels	Last date for harvest area planning in individual stands	Harvest area database with harvesting instructions	What stands on what date a certain machine group should harvest
How the information is used	Optimised harvest assessment in a DSS	Manually in a geographical information system.	Manually in a geographical information system.	Manually in spreadsheet-based systems
Information quality	Strata-based: high Area-based: lower, but sufficient	The stand inventory database and road network are considered uncertain	Mostly low	Irrelevant due to the manual approach
Main uncertainty strategies	1, 2, 3, and 4	1, 2, and 6 (to some extent, 3 and 4)	2 and 3	2, 4, 5, and 6

4.2 The cost of using uncertain forest information in a hierarchical forest planning process with misaligned objectives (Paper II)

Paper II evaluated the cost implications of using forest information of contemporary quality in a hierarchically subdivided planning process with misaligned objectives between the strategic and tactical stages. The results show, unsurprisingly, that using high-quality information and having aligned objectives yields the best performance (Table 8). Compared to the fully integrated reference case without uncertainty, the cases with high-quality information performed better than those with low-quality information. Furthermore, the cases with misaligned objectives performed worse than those with aligned objectives.

Table 8. The relative changes in objective function values with components across all scenarios compared to the reference in Paper II. Reported values include the total objective function value (Z), net present value (NPV) from forest management (Forest NPV), and total NPV, including access costs (Total NPV). Disc. denotes discounted values. Area and volume penalties reflect constraint violations in area and harvested volume, respectively. Scenarios vary by information quality (LQ: low quality; HQ: high quality) and degree of objective alignment (LA: low alignment; HA: high alignment).

Case	***Z***	**Forest NPV**	**Disc. accessing costs**	**Total NPV**	**Area penalty**
1-LQ-LA	-36.6%	-1.4%	+0.2%	-1.6%	+26.0%
2-LQ-HA	-31.5%	-0.1%	+6.6%	-0.9%	+23.3%
3-HQ-LA	-13.7%	-0.2%	+0.3%	-0.3%	+23.1%
4-HQ-HA	-8.7%	+1.3%	+4.5%	+0.9%	+17.6%

4.3 Transitioning to using remote sensing information in forest planning: the problem with regression towards the mean (Paper III)

Paper III evaluated the potential effects of transitioning from unbiased field surveys as the underlying information for long-term forest planning to remote sensing information, which in many cases has large random errors and is locally biased; i.e., affected by regression towards the mean.

The results of Paper III indicate that the evaluated airborne laser scanning-based map outperformed the satellite map when used in long-term forest planning (Table 9). This indicates that a decision maker using remote sensing information that is significantly affected by regression towards the mean will experience larger deviations from optimal outcomes. The larger deviations cannot be attributed solely to regression towards the mean, as random errors also affect the planning results. However, many harvests planned according to the satellite information had to be postponed, since the age for these stands was predicted to be above the lowest legal final felling age, which was not the case according to the reference. This pattern highlights the significant impact of regression toward the mean on planning outcomes.

When examining the specific indicators, it is evident that the carbon stock was substantially overestimated in the satellite map (Figure 5). The same figure shows a decline in realised carbon stock, even if the problem BIO-CARBON prohibits any decline. Harvest levels were highly variable and diverged significantly from the reference level (Figure 6). The satellite-based planning varied more and had larger deviations than the airborne laser scanning-based planning. The development of the ecological indicators (Figure 7) showed deviations for both datasets. Due to regression towards the mean, the satellite-based information lacked almost all old forests, resulting in a significantly underestimated initial area of ecologically important forests. The implemented actions also initially lowered this area, contrary to what was allowed in the model. Airborne laser scanning-based plans deviated less from the reference compared to the satellite-based plans.

Table 9. The results for net present value for both remote sensing-based stand inventories. Disappointment is the difference between the expected and the realised net present value. Regret is the difference between the reference and realised net present value. Satellite refers to optical satellite imagery, and ALS to airborne laser scanning.

Information used	Decision-maker	Disappointment	Regret
Satellite	HARVEST	-0.5%	-9.1%
Satellite	BIO-CARBON	+1.8%	-6.7%
ALS	HARVEST	+0.4%	-6.7%
ALS	BIO-CARBON	+0.4%	-6.5%

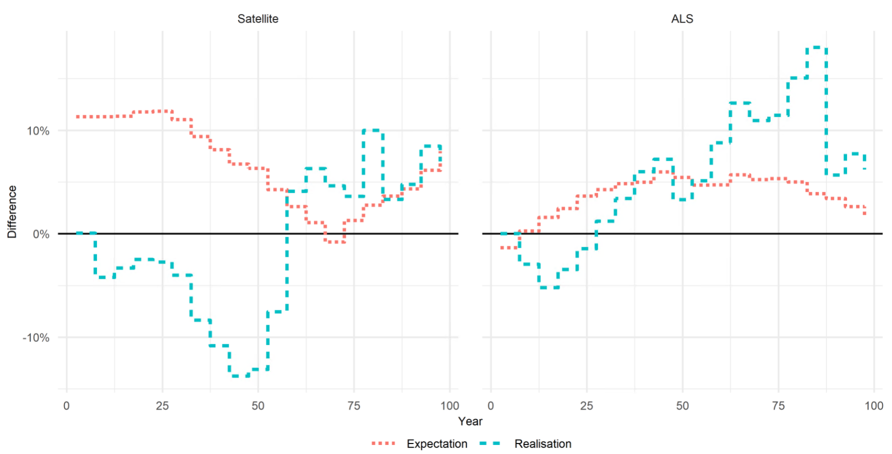

Figure 5. The relative differences to the reference (optimum) for the expected and realised carbon stock per year over the whole planning horizon for plans based on satellite data (left panel) and ALS-data (right panel) in the BIO-CARBON-problem of Paper III. The black line represents 0; i.e., the reference.

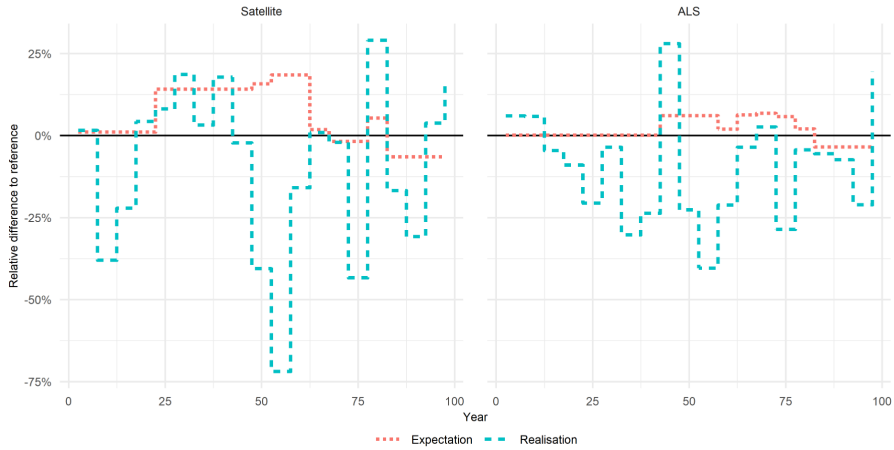

Figure 6. The relative differences to the reference (optimum) for the expected and realised harvested volume per year over the whole planning horizon for plans based on satellite data (left panel) and ALS-data (right panel) in the HARVEST-problem in Paper III. The black line represents 0; i.e., the reference.

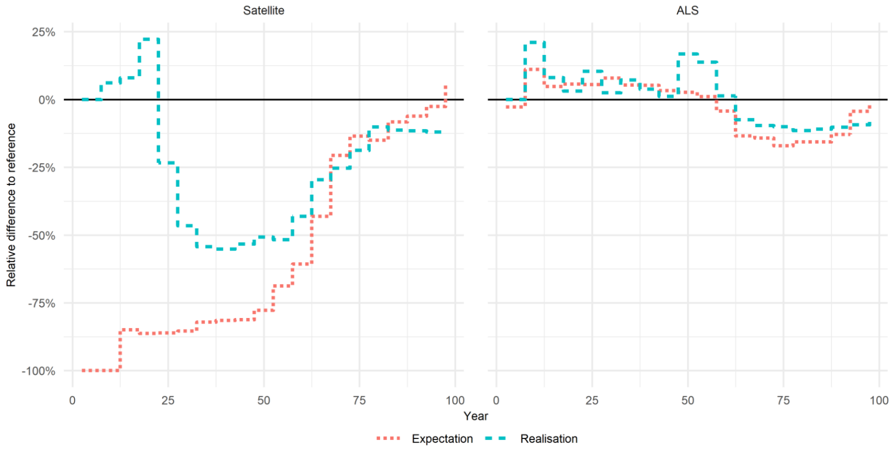

Figure 7. The relative differences to the reference (optimum) for the expected and realised areas of ecologically important forests over the whole planning horizon for plans based on satellite data (left panel) and ALS-data (right panel) in the BIO-CARBON-problem in Paper III. The black line represents 0; i.e., the reference.

4.4 The value of stochastic programming (Paper IV)

Paper IV investigated how stochastic programming could be implemented in a decision support system to provide methods for users to deal with forest information uncertainty using Heureka PlanWise as an example. This implementation was evaluated both quantitatively through a case study and qualitatively with the assistance of forest planning experts from large forest companies.

Case study

When solving the stochastic programming model across all uncertainty scenarios in the case study, the optimal objective function value increased by 20% compared to the expected value solution. This resulted in a 0.8% increase in the net present value of forest management. However, computing time increased by 30,454%, from 13s to 3,959s.

The higher objective function arose from the large deviations from various restrictions that could not be included sufficiently when solving the expected value problem. Instead, these deviations affected the solution when the uncertainty was realised, see Eq. (52) on page 60. The modest net present value gain is driven by initially higher harvest levels from final fellings for the stochastic programming model compared to EEV. This is likely due to the stochastic programming model identifying harvests that can be performed earlier when all information is available. The initially higher harvest levels lead to lower levels than EEV after 35-40 years. The timing of the first final felling shifted only slightly with stochastic programming. For stands with changes, it was most common to advance the final felling by five years, followed by postponing it by the same amount.

Focus group interview

During the focus group interview, discussions were held regarding uncertainty in general and the usability of forest decision support systems, with and without uncertainty handling capabilities.

The results from the interview show that uncertainty in forest planning is commonly discussed within forest companies. Apart from uncertainty in forest information, uncertainty connected to climate change and undiscovered natural values were also mentioned as important. In general, participants would prefer a decision support system like Heureka PlanWise to provide uncertainty estimates for both initial information and forecasted values, rather than the current case of total ignorance. Knowing something about the uncertainty of results would be very beneficial for users, especially when communicating with non-expert decision-makers. For this reason, participants emphasised that a pedagogical presentation of uncertainty is crucial. A suggestion was made to describe results using probability distributions instead of point values. After being shown how a traditional planning problem could be solved with stochastic programming, all participants agreed that having such a solution technique available would provide much additional user value. One participant exemplified this by noting that there were no apparent "*downsides for me as an analyst*" using stochastic programming.

A summary of the strengths and weaknesses of stochastic programming compared with standard deterministic optimisation, as perceived by the participants, is presented in Table 10.

Table 10. A summary of strengths and weaknesses for standard deterministic optimisation versus stochastic programming (SP) from the perspective of users of a decision support system. A (+) indicates added benefits for the user, and a (-) indicates the opposite.

	Deterministic	**Stochastic**
Potential to address uncertainty in information, from models and risk.	-	+
Potential to visualise uncertainty in the initial information.	-	+
Potential to visualise uncertainty in results.	-	+
Level of model complexity.	+	-
Potential to isolate what factors affect the result.	+	-
Potential to acknowledge catastrophic events.	-	+
Potential to achieve targets with a user-set probability.	-	+
Need for pedagogical explanations and examples.	+	-
Need of knowledge to use.	+	-

5. Discussion

This thesis examines how forest information uncertainty is addressed in forest planning at large forest companies today and how current practices and uncertainty levels impact the fulfilment of objectives. In light of this, it suggests and evaluates a forest planning approach for explicitly dealing with forest information uncertainty.

It was found that contemporary forestry employs rather rudimentary strategies to cope with uncertain forest information, which can lead to significant losses and unwanted outcomes. However, it was also found that employing stochastic programming to consider uncertain forest information explicitly is a value-adding approach in long-term forest planning.

5.1 Today's practice regarding information uncertainty

The mapping of the contemporary forest planning process (Paper I) provided knowledge on how this process is structured in practice; i.e., as a hierarchy of separate planning stages. This result confirms the hierarchical forest planning paradigm in this context (Weintraub & Cholaky 1991; Martell et al. 1998; Sessions & Bettinger 2001; Tittler et al. 2001; Andersson 2005; Ogden & Innes 2007; Eriksson 2008; Nilsson et al. 2012; Duvemo et al. 2014; Lämås et al. 2014; Gautam et al. 2015, 2017; Kangas et al. 2015:160). This mapping also revealed a significant dependency on traditional forest information, which was stored and continuously updated in the stand inventory database. Earlier studies have demonstrated the practical application of the stand inventory database (e.g. Nilsson et al. 2012), but we now understand its central role more clearly. In terms of updating the database, the use of (and interest in) remote sensing predictions appears to be increasing.

Paper I also revealed that strategies for dealing with forest information uncertainty mostly rely on either coping with uncertainty (e.g., using buffers and adapting plans after uncertainty is realised) or, to some extent, controlling it (e.g., collecting new data and performing sensitivity analyses). This is reflected in the literature with a focus on Sweden, where most work has been directed towards providing planning models without concerns for uncertainty (e.g. Öhman et al. 2011) and improving the quality of information used for planning (e.g. Barth et al. 2012). No company utilised any analytical approach to explicitly consider uncertainty during planning. A somewhat striking result was the relatively widespread non-use of and scepticism towards optimisation and other advanced analytical approaches outside strategic planning. This was unexpected, as foresters and forestry in Sweden are often regarded as mathematically oriented and fast adopters of new technology, perhaps best exemplified by the rapid computerisation of forest planning in the 1970s and 1980s (e.g. Sprängare 1975; Jonsson et al. 1993; Hagner 2005; Jonung 2006). Both practice and research appear to be more invested in bringing in remote sensing predictions and other high-resolution data rather than pondering how the data should be used.

Even though these results are interesting, some limitations must be mentioned. For example, the qualitative enquiry described in Paper I would have benefited from including a wider range of respondents, both within the included companies and across companies in other jurisdictions. If so, the analysis could have highlighted differences between countries and regions and would have strengthened the connection between what was said to be done and what was actually done in practice. In line with that, it could have been possible to observe the work within the companies rather than just gathering data through interviews. Here, one should also acknowledge the merits of a detailed investigation in a case study. Such investigations provide a deep understanding of the studied system, which is likely why they are common in qualitative research and in the social sciences (Foreman 1948). Furthermore, case studies can be tested against and used to expand theory (Tsang 2014). So, even if the study in Paper I could have been expanded, it should be seen as an important addition to the knowledge about current forestry practices. One avenue lacking from Paper I that was instead investigated in Papers II-III was the evaluation of the actual, not only the perceived, quality of the forest information.

5.2 The effects of not addressing information uncertainty

From Paper I, we now know that no analytical approach that deals with forest information uncertainty is employed in practice (at least not in Sweden), and that the stand inventory database and information based on remote sensing are important information sources for forest companies. Thus, Paper I was followed by investigations into the potential loss of not addressing forest information uncertainty, exemplified by stand inventory database and remote sensing applications.

Paper II demonstrated that observed levels of uncertainty in stand inventory database information result in losses of net present value from forest management and discounted road opening costs, ranging from 1-2%. This is on par with similar studies (Duvemo & Lämås 2006). The subdivision of the planning process into one strategic and one tactical stage does not appear to significantly impact the net present value. This result also aligns with earlier investigations. A study focusing on decision-making in the planning hierarchy found that subdividing forest planning problems can achieve near-optimal solutions (Eyvindson et al. 2018b). However, since the objective of the problems tested in Paper II included minimising the deviations compared to some area thresholds relating to productivity objectives and certification, it is evident that fulfilling these restrictions may be difficult. Since the exact cost of deviating one hectare from a restriction could not be realistically determined, these costs in the models were somewhat subjectively estimated. The interpretation of the resulting suboptimality should therefore not be very strict. However, the results do suggest that a decision-maker who does not consider uncertainty will face challenges in achieving set restrictions. A side effect of the methodological development within the scope of Paper II is that the data (covariances) necessary to simulate errors that behave like real errors in a stand inventory database, including how they covary with each other are now available (Table 2 and Table 3).

The results of Paper II also show that uncertainty affects objective fulfilment, but the question of how the size of the uncertainty impacts the fulfilment in hierarchical planning remains, at least to some extent, unanswered. It is, however, not unreasonable to believe that objective fulfilment would be worse with increasing uncertainty levels (e.g. Islam et al. 2009).

The growing use of predictions of forest attributes from remote sensing is beneficial in many ways. However, what is clear from Paper III, is that satellite-derived forest information should not be used for large-scale decisions concerning large areas, such as long-term strategic harvest levels for a forested landscape, unless the predictions are modified to avoid systematic errors. The satellite-derived information had significant problems with regression towards the mean, leading to erroneous decisions for the utilisation of the set of ecosystem services considered in the study. Important examples include the significant differences between expected and realised carbon stocks, as well as changes in carbon stock over time (Figure 5). Predictions from airborne laser scanning, on the other hand, performed significantly better, even if the suboptimality regarding net present value was not substantially less than that of the satellite-based plans. Thus, it seems better to avoid satellite-derived forest attribute predictions for long-term forest planning and scenario analyses, at least without calibration (e.g. Lindgren et al. 2022). Furthermore, Study III shows that it is possible, and probably preferable, to include value-of-information analyses when evaluating new information sources.

However, it should be mentioned that a major weakness of Paper III was that it was not possible to compare the datasets explicitly, since the same stands were not measured using both remote sensing methods; instead, two independent, representative samples of stands were used. This could have been avoided if a forest landscape had been described wall-to-wall with the relevant inventory methods one wanted to compare. Another weakness was that the same set of attributes was not available from both remote sensing maps, creating the need for modelling secondary variables.

5.3 Suggestion of a planning approach that acknowledges information uncertainty

Based on the results from Papers I-III, it was evident that today's practice requires tools to consider forest information uncertainty in the forest planning process. As pointed out in the introduction, various approaches exist; however, stochastic programming was deemed the most comprehensible, which is why it was tested both quantitatively and qualitatively in Paper IV.

Stochastic programming was shown to be a relevant and implementable alternative tool for practitioners to consider information uncertainty in long-term forest planning and harvest scheduling. Using the suggested approach increased the theoretical value of the solution (by 20%) and provided users with a basis for discussing and considering the uncertainty of both input data and results.

To successfully implement stochastic programming in a forest decision support system, Paper IV demonstrated that a pedagogical presentation of the decision-support-system settings, as well as the results, is crucial for improving user experience and adoption. If the process becomes too complex, users will shy away from the tool (Schulz 2021). However, great potential was shown in having stochastic programming available, as it added value to the planning process, according to the interviewed users. The study provides a road map for this implementation.

The most important open question from Paper IV that remains unanswered is how to realistically represent the distribution of erroneous values based on some input data. Since the input data (i.e., information from the stand inventory database) is itself a realisation of the distribution around the true state, the generated forest states will be inherently different from the true forest state. This is a natural effect of using the original forest state as a mean of a distribution since the generated states will contain more extremes. A potential solution is to employ a Bayesian approach, where input data are seen as a realisation of an unknown distribution about which we can assume some a priori knowledge.

The large increase (by 20%) in objective function value shows the potential of stochastic programming, but it should also be compared with the much smaller increase in net present value of approximately 1%. This big difference stems from how the objective is modelled (deviations from restrictions), which does not need to be a problem, since it is up to every decision-maker to formulate a good objective function. However, it is important for the interpretation and generalisation of the results. Stochastic programming will not improve all solutions by 20%, but there is potential for increases in many cases.

6. Conclusions and recommendations

This thesis demonstrates that forestry today employs rudimentary strategies to cope with the effects of using uncertain forest information in the forest planning process. Since the information used in practice contains large uncertainties, forest planning based on that information risks leading to suboptimal decisions. Some of that suboptimality can be avoided if information uncertainty is considered explicitly in planning models by seeing data as continuous distributions instead of point estimates and solving planning problems using stochastic programming.

Based on the results from the work underlying this thesis, the following recommendations can be made for both research and practice:

1. There is an untapped potential in using advanced decision support tools and analytical methods in tactical and operational planning. Forest companies should consider employing such methods, and research should investigate reasons why forestry is hesitant to do so.
2. Forest companies should adopt a strategy to explicitly address uncertainty in forest information in forest planning.
3. Forest companies should improve or control the quality of information in the stand inventory database before using it in long-term forest planning.
4. If forest information from remote sensing is used for decision-making and planning, forest companies should consider the risk of bias from regression towards the mean.
5. Forest companies and policymakers should refrain from using uncalibrated remote sensing predictions for high-stake and/or long-term decisions, such as deciding long-term harvest levels without considering potential consequences.
6. Research on new forest inventory methods should preferably include cost-plus-loss or value-of-information analyses. Such knowledge will better inform practice as to whether it is rational to invest in new information acquisition technology.
7. Forest decision support systems developers who aspire for their systems to consider uncertainty should see stochastic programming as a viable solution technique.

8. Research on how to generate forest information uncertainty scenarios while avoiding the problem of allowing a realisation of uncertainty to represent the true state should be prioritised.

As shown in this thesis, information uncertainty is important to consider. However, there are probably other sources of uncertainty that impact forestry more, especially in the long run. For example, climate change will likely drastically alter conditions for forest management worldwide. This mega-uncertainty should also be considered.

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Popular science summary

Forest planning is the process by which a decision-maker (for example, a forest owner) decides what to do with a forest (including when and where) in order to best achieve their objectives. The process involves first defining objectives and then evaluating the various management options available. Ultimately, the options that best align with those objectives are chosen. The result can be compiled into a forest management plan.

Forest planning is usually based on many different factors. One important aspect is the forest's current state. This state is often described using various types of information, such as the average age, height, and diameter of the trees in the forest. A forest is typically divided into units, and within each unit, trees are supposed to be similar to one another. Consequently, the information about the forest is usually organised by units, or stands, as they can be called.

It is common for forest stand information to contain errors. For example, the recorded age of a stand may differ from its true age. Such errors can have many causes. Often, the measurement method simply cannot capture the forest's exact state. Addressing this issue; i.e., what it means to plan forestry using imperfect data, is the focus of this thesis.

If the available information is assumed to be accurate and free of errors, the decisions based on that information risk being misguided. An example is when inaccurate age information leads to a decision to harvest a stand before it has reached the legally mandated minimum age for regeneration felling, according to forestry legislation. Such a decision is, of course, illegal, but erroneous information can also produce other undesirable outcomes. If a forest owner aims to maximise profit, harvesting a stand where the trees are not as thick as they are believed to be, the result can be lower revenues than expected. This is because, in some cases, a forest's value increases as trees grow larger over time. Thus, incorrect information can lead directly to suboptimal decisions.

The magnitude of these decision errors can be examined by comparing the decisions made using information containing errors with those made using information that does not. Decisions based on true information are referred to as optimal decisions (because they cannot be improved upon). What counts as optimal varies among forest owners, but in research, it is common to assume a forest owner seeks to maximise profit. Net present value is a standard measure of profitability in forestry. It is calculated by discounting all future revenues and costs from the forest to their present-day value. This is crucial in forestry because there are long time intervals between investments (e.g., planting) and returns (e.g., harvesting).

This thesis comprises four separate studies, each addressing what it means to plan forestry with imperfect information. The first study investigated how large forest-owning companies actually handle information errors when planning. It turned out they employ several strategies, but these are largely coping strategies. This means, for example, that the companies would rather wait to see if problems arise instead of anticipating what could happen.

The second and third studies examined how erroneous decisions can be when based on the types of information that the first study showed large companies use in their planning. The second study focused specifically on the traditional information typically found in forest companies' stand information databases. Using modelling, it explored how errors in this information affected objective achievement when planning was carried out in several separate steps. The result showed that net present value can drop by as much as around 2%. The third study examined errors in information collected via remote sensing, specifically satellite imagery and airborne laser scanning. Errors from these remote-sensing methods tend to regress toward the mean, meaning they overestimate small true values and underestimate large ones. A large tree may therefore appear smaller in the collected information and vice versa compared to reality. This study found that satellite-derived information contained larger errors and that decisions based on that information were more erroneous than those based on laser-scanned information. Planning based on satellite imagery led to a reduction in net present value of up to 9%, whereas planning based on laser scanning resulted in a loss of approximately 6%.

In the fourth and final study, it was proposed how a forest owner could plan forestry using a computer program that accounts for errors. Together with representatives from large forest companies, the program's usability was tested. It was found that the new computer program was more complex than the old, error-ignorant one. However, the new program provided value in handling information errors, provided that the user interface was clearly and pedagogically presented. In a practical test, the new program produced a management plan for a forest area that was 20% more effective, thanks to its ability to account for errors.

In summary, this thesis shows that large forest owners today do not adequately manage information errors and that this likely leads to poorer decisions than if such errors were considered. This shortcoming can be remedied, for example, by developing and using computer programs of the kind evaluated in the fourth study.

Populärvetenskaplig sammanfattning

Skoglig planering är processen där en beslutsfattare (exempelvis en skogsägare) bestämmer sig för vad (inklusive var och när) som ska göras med en skog för att uppnå sina mål. Processen innebär att skogsägaren först identifierar sina mål och sedan utvärderar olika skötselalternativ. Det hela avslutas genom att välja det alternativ som bäst uppfyller målen. Resultatet kan sättas ihop till en skogsbruksplan.

Planeringen kan baseras på många olika saker. Något som är viktigt är hur skogen ser ut idag, vilket ofta beskrivs genom någon form av information. Informationen kan till exempel vara uppgifter om träden i skogens medelålder, medelhöjd eller medeldiameter. En skog brukar delas in i områden där träden i varje område är lika varandra. Dessa områden kan kallas avdelningar. Informationen om skogen brukar därför också vara uppdelad per avdelning.

Det är vanligt att informationen om skogens avdelningar innehåller felaktigheter. Ett exempel på fel är om skogsavdelningens ålder skiljer sig från den verkliga och sanna åldern. Felet kan bero på många saker, men det är vanligt att det sätt man mätt skogen med inte är exakt. Det är detta problem som den här avhandlingen handlar om, det vill säga vad effekten blir av att planera skogsbruk med felaktig information om skogen.

Om skogsägaren tror att den informationen som finns om skogens avdelningar är sann och inte innehåller några fel riskerar besluten som fattas att leda till att resultatet inte blir som förväntat. Ett konkret exempel är om informationen om skogens ålder leder till ett beslut att avverka skogen innan den blivit så gammal att den uppnått lägsta ålder för föryngringsavverkning enligt skogsvårdslagen. Det beslutet är såklart olagligt, men det kan också leda till andra oönskade effekter. Om skogsägaren vill tjäna så mycket pengar som möjligt på sitt skogsbruk kan det felaktiga beslutet att avverka en skog innan träden blir tillräckligt grova leda till lägre intäkter än förväntat. Felaktig information kan alltså leda till felaktiga beslut.

Hur felaktiga besluten blir kan man undersöka genom att jämföra ett beslut som fattats baserat på information som innehåller felaktigheter med ett beslut som fattats baserat på information som är närmare sanningen. Beslut som fattas baserat på sann information kallas för optimala beslut (eftersom de inte kan bli bättre). Vad som är optimalt varierar dock med målsättningen och är därför olika mellan olika beslutsfattare. Ett vanligt mål är att vilja tjäna så mycket pengar som möjligt. Ett mått som används för att visa hur mycket man tjänar på skogsbruk är nettonuvärde. Det räknas ut genom att lägga ihop alla framtida intäkter och kostnader från skogen och justera detta med en ränta för att det ska motsvara dagens ekonomiska värde. Detta är viktigt när man räknar på skogsbruk eftersom det tar lång tid mellan investering (till exempel plantering) och intäkt (till exempel avverkning).

Denna avhandling består av fyra studier som var och en behandlar frågan om vad det innebär att planera skogsbruk baserat på information med fel. I den första studien undersöktes hur större skogsägande företag i praktiken hanterar fel i uppgifter om skogen när de planerar. Det visade sig att de framförallt använder sig av så kallade hanteringsstrategier. Detta innebär att företagen snarare väntar och ser om några problem uppstår, än att de försöker förutsäga och minska problemen innan de inträffar.

Den typ av felaktig information som den första studien visade att stora skogsföretag ofta använder i sin planering analyserades sedan i den andra och tredje studien. I dessa undersöktes hur mycket felen påverkar besluten. Den andra studien fokuserade specifikt på den traditionella information som brukar finnas i skogliga företags avdelningsregister. Med hjälp av modellering undersöktes hur fel som dessa påverkade måluppfyllnaden när planeringen genomförs i flera separata steg. Resultatet var att nettonuvärdet kan sjunka med upp till ca 2%.

I den tredje studien undersöktes istället fel som förekommer i information som samlats in med hjälp av mätningar i satellitbilder och laserskanningar från flygplan. Vad som är speciellt med fel från dessa fjärranalysmätningar är att de drar mot mitten. Det innebär att mätningarna överskattar små sanna uppgifter medan de underskattar stora sanna uppgifter. Ett stort träd i verkligheten kommer därför se ut som att det är mindre än vad det är och tvärt om. Den tredje studien visade att information insamlad med satellitbilder hade stora fel och att beslut fattade baserade på den var mer felaktiga än de som istället fattats baserats laserskannad information. Planering baserad på satellitbilder innebar upp till 9% lägre nettonuvärde, medan planering baserad på laserskanning istället förlorade ca 6%.

I den fjärde och sista studien föreslogs hur en skogsägare skulle kunna planera sitt skogsbruk med hjälp av ett datorprogram som tar hänsyn till fel i information om skogen. Tillsammans med representanter från stora skogsföretag testades datorprogrammets användarbarhet. Representanterna tyckte att det nya datorprogrammet var mer komplext än det gamla som inte hanterar fel. Men de tyckte också att det var värdefullt att kunna hantera fel, men att det var viktigt att datorprogrammet var pedagogiskt upplagt. I ett praktiskt test skapade det nya datorprogrammet en plan för ett skogsområde som var 20% bättre tack vare att hänsyn togs till fel.

Sammantaget visar denna avhandling att större skogsföretag idag inte hanterar felaktigheter kopplade till information om skogen särskilt bra och att detta troligtvis leder till sämre beslut än om man gjorde det. Detta kan avhjälpas genom att till exempel utveckla och använda datorprogram av den typ som utvärderades i den fjärde studien.

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Handling uncertainties in forest information: the hierarchical forest planning process and its use of information at large forest companies

Patrik Ulvdal[1,*], Karin Öhman[1], Ljusk Ola Eriksson[2], Dianne Staal Wästerlund[1] and Tomas Lämås[1]

[1]*Department of Forest Resource Management, Swedish University of Agricultural Sciences, Skogsmarksgränd 17, SE-907 36 Umeå, Sweden*
[2]*Department of Southern Swedish Forest Research Center, Swedish University of Agricultural Sciences, Sundsvägen 3, P.O. Box 190, SE-234 22 Lomma, Sweden*

*Corresponding author: Tel: +4690 786 83 48; E-mail: patrik.ulvdal@slu.se

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This qualitative study aimed to map what information is used in the forest planning process at large forest-owning companies, how it is used, its level of uncertainty and currently employed strategies to handle forest information uncertainty. An additional aim was to assess the status of the paradigm of the forest planning hierarchy in forestry. We used data from semi-structured interviews with representatives of six large forest-owning companies in Sweden, representing 30 per cent of the productive forest land in the country. Our results show that the forest planning process is a hierarchical system of decisions where the information used in the different planning stages is of varying quality and that the traditional hierarchical planning paradigm still plays a vital role in forestry. The most central source of information in the whole forest-planning process is the forest stand database (forest inventory). This includes uncertain information from various sources, including subjective field measurements and aerial image interpretation. However, the use of remote sensing estimates to feed the databases is increasing, which will probably improve the overall quality. Another important finding is that forest companies tend not to use decision support systems or optimization models to solve planning problems outside the scope of strategic planning; thus, most planning is done manually, e.g. in a geographic information system (GIS) environment. Apart from the hierarchical division of the planning process itself, we identified six main strategies that the companies use to control information uncertainty, namely locking the future by making a decision, utilizing a surplus of available harvests, updating information before a decision is made, replanning when the plan is found to be infeasible, planning by looking back and ignoring the uncertainty, either intentionally or unintentionally. The results from this study increase our understanding of contemporary forest-planning practices and will be helpful in the development of decision support systems and methods for information collection.

Introduction

Forest planning is essential for achieving sustainability in forestry (MacDicken *et al.* 2015), and the dominating paradigm of forest planning rests on a planning hierarchy (e.g. Weintraub and Cholaky 1991; Martell *et al.* 1998; Church *et al.* 2000; Sessions and Bettinger 2001; Gautam *et al.* 2017). According to this paradigm, the planning hierarchy consists of three stages, namely, strategic, tactical and operational planning. Strategic planning (the highest stage) deals with company-wide questions such as plans for sustainable harvest levels over more extended time periods and areas (e.g. Gunn 2007). Operational planning (the lowest stage) focuses on the day-to-day scheduling of harvest machines and how to meet delivery demands (e.g. Epstein *et al.* 2007). Finally, the tactical planning (intermediate stage) works as a bridge between the other stages and mainly facilitates the scheduling of what stands (i.e. treatment units) to harvest in what year in order to fulfil the strategic aims (e.g. Church 2007). Traditionally, this stage also includes the planning of road maintenance and the detailed planning of individual harvest areas (e.g. Church *et al.* 2000; Mobtaker *et al.* 2018). Due to the dominance of the paradigm, neither the hierarchy's implementation in forestry nor its effectiveness has been heavily researched. This is especially the case for large forest-owning companies, and there are only a few publications on the forest planning process at such organizations (Tittler *et al.* 2001; Eriksson 2008; Laamanen and Kangas 2011; Nilsson *et al.* 2012). See Figure 1 for a graphical summary of the current paradigm.

Planning on all hierarchical stages relies on information about the forest resource (Nilsson *et al.* 2012). This forest information is structured data about the current and future (modelled) states and properties of forests and related management (Ackoff 1989). In the Nordic countries, forest information for operational use is commonly stored as tabular stand mean values in forest

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stand databases (stand inventories) combined with maps showing boundaries between stands (Nilsson *et al.* 2012). The forest stand databases are a typical case of wall-to-wall information, i.e. they contain information about all stands.

The information in the forest stand databases has historically been collected in large-scale field-based forest management inventories (FMIs, see Kangas *et al.* 2018 for definition) and stand delimitation campaigns where all stands were subjected to measurements of some kind (Maltamo *et al.* 2021). Both objective and subjective (ocular) field-based inventory methods have been used in these inventories, even if the latter has been more common (Ståhl 1992; Koivuniemi and Korhonen 2006). In addition, manual interpretation of aerial and satellite imagery (Hesselman 1939; Åge 1985; Iverson *et al.* 1989) has aided the field inventories during the latter half of the twentieth century. During recent decades, however, estimates from other satellite-based sensors (Holmgren and Thuresson 1998; Reese *et al.* 2002); aerial light detection and ranging (LIDAR) (Næsset *et al.* 2004); terrestrial LIDAR (Maas *et al.* 2008) and digital photogrammetry (Bohlin *et al.* 2012) have emerged as viable alternatives to field-based inventory methods and have been successfully implemented in forestry (Næsset 2014; Nilsson *et al.* 2017). The main strength of these remote sensing (RS) methods is that they produce wall-to-wall forest resource maps for large areas at short intervals with greater spatial and temporal detail than traditional field-based FMI information in forest stand databases (Nilsson *et al.* 2017). However, RS methods also have weaknesses, e.g. some parameters like site index and age are difficult to estimate; estimates for some forest types, for example, young forests, have high uncertainty; and most estimates based on regression or imputation tend towards the mean (Barth *et al.* 2012; Kangas *et al.* 2018).

Depending on the underlying forest information that is used, forest planning can be performed with either an area-based or strata-based approach. Area-based planning (ABP) uses the information in the entire forest stand database as the basis for the planning process (Nelson *et al.* 1991; Murray 1999). However, this approach has some limitations when applied to strategic planning. First, the size of the planning problem for large forest holdings typically includes more than 100 000 stands, making planning problems complex and complicated to solve (Liittschwager and Tcheng 1967). Second, the low or unknown accuracy of the forest stand database information makes it less appropriate as a basis for strategic planning (Duvemo *et al.* 2014). Turning to the strata-based planning (SBP) approach reduces the problem size by aggregating stand-level information into strata based on properties like species, age and timber volume (Daust and Nelson 1993; Church *et al.* 2000). The planning problem is then to find the optimal area of each stratum to be harvested at each time point. An extended version of SBP is to perform a sample-based FMI. Here, a stratified sample of stands is selected (with the forest stand database as the sampling frame), and each sampled stand is surveyed with field plots (Lindgren 1984). Each sample stand thus represents a proportion of the total area of the forest holding. In comparison with ABP, this version of SBP reduces the problem size and avoids uncertainty from forest stand database information. This approach has dominated strategic planning at large forest companies in Sweden since the 1980s (Jonsson *et al.* 1993). ABP, on the other hand, has received more attention outside Sweden (Nelson *et al.* 1991; Murray 1999). Because ABP uses wall-to-wall forest information, it can in contrast to SBP facilitate explicit spatial considerations. These consideration are, however, of higher importance in tactical and operational planning situations (Rönnqvist *et al.* 2015). These planning phases concern economic aspects like the concentration of harvests along roads (Naderializadeh *et al.* 2020) as well as environmental aspects like the spatial allocation of potential habitats for species (e.g. Öhman *et al.* 2011). Ideally, spatial aspects should be considered on the strategic stage too, but the typical long planning horizons and large geographical areas and the consequently large problem sizes make it cumbersome (Næsset 1997; Bouchard *et al.* 2017; Mobtaker *et al.* 2020).

Potentially, ABP can be developed even further in parallel with the development of RS (which nowadays provides information with high resolution), optimization methods (which are becoming more efficient) and recent increases in computation capacity. For example, the dynamic-treatment-unit approach aggregates elements (e.g. forest information in a 10×10 m^2 raster) into temporary treatment units in both time and space without considering traditional (permanent) stand boundaries (Holmgren and Thuresson 1997; Heinonen *et al.* 2007; Magaña *et al.* 2013; Wilhelmsson *et al.* 2021). However, no matter which approach to forest planning one chooses, the uncertainty of information should be considered (Kangas 2010).

Perfect forest information with complete certainty is rare or maybe even impossible, i.e. forest information will always have some degree of uncertainty. We define uncertainty as the incompleteness of the knowledge about something's true state (Ayyub 2010). This uncertainty can be either objectively assessed as a statistical element describing the probability distribution of something's true state (Tannert *et al.* 2007) or as some subjective notion of a decision-maker, depending, for example, on the decision-maker's risk preferences (Pukkala and Kangas 1996; Blennow *et al.* 2014; Rinaldi and Jonsson 2020). Therefore, both the objective and subjective natures of uncertainty must be considered when addressing the impact of uncertainty on forest management.

Pasalodos-Tato *et al.* (2013) give an overview of common sources of uncertainty in forest management, of which two are relevant for this study: uncertainty of measurements or estimations and uncertainty from models. Traditional field-based measurements for central stand attributes, like stand basal area, yield estimation errors of ~10–20 per cent for subjective methods and ~2–10 per cent for objective methods (Ståhl 1992). When using field measured ground truths as reference data, measurement errors also affect RS estimates. However, model uncertainty also plays a significant role in RS because most such estimations are modelled from indirect measurements from sensors. One of the more common RS methods is airborne LIDAR, which can produce estimates with errors smaller than 10–20 per cent (Hyyppä *et al.* 2008; White *et al.* 2016). Estimates from airborne LIDAR have similar quality as traditional field-based inventories commonly used in the Nordic countries (Bergseng *et al.* 2015; Nilsson *et al.* 2017) or even better (Persson *et al.* 2022).

There is a trade-off between the cost of lowering the uncertainty of forest information and the increased benefit from better decisions based on improved or new information (Duvemo and Lämås 2006). This trade-off can be examined with a Cost-plus-loss analysis that minimizes the sum of the costs of information acquisition and the losses from suboptimal decisions based on that information. Cost-plus-loss is suitable for evaluating information acquisition methods and the value of information before using it in forest planning procedures (Gilabert and McDill 2010). Finding the minimum cost solution can be accomplished through either an analytical (Hamilton 1970; Ståhl *et al.* 1994) or a simulative approach (Sprängare 1975; Larsson 1994; Eid 2000; Holmström *et al.* 2003; Holopainen *et al.* 2010; Mäkinen *et al.* 2012; Duvemo *et al.* 2014). However, utilizing knowledge about information uncertainties when solving actual planning problems can also be approached with other operation research methodologies (Pasalodos-Tato *et al.* 2013). There is a steady flow of suggestions about such methods and how to include them in a decision support system (DSS) (Eyvindson and Kangas 2014; Eyvindson *et al.* 2018; Alvarez-Miranda *et al.* 2019; Alonso-Ayuso *et al.* 2020; Rinaldi and Jonsson 2020). However, few methods appear to be easily implemented in practice, most likely due to the exponentially growing size of the problem and results that perhaps are difficult to understand and interpret for a non-expert.

The development of new methods for forest information acquisition is a highly active field of research (White *et al.* 2016). However, how information is used in practical forest planning, its current value for decision-making and how its quality might be improved to increase its value are also important topics. Kangas (2010) suggested that the actual use of the collected information should be mapped together with what decision-makers need from such information in terms of quality. Such a mapping would help researchers and forest practitioners to focus on the most beneficial development of new information acquisition methods. Unfortunately, only a few studies have examined what (and how) forest information is used in practice in large-scale forestry (Laamanen and Kangas 2011; Nilsson *et al.* 2012; Borges *et al.* 2014).

Sweden has an international reputation for its thriving forest industry sector (Lindahl *et al.* 2017). Furthermore, the country is heavily forested and has a high production of industrial round wood considering its small size and boreal location (Ahti *et al.* 1968; FAO 2020a, b; SLU 2020). Some reasons behind this productivity are the focus of many actors on high forest production through intensive even-aged forest management, combined with a highly developed forest industry, a low degree of regulations (Lindahl *et al.* 2017), a long tradition of computer-aided planning (Stridsberg 1959; Jonsson *et al.* 1993) and a significant share of the forests (∼37 per cent) owned by for-profit organizations (Swedish Forest Agency 2018). Studying the implementation of forest planning in Sweden should therefore provide interesting results for the international community.

This study aimed to map the information available for the forest planning processes at large forest-owning companies, how it is used, its level of uncertainty and currently employed strategies to handle forest information uncertainty. An additional aim was to assess the status of the paradigm of hierarchical forest planning, especially concerning the management of information uncertainty. The following research questions guided our study:

- **RQ1:** Is the hierarchical forest planning paradigm implemented in large forest-owning companies? If so, how?
- **RQ2:** What forest information is used by large forest-owning companies, and how?
- **RQ3:** What level of uncertainty does this forest information have?
- **RQ4:** What strategies do large forest-owning companies employ to handle or control the effects of forest information uncertainty?

RQ1 and RQ2 relate to the forest planning process, how it is structured and how it facilitates different uses of forest information. RQ2 and RQ3 relate to the input of information in the process and its quality. RQ4 covers the potential strategies that forest companies use to handle or control the effects of information uncertainty. We argue that we cannot answer RQ4 without first mapping the overall forest planning process with the information used (RQ2), how it is used (RQ2), the level of information uncertainty (RQ3) and how the traditional planning stages relate to each other (RQ1).

Methods

This study employed a qualitative research methodology with semi-structured interviews of representatives from large forest owning companies in Sweden (Miles and Huberman 1994). The sample consisted of six production-oriented forest companies managing more than 200 000 ha of productive forest land (see Figure 2 and Table 1 for a map and an overview). The total area in the sample represented more than 30 per cent (7.8 million ha) of the productive forest land in Sweden. The purpose of this sampling strategy was that the larger companies would have greater incentives for employing a formal forest planning process (Eriksson 2008).

The sampled companies were asked who in their company knew the most about the overall forest planning procedures, from forming strategies to the actual harvesting of a single stand. The suggested persons had titles such as head of forest planning, forest management specialist and head of forest management, and these persons were chosen to be our respondents. We interviewed the respondents in person or via an online video conferencing system (due to covid-19 restrictions). All interviews were recorded and transcribed into written language, averaging 177 min and 24 192 words in length. The interviews were aided by an interview guide that was developed from our research questions with inputs from a read-through of internal documents provided by three of the companies (see supplementary files online). Because the interviews were semi-structured, questions not included in the guide were asked if needed, e.g. for clarification purposes. In addition to answering the questions, the respondent and the interviewer created a process map including all actions and decisions that needed to be made throughout the company's organization before a stand could be harvested (see Figure 3). The map included the information used for each activity or decision, its perceived certainty and how it was used, i.e. in what system or DSS it was used. The respondents categorized all activities and decisions as either strategic, tactical or operational. The interviews did not cover planning related to local timber purchases. All collected information was stored in a

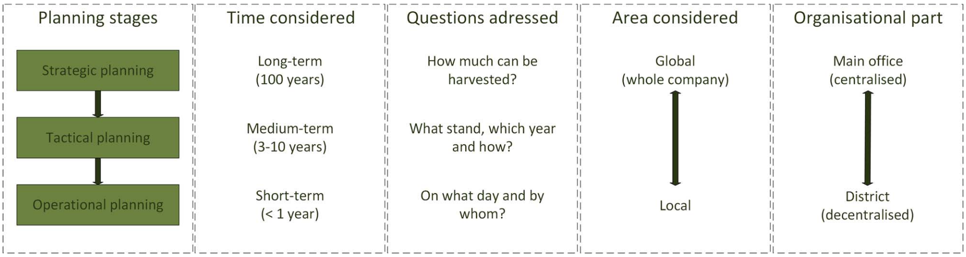

Figure 1 Conceptual summary of how forest planning at large forest-owning companies in the Nordic countries is described in the forest-planning literature. After Eriksson (2008).

Table 1 An overview of the six companies in the study. The numbers indicate in what region of Sweden each company has holdings, from north to south: (1) Norra Norrland, (2) Södra Norrland, (3) Svealand, (4) Götaland. See Figure 2 for a map. The sources of the information in this table are the companies themselves.

Company name	Productive forest land	Connection to industries	Ownership	Geography
BillerudKorsnäs AB	Manages Bergvik Skog Öst's forests, 295 000 ha, and its own forests, 50 000 ha. In total: 345000 ha	Owns multiple pulp and paper mills	Private, primarily institutional owners	Mainly in 3
Holmen AB	1043 000 ha	Owns multiple pulp, paper and sawmills	Private	Mainly in 1 and 2. Some in 3 and 4.
Kopparfors Skogar AB	230 000 ha	Independent. Sells felling rights to harvesting companies. Does not own any industries.	Private. Private foundations own the parent company	2, 3, and some in 4
Stora Enso AB	1139 000 ha	Owns multiple pulp, paper and, sawmills	Private, primarily institutional owners	Mainly in 3. Some in 2 and 4
Sveaskog AB	3050 000 ha	Owns 50% of Setra Group AB, a sawmill company	100% government owned	Mainly in 1 and 2. Some in 3 and 4
Svenska Cellulosa Aktiebolaget SCA	2000 000 ha	Owns multiple pulp, paper and, sawmills	Private, primarily institutional owners	1 and 2

computer-assisted qualitative data analysis software that aided the analysis, which aimed to find general trends and patterns in the material from all companies. The process maps were essential for the analysis, especially in searching for similar or dissimilar practices between companies.

Results

The results are divided according to our research questions. The most important results are summarized in Table 2. See Figure 3 for a graphical summary of the planning process based on the collected process maps.

RQ1: Is the hierarchical forest planning paradigm implemented in large forest-owning companies? If so, how?

The results from our interviews show that the structure of the forest planning process at large forest-owning companies in Sweden is set up as a hierarchy, adhering to the traditional paradigm, with three distinct stages. The stages answer different questions; they use different information (see RQ2), they are the responsibility of different parts of the organization and the lower stages follow the aims and boundaries set by the higher stages.

The companies themselves describe their planning processes as consisting of three stages—strategic, tactical and operational. In the strategic stage, the companies set up overall aims and strategies for sustainable use of the forest resource. These strategies are then transformed into sustainable harvest levels with an optimized harvest assessment (see RQ2) conducted by the main office. The final decision about these levels is made by executive management or the company's board. The harvest levels are the only formal connection between the strategic and tactical stages because they function as targets for the lower stages.

The tactical stage's primary purpose is to plan when to perform harvest activities in individual stands in order to fulfil the harvest levels set by the strategic stage. This stage also includes the clustering of harvest areas to road networks and road

Table 2 A summary of the most important results.

	Planning stage			
	Strategic	Tactical	Harvest area planning (part of the operational planning)	Operational
Questions addressed	How much can be harvested sustainably in the coming 100 years?	What stands should be harvested in what year to fulfil the strategic harvest levels?	How should this stand be treated?	What week/day should this stand be harvested, and by whom?
Time considered	100 years	3–10 years	One year	Months
Area considered	The whole company	Regional level or smaller	A small group of neighbouring stands	District level or smaller
Part of the organization	Specialists and managers at the main office	Planners at the regional, district, or planning department	Planners at the district or planning department	Production leaders at the district or production department
Information used	Strata-based: sample-based FMI Area-based: wall-to-wall forest stand database	Forest stand database and information about roads	Forest stand database, public and internal GIS layers about natural, technical and cultural values	Harvest area database, forest stand database, delivery plan and weather forecasts
Main output	Strategic plan, i.e. harvest levels	Tactical plan, i.e. latest date for harvest area planning in individual stands	Harvest instructions. Summarized in the harvest area database	Operational plan, i.e. a list of stands that machine group X should harvest on what day
How the information is used	Optimized harvest assessment in a DSS	Manually in a GIS aided by either a GIS filter or an optimization model	Manually in a GIS	Manually in spreadsheet-based systems
Level of certainty in the information	Strata-based: high Area-based: low, but sufficient	The forest stand database is considered uncertain. The same goes for road information.	Mostly low	Non-relevant due to the manual approach
Main strategies to handle information uncertainty	(1) locking the future, (2) buffering and (3) gathering of new information, and to some extent: (4) replanning	(1) locking the future, (2) buffering, (6) ignoring the uncertainty and to some extent (3) gathering new information and (4) replanning	(2) buffering and (3) gathering new information	(2) buffering, (4) replanning, (5) looking backwards and (6) ignoring uncertainty

maintenance planning. The aims for the extent of the tactical plan vary among the companies but range from 3 to 10 years' worth of timber harvest volumes with a temporal detail of individual years. At the smallest company, the planners make sub-plans for their district (∼25 000–40 000 ha), later aggregated to the company level. With increasing sizes of companies comes more centralized tactical planning, with specialized personnel making plans for larger areas.

The operational stage consists of two parts, namely harvest area planning and operational planning. Harvest area planning produces detailed harvest plans and instructions for individual stands grouped into harvest areas. The organization of this work differs among companies. The larger ones have more specialized processes, with the harvest area planners working most of their time with this detailed planning. When the harvest area planning for an area is finished, the responsibility to fulfil the harvest levels by creating the actual operational plan is transferred from one department (often called the Planning department or District X) to another (often called the Production department). At the same time, there is also a subtle shift of focus from a long-term and silvicultural planning perspective, where the aim is to maximize the utility and production of wood, to a more short-term planning perspective aiming to minimize costs in the production apparatus.

RQ2: What forest information is used by large forest-owning companies, and how?

The companies use many different sources of information throughout the planning process. Most forest information has been either assessed with RS or subjectively estimated in the

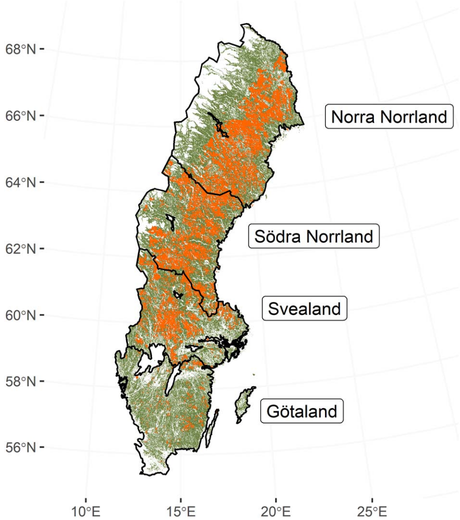

Figure 2 The approximate extent of the forest land managed by the studied companies is shown in orange, while the approximate extent of the additional forest land in Sweden is shown in green. Sweden's regions are indicated by their respective name and black outline.

field. The use of objective inventories is only standard practice in strategic planning.

All companies use Heureka PlanWise, a DSS developed for Swedish conditions, for the optimized harvest assessment on the strategic level (Wikström *et al.* 2011). The system includes a stand simulator with ecological, silvicultural and economic models that produce alternative treatment programmes and an optimization module that assigns treatment programmes to stands. The companies use the system to calculate harvest levels for 100 years with linear or mixed-integer programming with a model I formulation (Johnson and Scheurman 1977) that maximizes the net present value (Arnold 2014) of all future forest management with mathematical restrictions that emulate real-world limitations and aims (Kaya *et al.* 2016). Some examples of these restrictions are requirements of sustainable yield, an even flow of harvested timber volumes, an even geographical distribution of harvest operations, and a demand for a certain surplus of harvestable stands at any given moment in the future (a planning reserve).

The type of information the companies use as input for the optimized harvest assessment depends on their planning approach, i.e. whether they use SBP or APB. For companies using SBP, the input is a sample-based FMI with tree-level surveys in a set of sample stands, each inventoried on ~10 circular field plots per stand (for further details, see Lindgren 1984). Even though this strata-based approach is the most common, there is an increasing interest in using the area-based approach instead. Two companies have already implemented or plan to implement such an approach soon. An overview of the information used in both

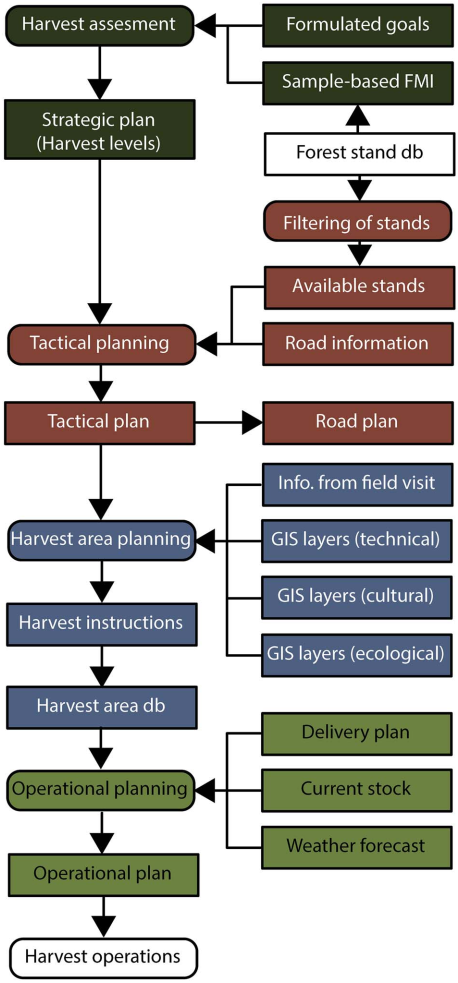

Figure 3 A generalized and simplified example of the process maps created during the interviews. The colours of the boxes indicate the planning stage: dark green for strategic planning, brown for tactical planning, blue for harvest area planning (part of the operational planning) and light green for operational planning. Rounded boxes are activities, while those with sharp corners are information used for these activities.

approaches for strategic planning is found in the supplementary files online.

Outside the strategic stage, most planning activities and decisions are not supported by any DSS. The companies use systems that support the process, but no system formally qualifies as a DSS (Vacik *et al.* 2015). When asked why they do not use optimization, one company stated that the manual solution performs better when considering the real world. Alternatively, as the respondent put it: '*An optimizing tool tends to optimize only the thing you ask for and leave the rest unanswered. To really benefit from an optimization, the description of the reality needs to be sufficiently good*'.

According to the respondents, the forest stand database is the most central forest information source in all planning stages. The forest stand database generally consists of a forest map with delineated stands and corresponding tables of information on each stand. The information is primarily made up by traditional forest parameters such as timber volumes, tree height, stem diameter, stand basal area, age and site index. The database also keeps track of previous and planned management activities. The sources of forest information are diverse. Some are from aerial LIDAR and some are from objective inventories, but most are from subjective inventories and ocular estimates by individual forest officers. Most companies have historically updated the forest stand databases with large-scale field-based FMIs at uneven intervals, but none have conducted any during the last decades. Instead, the strategy is to update the database on the go, meaning that forest officers update any information when needed. Updates of the forest stand database with estimates from nationwide LIDAR-based forest resource maps have also been done (Nilsson *et al.* 2017).

The companies use one of two methods in their tactical planning, namely filtering or optimization. With filtering, geographic information system (GIS) models produce subsets of stands from the stand database available for harvest by removing all stands younger than the lowest legal age for harvest and those newly fertilized or thinned. With optimization, Heureka PlanWise, with an area-based mixed-integer model, is used to distribute the harvest levels on the stands in the database, i.e. to decide what stands to harvest in order to fulfil the strategic harvest levels. The settings are similar to the optimized harvest assessment at the strategic stage, with two notable differences: the wall-to-wall forest stand database is used as the underlying information, and a restriction forces the solution to fulfil the harvest levels in the strategic plan. Irrespective of the approach, planners choose stands manually from the resulting GIS layer in order to make up the tactical plan. Thus, a planner following an optimization approach often disregards suggestions made by the optimization or at least tweaks the solution. In addition, the planners can use any other information available in the company's GIS databases for their decisions, e.g. aerial photos and thinning indexes. A thinning index is a wall-to-wall raster data map modelled from LIDAR-estimated forest density and height together with traditional thinning guidelines or growth and yield tables, i.e. for every point in the forest, the map will show the user an estimated need for thinning. The index is one of the most appreciated GIS layers among planners because it is found to be much more accurate than traditional thinning planning based on stand averages. The planners are aided in their work by a business intelligence system that summarizes the tactical plan in a digital dashboard as the work progresses. The dashboard compares the current version of the plan with the harvest levels from the strategic plan.

In the operational stage, the harvest area planning phase consists of preplanning, a field visit, and the compilation of harvest instructions for the machine operators. The first and last are mainly conducted in the office, even if field-adapted software and hardware allow it to be conducted in the field. The harvest area planners manually choose potential stands for field visits from the tactical plan and group them into harvest areas. The resulting harvest instructions include information about the harvest area, with directives for the operations, a map, a yield forecast and instructions for environmental and cultural considerations. There are no DSSs aiding the planners. Instead, they have to interpret a large number of GIS layers manually. A list of information sources used in harvest area planning is found in the supplementary files online. Finally, the finalized harvest instructions are sent to the harvest area database, which makes up the primary information used later in the operational stage.

The creation of the operational plan consists mainly of production leaders manually choosing suitable harvest areas from the harvest area database and assigning them to machine groups on specific dates. The resulting plan indicates what stand should be harvested, by what machine and on what day/week. To create the plan, production leaders need to know what volumes particular customers or internal industries demand. They also use current geographical positions of machine groups, weather forecasts and updated yield forecasts. Additionally, the production leaders use the overall composition of the harvest area database in trying to predict future scenarios.

RQ3: What level of uncertainty does this forest information have?

Even though the respondents considered the general quality of the information to be quite low, they did not think it was impossible to work with, as exemplified by this statement: '*It depends on what you mean with large uncertainties. If one discussed that with a chemist, he or she would think that all we have [in forestry] are large uncertainties. However, the deviations combine in such a way as when looking at the complete picture, it works.*'

The sample-based FMI in the strategic stage is considered certain by the respondents. Even when standard errors for total timber volume estimates are as large as 2 per cent, only the fact that the uncertainty levels are known makes them see it as certain. The harvest levels based on these FMIs are also considered certain. On the other hand, the forest stand database is viewed as uncertain, with the primary reason being the diversity and sometimes unclear origin of its underlying information. Moreover, all companies use growth models to update the information in the database annually, resulting in higher levels of uncertainty (see, e.g. Holopainen *et al.* 2010). One company stated that the information in the database has relatively small systematic errors because of an update with LIDAR estimates a decade ago. However, because the forest stand database is constantly being edited by many forest officers and continuously updated by growth models, the company does not fully trust it for large-scale decisions or analyses, such as the optimized harvest assessment. On the other hand, small-scale decisions and analyses, like the scheduling of harvests in the tactical plan, are heavily dependent on information from the forest stand database. One of the respondents reflected on the lack of maintenance of the database and concluded that it is not surprising that there are many errors in the database when so little focus is set on improving it or on registering high-quality information in the first place. Even if some planners want to improve the information, it is often difficult to do so. For example, at one of the companies, changes regarding stand boundaries have to be made at the main office and cannot be made by the individual planner. There are no plans at any of the companies to do any full-scale field-based FMI to gather new information for all stands. Some companies, however, plan to update their databases with new LIDAR estimates from the second nationwide campaign. Notably, no automatic error detection protocols are included by default in the most commonly used forest stand database system.

A forest stand database with many errors and uncertain, or non-existing, information on positions and quality of nature conservation values is a challenge, especially with a shortage of mature forests. One of the respondents summarized the challenges: *'We are currently harvesting the last remains of the older forests (. . .) and we are doing it with the support of a forest stand database that contains errors (. . .). Proportionally, there are more errors in the small share of remaining semi-natural forests.'* In summary, many of the stands the companies plan to harvest have erroneous information and many nature conservation values to consider, making it challenging to fulfil the strategic harvest levels when parts of or whole stands need to be set aside due to legal or certification reasons.

For tactical planning, the respondents consider the thinning index (see RQ2) much better for identifying stands in need of thinning than the information in the forest stand database (stand averages). One of the respondents explained the preference: '*We have used this [thinning index] and have had great success. We have thinned where thinning was needed instead of where one thought it was needed.'* While the thinning index is viewed as certain, the quality of the information on road status is low, resulting in field visits to ensure that roads fulfil the status requirements before sending harvest machines there.

At one of the larger companies, the harvest area planners have more than 100 internal and external GIS layers available to consider (for an overview, see supplementary files). The respondents saw these information layers as certain, except for the governmental database on cultural heritage sites. Its low quality forces the planners to conduct comprehensive inventories of every harvest area to locate unregistered sites, because they are protected by law. The most significant problem is the database's incompleteness. The same goes for information about nature conservation values. The companies do not know whether the information they have is to be trusted or not because it can be old, incomplete or erroneous. Nevertheless, when the information gathered during the harvest area planning is transformed into the harvest instructions, most companies consider it very certain—at least in the sense that the considerations towards cultural and natural values are precisely documented on a map and marked in the field. The case is similar for information about technical aspects in the instructions, such as harvest road quality, terrain slope class and soil wetness. However, the quality of the information on volumes of timber assortments is low. When considering all these aspects, the general view of the quality of the harvest area database is that it is not to be fully trusted.

RQ4: What strategies do large forest-owning companies employ to handle or control the effects of forest information uncertainty?

The division of the forest planning problem into a hierarchical structure is, in itself, a strategy for controlling the effects of forest information uncertainty. By answering specific questions associated with the different stages, the companies use the information that is best suited for the question and can balance the cost of the information with its utility. When introducing a hierarchical structure, the companies also reduce the problem complexity making it easier to foresee the effects of uncertain information in a more limited problem space. An example of this is the use of information from a sample-based FMI to decide harvest levels at the strategic stage. Of course, the companies could use the forest stand database as a basis for that decision. However, by calculating harvest levels based on an objective sample of inventoried stands, the companies are more confident that the decision is feasible. By deciding the harvest levels in this fashion, with no explicit linkage to what actual stand should be harvested, the companies have, in a sense, created a hierarchical planning process.

Apart from the hierarchical division of the planning process, we found six additional main strategies that forest companies employ to control or handle uncertainties in forest information: (1) locking the future by deciding on a plan that should be followed, which means that the company can forget about the uncertainties and pretend that the plan is certain, (2) utilizing a buffer of available stands, thus making the plan more implementable, (3) controlling or updating forest information that highly impacts the downstream planning process, which can be done automatically, for example, with LIDAR-estimates, and manually, as in the inventory by harvest area planners, (4) replanning the actions in the immediate future to make up for differences between the plan and the realized outcome, i.e. the same concept as adaptive planning (Eyvindson and Kangas 2018), (5) looking backwards to decide the future, with the best example being how the companies procure harvesting resources by looking at the previous years' harvest levels instead of the contents of the tactical plan and (6) ignoring the uncertainty, either intentionally or un intentionally.

Strategy 1 (locking the future) is used by companies when they make decisions and create plans to handle information uncertainty. One of the respondents exemplified this in the reasoning behind conducting an optimized harvest assessment and sample-based FMIs: *'That is how we have done it, anyway. It feels safe, and the reason is that we want objectively measured data, some kind of momentary truth, that we will not deviate from. This is the world, this is how it looks, and we will manage it in this way. And then we use that truth for a couple of years until we realize that the world has changed compared with the models and that we have to create a new starting point.'*

Strategy 2 (using buffers) is common throughout the planning process. The companies use the optimized harvest assessment on the strategic stage to account for forest stand database errors on the tactical stage by ensuring a surplus of stands available for harvest at any given moment in the future, i.e. a planning reserve. A respondent exemplified the reason for the reserve: '*If we have enough slack in the system, we can cope with quite large errors*'. The planning reserve gives the planners more stands to choose from, thus increasing the likelihood of creating a complete and feasible plan. Incidents not easily forecasted, such as storms or agreements with reindeer herders, would otherwise lead to unrealizable plans. Even though most companies implement a planning reserve, they aim to minimize it because maintaining a surplus of unharvested stands restricts the total harvest and income, especially when having a shortage of mature forests. Tactical planning has a similar strategy. As with the planning reserve, the tactical plan includes extra volumes to make it easier for the harvest area planners to reach their targets on the planned volume for harvest. At one company, this extra volume amounts to 30 per cent of the total volume in the plan. The reason is that the companies do not trust the forest stand database information and cannot be entirely sure that a planned harvest is possible to do.

Strategy 3 (controlling or updating forest information) is used by companies when they perform controls of the information they use or gather new information (or update it). In the strategic stage, for example, most companies conduct sensitivity analyses of the optimized harvest assessment by performing multiple reruns with varied settings to assess the robustness of the original solution. These sensitivity analyses also investigate consequences for various uncertainty-related scenarios, like climate change acceleration or increased demand for set-asides.

Harvest area planning in the operational planning stage (see RQ2) is a great example of an activity that handles information uncertainty, or the complete lack of information, by gathering new information. One of the respondents described the situation: "*When talking about uncertainties, it is so fascinating that we, in fact, judge all the information we utilize to be of such an insufficient quality that we have to verify everything out in the forest. This means that everything we do before we have been to the forest to gather information in the harvest area planning is very much a guessing game*". Moreover, because the companies are heavily incentivized not to make any mistakes regarding natural and cultural values due to legal and certification concerns, the harvest area planning focuses on planning considerations for these values. Not much time is spent on improving estimates on standing timber volume compared with the time spent finding cultural heritage sites or trees with high nature conservation values. None of the companies routinely measure the tree layer, but if they do, they use subjective methods.

Strategy 4 (replanning) has its best example in operational planning. During the creation of the operational plan, the focus is on minimizing costs, such as avoiding the high cost of sending expensive forest machines to harvest areas that are not harvestable. In principle, the whole forest planning process is a strategy to prevent this from happening in the operational stage. When the planning in the higher stages fails to acknowledge aspects relevant to forest operations, the operational plan needs to be adapted. For example, if there are significant uncertainties in the information in the harvest area database, e.g. on road quality, soil wetness or soil bearing capacity, the production leaders face challenges in periods of thawing or heavy rain. In addition, errors in harvestable volume estimates from yield forecasts affect operational planning. If volume estimates are too high, the companies need to either increase the production pace or reschedule planned harvests to stands that can fill the gaps in the delivery plan. If the estimates are too low, the companies have to handle the surplus of wood instead.

Strategy 5 (looking backwards) is used, for example, when companies decide the levels of procurement of machine resources and future sales of harvested volumes. Rather than trusting their plans, the companies tend to lean more on historic outcomes. If the companies had trusted their plans, these two examples could have been decided by only looking at the plan. Instead, many companies look at the outcome from previous years and determine current levels accordingly.

Discussion

In this study, we wanted to assess the role of forest information uncertainty in practical forest planning and how forest companies try to mitigate the effects of that uncertainty. We also investigated how the information is used and the relevance of the theory of a planning hierarchy in this context.

According to our results, the three-level hierarchical planning paradigm appears valid when describing practical forest planning. There could be several reasons for the persistence of hierarchical planning, like organizational inertia (Ashok *et al.* 2021) and the possibility of withholding sensitive information (Eriksson 2008). Furthermore, decision-making and planning may benefit from dividing the problem into sub-problems, i.e. into a hierarchy, or *'to be departmentalized and sub-departmentalized',* in order to increase solvability (Simon 1960). Solving forest planning problems in this hierarchical fashion has proven to be a good compromise when the size of the problem grows too large to be efficiently handled as one single model, even if doing so may lead to suboptimal or infeasible solutions (Eyvindson *et al.* 2017). Furthermore, the hierarchical structure helps to deal with information uncertainty.

It is not a surprise that using an SBP approach with Heureka PlanWise and a sample-based FMI is standard procedure for strategic planning since this set-up has been the norm in Sweden since the 1980s (Jacobsson and Jonsson 1991). The dominance of SBP is probably best explained by how the predecessor of Heureka PlanWise, the Forest Management Planning Package, functioned (Jonsson *et al.* 1993). Therefore, all actors in large-scale forestry in Sweden are familiar with how the FMI gathers information of a certain quality, how that information can be used in a DSS and how the results should be interpreted. However, this dominance might change in the future.

Our results indicate a trend for large forest-owning companies to move towards an ABP approach for their strategic planning instead of SBP. This change opens up the development towards a more integrated planning process where the same wall-to-wall information and models are used to decide harvest levels in the long term and simultaneously what stands should be harvested, and when, in the short term (Andersson 2005; Bouchard *et al.* 2017). Such development can reduce the risk of suboptimality, e.g. by including spatial concerns in forest planning (Bettinger and Sessions 2003; Baskent and Keles 2005; Öhman and Eriksson 2010; Öhman *et al.* 2011; Paradis *et al.* 2013). Furthermore, it might make the planning process less hierarchical or at least remove one of the three stages, for example, by uniting strategic and tactical planning.

Our results show that the companies use forest information of relatively low quality in many procedures, at least according to their own standards and perceptions. Due to this study's qualitative approach, we could not assess the uncertainty of the information in a statistical sense, but our respondents were generally unhappy with the quality of the information they used. This knowledge is important for ongoing research for improving forest information acquisition methods, like RS and data assimilation (Lindgren *et al.* 2022).

Many RS studies report LIDAR-estimates to have objectively as good quality as traditionally field-measured forest information like stand basal area (Bergseng *et al.* 2015; Nilsson *et al.* 2017; Persson *et al.* 2022). Therefore, we see no apparent reason not to increase the use of RS information in forest planning. It is comprehensive, has a better-known error structure compared with the commonly used subjective forest information, has relatively low uncertainty and can be gathered with higher frequency for large areas than traditional FMIs. However, future research is needed on how the errors in various information sources interact when forest information is gathered with multiple acquisition methods at different points in time (cf. Lindgren *et al.* 2017).

Companies show little interest in using DSS and optimization. One argument from our respondents was that they could not trust an optimized solution to be truly optimal when implemented in practice. The reluctance to use optimization seems to stem from the fact that optimization models simplify real-world problems and are based on uncertain information. We see two possible actions to address this, namely to decrease the uncertainty in forest information, e.g. by better information acquisition methods and improved growth and yield models, or to employ problem-solving techniques that address information uncertainty, e.g. stochastic or robust optimization. The first is currently ongoing, not only within the research community but also in forestry, with an example being the implementation of RS estimates in the forest stand databases. On the other hand, the second is still primarily a topic for ongoing research (Eyvindson and Kangas 2014; Alvarez-Miranda *et al.* 2019; Alonso-Ayuso *et al.* 2020; Rinaldi and Jonsson 2020). Having access to both would probably develop the planning process in many ways, leading to better decisions and improved sustainability in forest management. Based on our gathered material, we think of the following areas for potential improvement when higher quality forest information and uncertainty-handling DSSs are available: (1) less extensive planning reserves on both the strategic and tactical stages, resulting in increased profits, (2) less and easier work for forest planners due to more comprehensive information, resulting in reduced costs but improved quality of plans, (3) automated harvest area planning, resulting in reduced costs, (4) improved considerations towards nature conservation values due to comprehensive information, (5) less need for short-notice replanning, resulting in lower harvesting costs, (6) lower risk for unsustainable harvest levels, (7) better timing for silvicultural treatments, leading to higher production and lower costs and (8) better adaptability towards climate change.

However, we believe that while waiting for new and implementable uncertainty-handling methods the companies might try already available optimization tools and DSSs for problem-solving to save some effort and money in the planning process. There are already models available for various forestry-related problems, like forest machine scheduling (Frisk *et al.* 2016; Santos *et al.* 2019), optimized placement of harvest roads (Bont *et al.* 2018; Flisberg *et al.* 2021) and integration of road maintenance and clustering in tactical planning (Flisberg *et al.* 2014; Mobtaker *et al.* 2020), even if none of them fully address information uncertainty.

Apart from the hierarchical division of the planning process itself, we identified six strategies companies employ to control or handle forest information uncertainties in forest planning. The strategies we found were (1) locking the future by deciding on a plan that should be followed, (2) utilizing buffers, (3) controlling or updating forest information, (4) replanning, (5) looking backwards to decide the future and (6) ignoring the uncertainty. Reports from central Europe show somewhat similar strategy patterns (von Detten and Hanewinkel 2017), but with a broader focus than forest information uncertainty. The strategies we found can all be placed in the spectrum of uncertainty, from total determinism via statistical uncertainty (strategy 3), to scenario uncertainty (strategies 4 and 5) and recognized ignorance (strategies 1, 2 and 6), to total ignorance (Walker *et al.* 2003). In the future, we hope that the companies can employ a seventh strategy, namely using formal problem-solving methods that handle uncertainties (Pasalodos-Tato *et al.* 2013).

Our results are based on qualitative data from semi-structured interviews, which is not uncommon in forest planning research (Laamanen and Kangas 2011; Nilsson *et al.* 2012; Meo *et al.* 2013; Wurtzebach *et al.* 2019). With our method, we quickly gathered large amounts of information that provided deep insights into how the companies organize their work internally and their reflections on that. The sample was small but should still be a good representation of the case for forest planning in Nordic countries, at least in industrial and large-scale forestry. Nevertheless, similar studies in other jurisdictions and climate zones are needed to increase the generalizability of the results. Moreover, because our analyses were limited to the perceived information uncertainties in practical forestry, i.e. we did not estimate the uncertainty with measurements and statistical methods, such endeavours are also encouraged.

Conclusions

We can conclude that the forest planning process is a hierarchical system of decisions where the information used in the different planning stages is of varying quality. All of our data supported that the traditional hierarchical planning paradigm still plays a vital role in large forest-owning companies. The forest stand database (stand inventory) is the most central source of information in the forest planning process, but it contains uncertain information primarily based on subjective field measurements or other estimates with unknown errors. However, the use of RS estimates to feed the databases is increasing, which will probably improve the overall quality of the databases, at least compared with the current standard of subjective and ocular estimates. Large forest-owning companies tend not to use DSSs or optimization models to solve planning problems outside the scope of strategic planning; thus, planning on the tactical and operational stages is done by hand, e.g. by manually selecting stands on a map in a GIS. Apart from the hierarchical division of the planning process itself, we identified six main strategies that companies employ to control or handle uncertainties in forest information in forest planning: (1) locking the future by deciding on a plan that should be followed, (2) utilizing buffers, (3) controlling or updating forest information, (4) replanning, (5) looking backwards to decide the future and (6) ignoring the uncertainty. Few activities in the planning process improved the basis for the decision, like gathering better information, with harvest area planning as a notable exception. Furthermore, no company used tools that formally incorporated uncertainty in the decision-making process. We hope that the results from this study increase the understanding of contemporary forest planning practices and will be helpful in the development of forest DSSs and methods for information collection.

Data Availability

The data underlying this paper consists of transcribed interviews and cannot be shared publicly due to privacy concerns.

CRediT author statement

Conceptualization: TL (lead), KÖ, LOE; Methodology: PU, DSW, TL; Formal Analysis: PU (lead), KÖ, LOE, DSW, TL; Writing—Original Draft: PU; Writing—Review & Editing: PU (lead), KÖ, LOE, DSW, TL; Project administration: PU; Funding acquisition: TL (lead), KÖ; Supervision: TL (lead), KÖ, LOE, DSW.

Supplementary material

The following supplementary material is available at *Forestry* online: (1) the interview guide, (2) a table with an overview of the forest information used in strata-based and area-based strategic planning and (3) a table with an overview of forest information in harvest area planning.

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Conflict of interest statement

During his work with this study, PU was employed part-time by Holmen Skog AB, one of the participating companies that also funded the study.

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II

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

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Patrik Ulvdal[1*], Karin Öhman[1], Mikael Rönnqvist[2], Göran Ståhl[1], Ljusk Ola Eriksson[3], Lars Sängstuvall[1,4], and Tomas Lämås[1]

[1] Department of Forest Resource Management, Swedish University of Agricultural Sciences, Umeå, SE-901 83, Sweden

[2] Département de génie mécanique et de génie industriel, Université Laval, Québec, Canada

[3] Department of Southern Swedish Forest Research Center, Swedish University of Agricultural Sciences, Alnarp, SE-230 53, Sweden

[4] Present adress: Bergvik Skog Öst AB, Gävle, SE-801 39, Sweden

*Corresponding author: Tel: +4690 786 83 48; 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.

Keywords

optimisation under uncertainty; forest management; data uncertainty; Monte Carlo simulation; objective alignment;

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 Jaramillo 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 clear-cut 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 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 to 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; Pietilä et al. 2010; Holopainen et al. 2010; Kangas 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.

Material 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 (Eq. 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 is 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 was 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 (maximising 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.

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

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

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.

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). 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.

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}

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

Equation (Eq.) (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 equations 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 2025a)) and 1,000 SEK ha^{-1} (subjectively set after initial testing).

The objective function is subjected to the following restrictions (Eqs. 2-17).

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

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

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

Eq. (3) states that z_{sphk} is a binary variable.

(4) $$\beta_{rsp} \geq 0 \qquad \forall r \in R, \forall s \in S, \forall p \in P$$

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

(5) $$y_{slp} \in \{0,1\} \qquad \forall s \in S, \forall l \in L, \forall p \in P$$

Eq. (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).

(6) $$\sum_{j \in J_i} x_{sij} = 1 \qquad \forall s \in S, \forall i \in I$$

Eq. (6) ensures that the proportions of assigned TPs in each stand sum to 1.

(7) $$\sum_{j \in J_i} f_{sij} x_{sij} \geq 0.1 \qquad \forall s \in S, \forall i \in I$$

Eq. (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 2025b). f_{sij} is 1 in scenario s, in stand i with TP j if the stand is unmanaged in all periods, otherwise 0.

(8) $$\sum_{l \in L} y_{slp} = 1 \qquad \forall s \in S, \forall p \in P$$

Eq. (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.

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

Eq. (9) ensures that the final felled area does not exceed the largest allowable area according to Swedish law in all periods and scenarios. g_{sijp} is 1 in scenario s, 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 $m^3ha^{-1}year^{-1}$, 0.011 if it is between 8 and 4 $m^3ha^{-1}year^{-1}$, 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.

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

Eq. (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 $m^3ha^{-1}year^{-1}$, 90 years if it is between 8 and 4 $m^3ha^{-1}year^{-1}$, otherwise 110 years.

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

Eq. (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.

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

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

Eq. (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.

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

Eq. (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 $r = 5$.

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

Eq. (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 wet, otherwise 0.

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

Eq. (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).

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

Eq. (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).

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

Eq. (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.

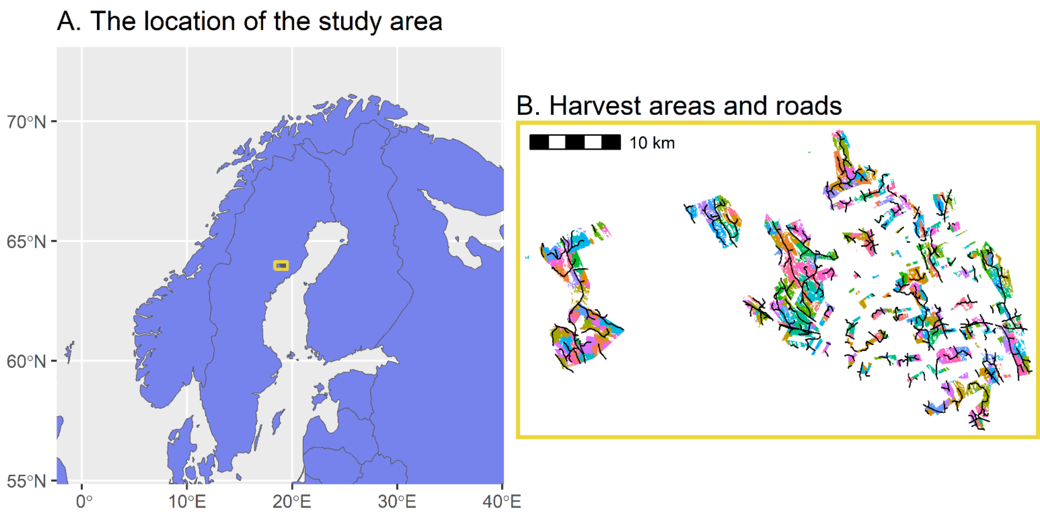

Figure 1. Panel A: The location of the study area in northern Sweden, indicated by the yellow box. Panel B: An overview of the study area with the segments of road network (black lines) adjacent to stands and harvest areas (coloured polygons). The orange box in panel B corresponds to the orange box in 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.

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 hectares of productive forest land (see Figure 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^3ha^{-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 was 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 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 is 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^2ha^{-1}), stand age (years), and site index (m).

The reference data were collected in 2019 as stand-wise 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.

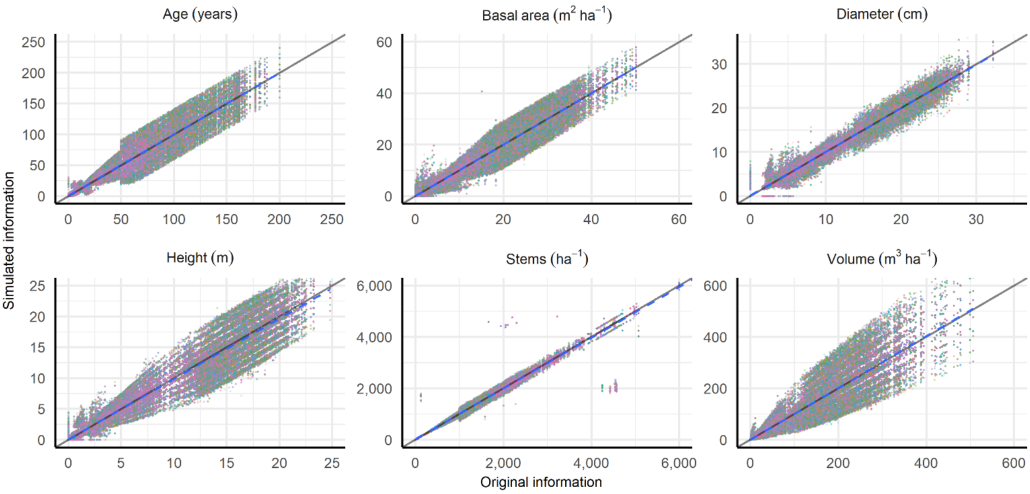

Figure 2. The simulated attributes (average tree diameter, average tree height, number of stems, stand basal area, stand age, and site index) are shown with each point representing one realised value in a stand in one scenario. The colours represent each of the 100 simulated scenarios. The dashed blue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

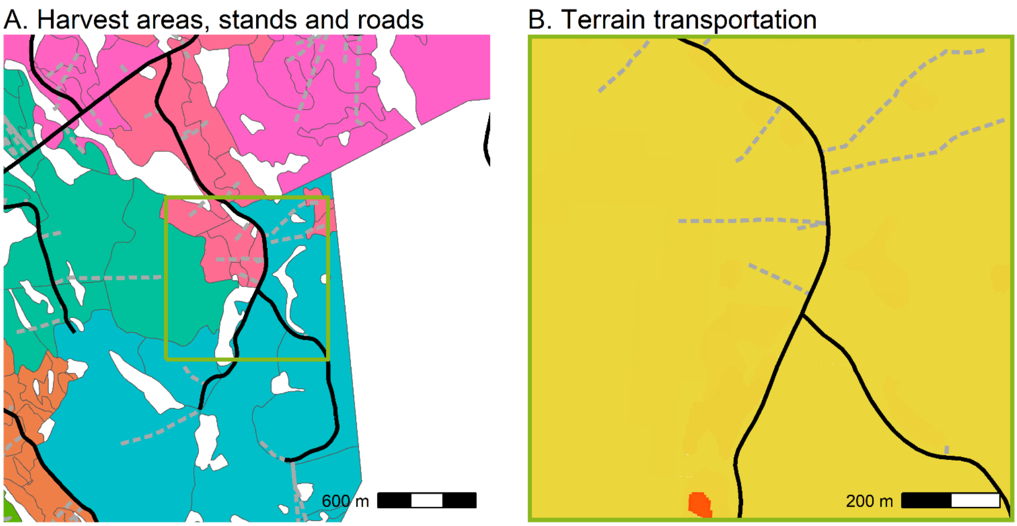

Figure 3. Panel A: Stands (delineated by thin black lines) grouped into harvest areas (coloured polygons) depending on the nearest road segment (thick black lines). Distance to the nearest road was calculated from the stand centroid over a cost raster. Panel B: The cost raster (background), where light 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.

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) was 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 Figure 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 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 × 5 m² 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 Figure 1, panel B and Figure 3 for maps showing the aggregation of stands in harvest areas.

Table 3. Relative weights representing the traversability of forest machines in different land-use types used in the cost-raster. The weights were used to calculate the shortest terrain transport distance.

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

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. GIS operations 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 (Figure 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 (Figure 5). During the later parts of the planning horizon, the harvest levels were somewhat higher in the uncertainty cases.

Table 4. The objective function value (Z) and its components for all cases. Forest NPV is net present value (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.

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

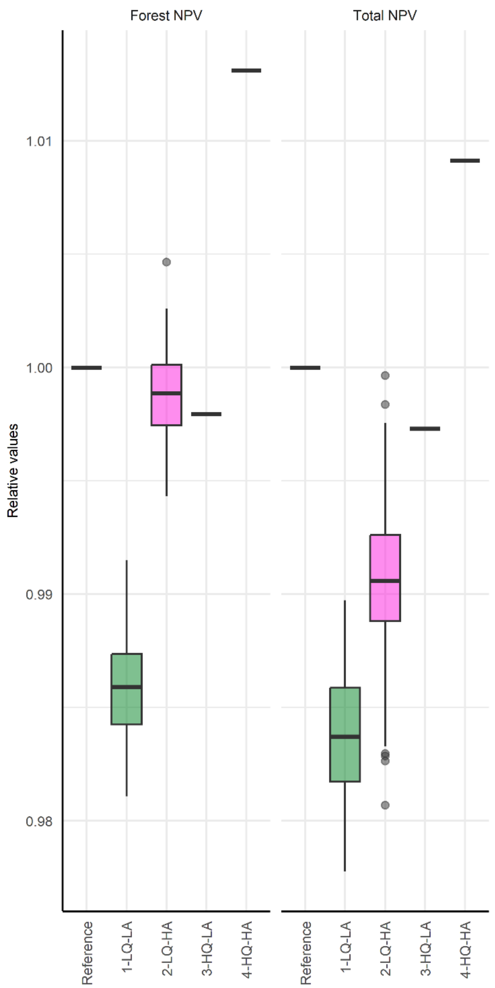

Figure 4. The relative net present value (NPV) from forest management (Forest NPV) and NPV including accessing costs (Total NPV) for the cases independendtly compared to the reference case (1). The horizontal bars show the median. The boxes and whiskers show the spread of the cases with uncertainty.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

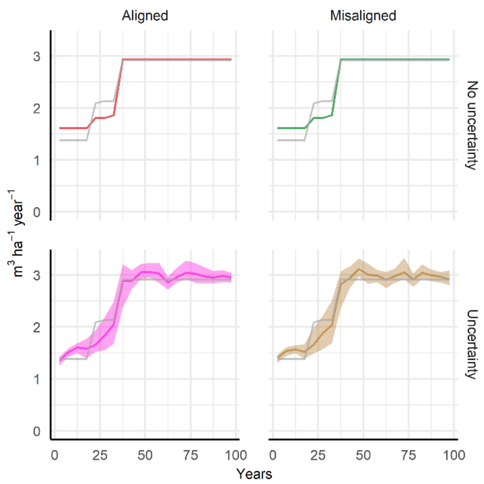

Figure 5. The average final felling harvest levels over the planning horizon for the different cases. Case 1-LQ-LA is the brown line and area on the bottom right. Case 2-LQ-HA is purple line and area on the bottom left. Case 3-HQ-LA is green line on the top right. Case 4-HQ-HA is the red line on the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

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 (Figure 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 at least maintaining the same objective between planning stages, yields superior overall performance.

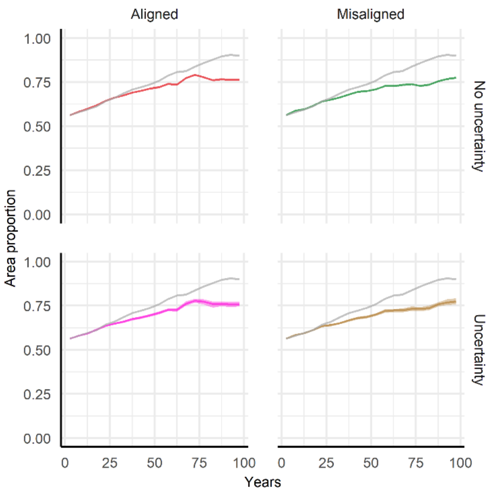

Figure 6. The area proportion of stands with >10% broadleaf trees over the planning horizon for the different cases. Case 1-LQ-LA is the brown line and area on the bottom right. Case 2-LQ-HA is purple line and area on the bottom left. Case 3-HQ-LA is green line on the top right. Case 4-HQ-HA is the red 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.

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 errors for the set of attributes included in the study. 100 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, 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 (Figure 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 2025a), 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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Competing interests statement

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.

Author contribution statement (CRediT)

Conceptualisation: PU, TL, KÖ, LOE; Methodology: PU (lead), TL, LS, MR; Software: PU, LS; Formal Analysis: PU (lead), TL, KÖ, LS, LOE, MR, GS; Data Curation: PU; Writing - Original Draft: PU; Writing - Review & Editing: PU (lead), TL, KÖ, LS, LOE, MR, GS; Visualisation: PU; Project administration: PU; Funding acquisition: TL (lead), KÖ; Supervision: TL (lead), KÖ.

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Data availability statement

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.

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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

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

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

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 $\boldsymbol{1}_n$ is a size n vector of 1s. From the covariance matrix $\boldsymbol{C}$, the Cholesky decomposition as a lower triangular matrix $\boldsymbol{L}$ was computed such that,

(A3) $$\boldsymbol{C} = \boldsymbol{L}\boldsymbol{L}^T, where$$

$\boldsymbol{L}^T$ 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 $s = \{1, 2, \dots, S = 100\}$ such that

(A4) $$\boldsymbol{E}_s = \{\boldsymbol{LZ}_{1j}, \dots, \boldsymbol{LZ}_{ij}\}, \text{ where}$$

$\boldsymbol{E}_s$ 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 $j = \{1, 2, \dots, J = 10\}$ vectors, each in the form of

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

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

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

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

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

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

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

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

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 $\boldsymbol{R}_{s,relative}$ or $\boldsymbol{R}_{s,absolute}$, 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^3ha^{-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 1,000 ha^{-1}, the basal area was under 18 m^2ha^{-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 Table A1 and Table A2.

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

	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^2ha^{-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 deviations.

	Diameter	**Height**	**Stems**	**Basal area**	**Age**	**Site index**
Diameter (cm)	8.2	3.0	-684	2.4	8.2	0.34
Height (m)		3.2	-323	1.8	3.7	0.37
Stems (ha^{-1})			287,227	1231	-753	-63
Basal area (m^2ha^{-1})				26	-1.7	1.2
Age (years)					331	-6.3
Site index (m)						5.9

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.

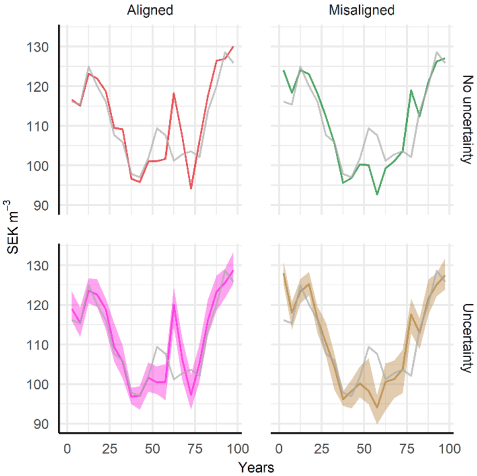

Figure B1. The average cost in SEK per m^3 of harvested wood over the planning horizon for the different cases. Case 1-LQ-LA is the brown line and area on the bottom right. Case 2-LQ-HA is purple line and area on the bottom left. Case 3-HQ-LA is green line on the top right. Case 4-HQ-HA is the red line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

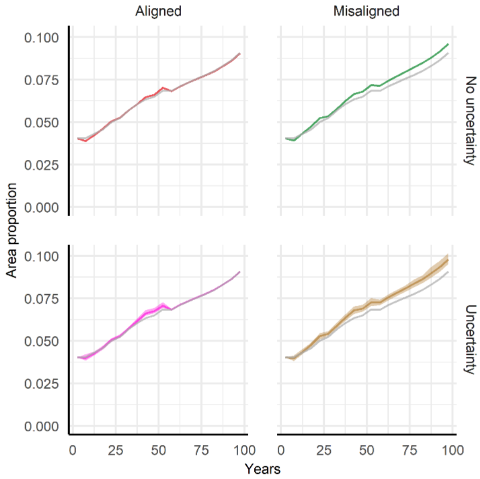

Figure B2. The area proportion of stands older than 140 years over the planning horizon for the different cases. Case 1-LQ-LA is the brown line and area on the bottom right. Case 2-LQ-HA is purple line and area on the bottom left. Case 3-HQ-LA is green line on the top right. Case 4-HQ-HA is the red line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

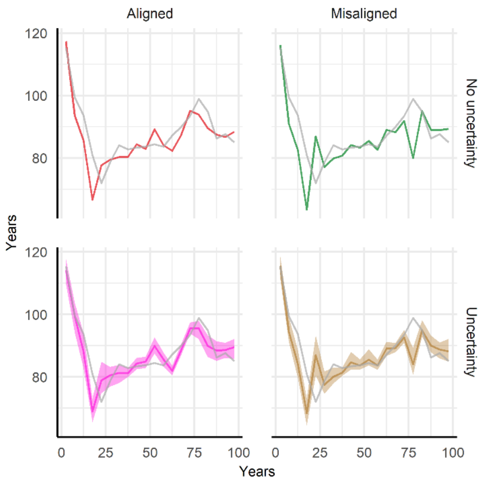

Figure B3. The average volume-weighted final felling age over the planning horizon for the different cases. Case 1-LQ-LA is the brown line and area on the bottom right. Case 2-LQ-HA is purple line and area on the bottom left. Case 3-HQ-LA is green line on the top right. Case 4-HQ-HA is the red line on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

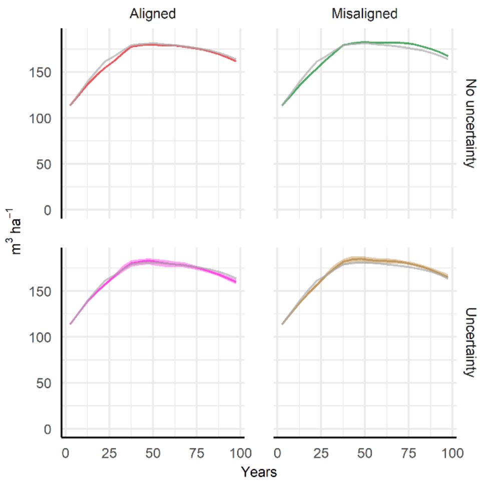

Figure B4. The average standing volume over the planning horizon for the different cases. Case 1-LQ-LA is the brown line and area on the bottom right. Case 2-LQ-HA is purple line and area on the bottom left. Case 3-HQ-LA is green line on the top right. Case 4-HQ-HA is the red line on the top left. The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

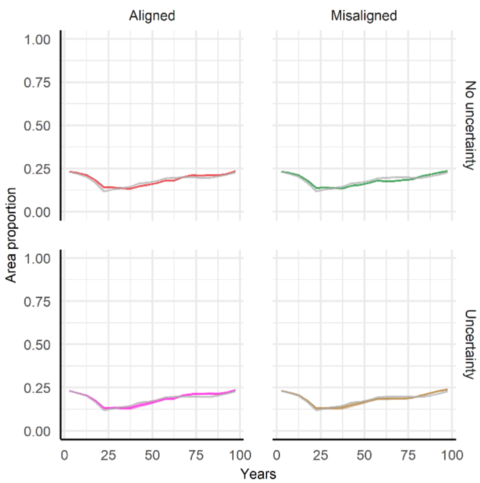

Figure B5. The area proportion of forests <20 years over the planning horizon for the different cases. Case 1-LQ-LA is the brown line and area on the bottom right. Case 2-LQ-HA is purple line and area on the bottom left. Case 3-HQ-LA is green line on the top right. Case 4-HQ-HA is the red line on the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

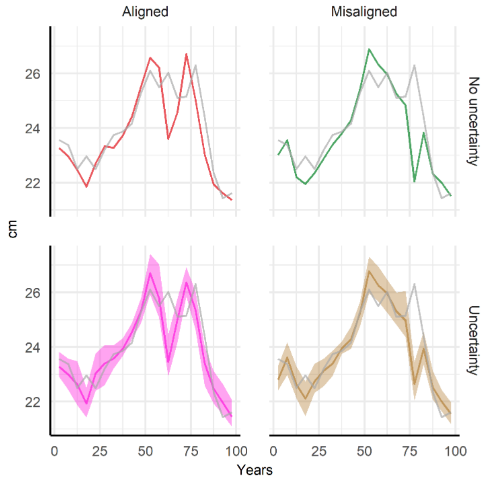

Figure B6. The average volume-weighted diameter in final fellings over the planning horizon for the different cases. Case 1 is the brown line and area on the bottom right. Case 1-LQ-LA is the brown line and area on the bottom right. Case 2-LQ-HA is purple line and area on the bottom left. Case 3-HQ-LA 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.

III

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

Patrik Ulvdal, [a*] Göran Ståhl, [a] Lars Sängstuvall, [a] Ljusk Ola Eriksson, [b] Karin Öhman. [a]

a: Department of Forest Resource Management, Swedish University of Agricultural Sciences, Umeå, Sweden.
b: Department of Southern Swedish Forest Research Center, Swedish University of Agricultural Sciences, Alnarp, Sweden.
[*]Corresponding author: E-mail: patrik.ulvdal@slu.se

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ABSTRACT

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

INTRODUCTION

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

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

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

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

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

MATERIAL AND METHODS

Data and pre-processing

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

Satellite predictions

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

ALS predictions

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

Field-surveyed reference data

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

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

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

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

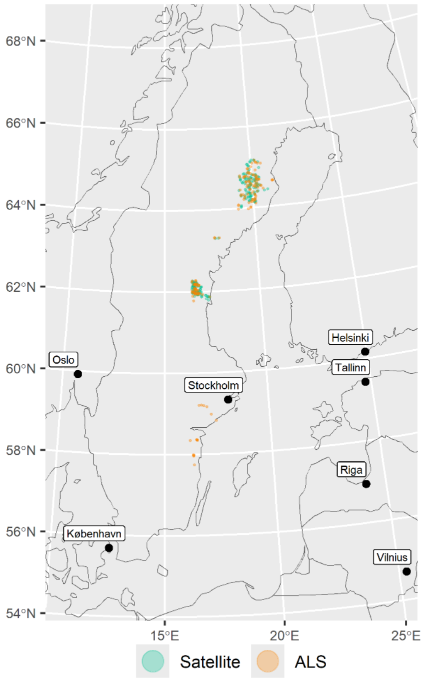

Figure 1. The positions of the included stands shown with coloured points. Satellite indicates those stands surveyed in 2010 used with the satellite map. ALS indicates those stands surveyed in 2019 used with the ALS map. ALS is airborne laser scanning. Projection: SWEREF 99 TM (EPSG:3006). Source of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

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

Standardisation of age distributions

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

Finalised stand averages

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

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

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

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

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

Simulation of tree lists

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

Examination of data and errors

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

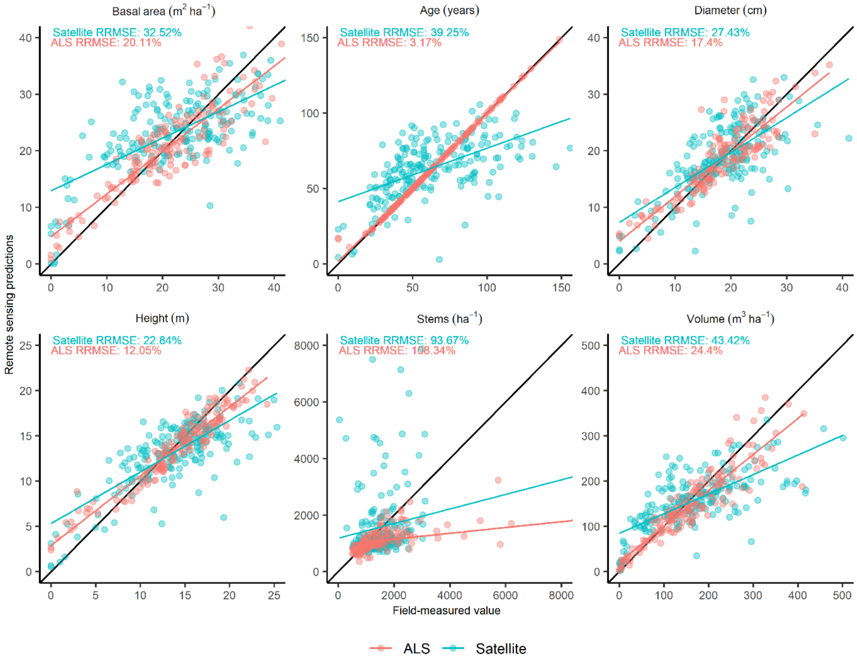

Figure 2. The relation between field-measured reference data (x-axis) and complemented remote sensing predictions (y-axis) from remote sensing-based forest inventories with optical satellite imagery (blue) and ALS (red) for the attributes basal area, mean age, basal area weighted diameter at breast height,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

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

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

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

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

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

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

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

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

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

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

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

SIMULATING FOREST DEVELOPMENT AND MANAGEMENT ACTIVITIES USING HEUREKA PLANWISE

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

Heureka PlanWise

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

Management strategies

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

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

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

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

MAKING PLANS WITH THE HELP OF OPTIMISATION

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

Optimisation models

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

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

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

Subject to

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

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

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

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

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

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

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

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

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

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

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

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

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

Where,

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

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

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

Outcomes from the optimisation

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

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

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

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

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

RESULTS

Net present value

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

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

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

Harvest levels

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

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

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

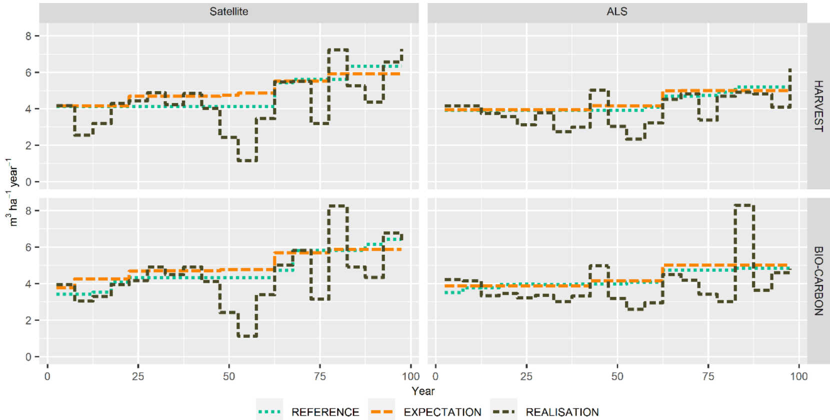

Figure 3. The average harvested volume per hectare and year according to the three outcomes REFERENCE, EXCPECTATION, and REALISATION and the problems HARVEST and BIO-CARBON. Satellite refers to optical satellite imagery, and ALS to airborne laser scanning.

Carbon stock

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

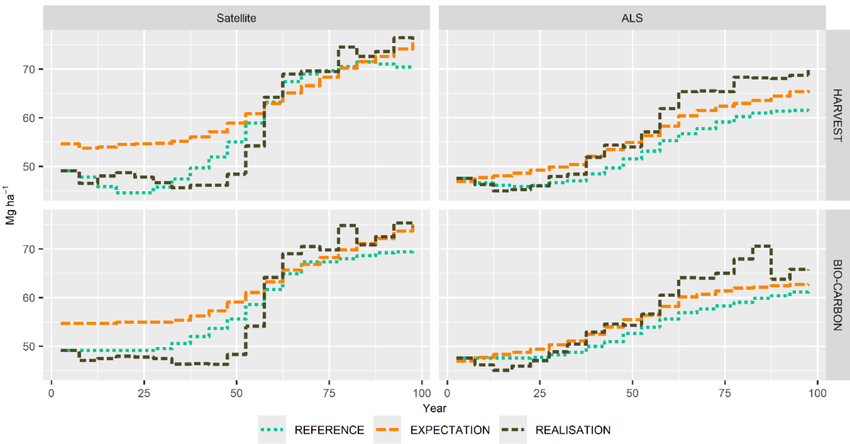

Figure 4. The average carbon stock per hectare according to the three outcomes REFERENCE, EXCPECTATION, and REALISATION and the problems HARVEST and BIO-CARBON. Satellite refers to optical satellite imagery, and ALS to airborne laser scanning.

Ecologically important forests

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

Figures for the individual indicators are presented in Appendix B.

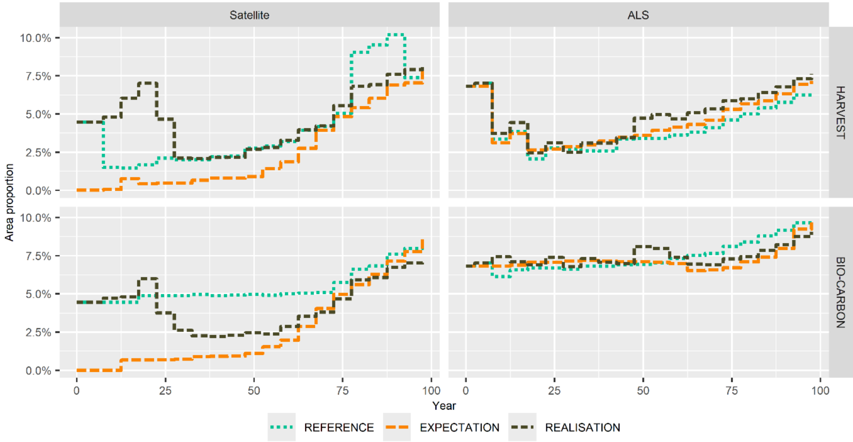

Figure 5. The area proportion of forest where any of the ecological indicators old forest, mature broad-leaf forests or forests with large trees were true according to the three outcomes REFERENCE, EXCPECTATION, and REALISATION and the problems HARVEST and BIO-CARBON. Satellite refers to optical satellite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

Differences during the first 10 years

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

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

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

DISCUSSION

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

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

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

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

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

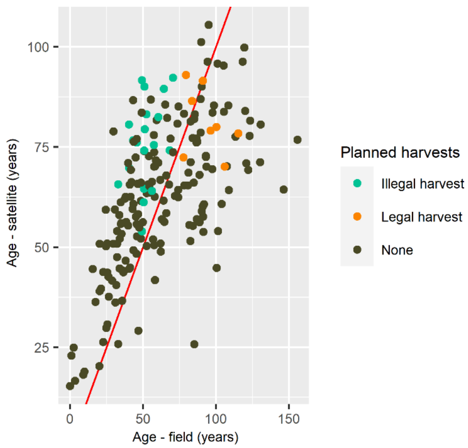

Figure 6. The stand ages according to both the reference data and predictions from satellite data, at year 0 in stands with planned harvests in the second period (year 5-10) of the problem HARVEST where decisions were based on the satellite-based predictions. The planned harvests are coloured depending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

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

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

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

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

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

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

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

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

CONCLUSIONS

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

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

AVAILABILITY OF DATA AND MATERIAL

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

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

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

CODE AVAILABILITY

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

CONFLICTS OF INTEREST

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

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APPENDIX A

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

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

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

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

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

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

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

APPENDIX B

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

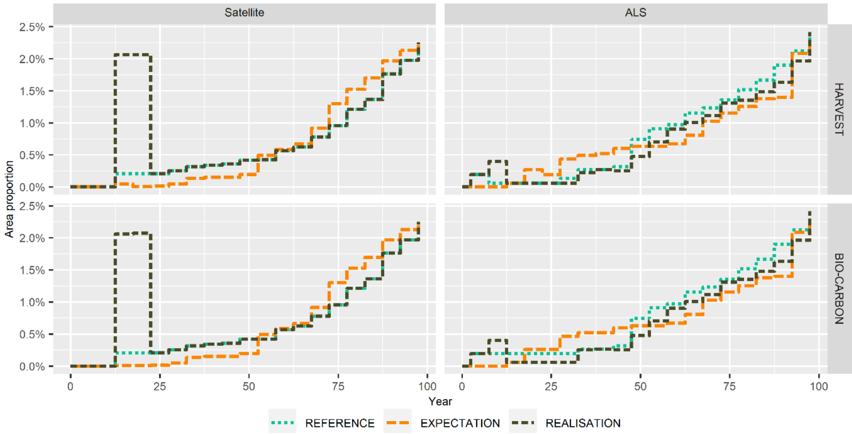

Figure B1. The area proportion of forests with more than 60 large trees per hectare according to the three outcomes (REFERENCE, EXCPECTATION, and REALISATION) and the two problems (HARVEST and BIO-CARBON). Satellite refers to optical satellite imagery, and ALS to airborne laser scanning.

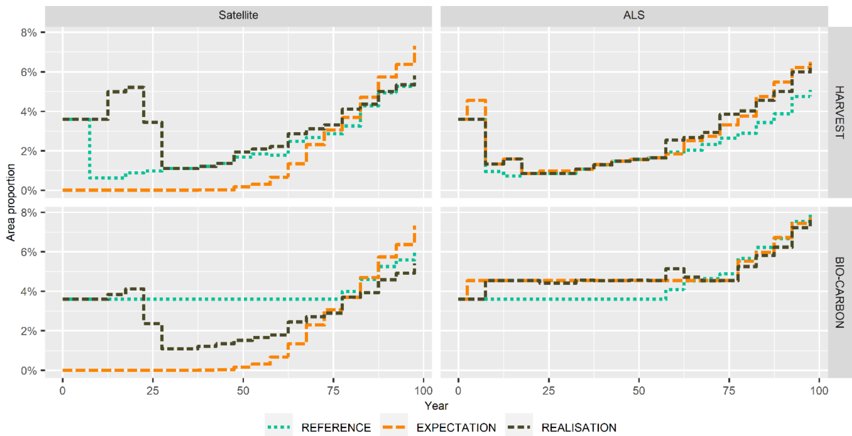

Figure B2. The area proportion of old forests according to the three outcomes (REFERENCE, EXCPECTATION, and REALISATION) and the two problems (HARVEST and BIO-CARBON). Satellite refers to optical satellite imagery, and ALS to airborne laser scanning.

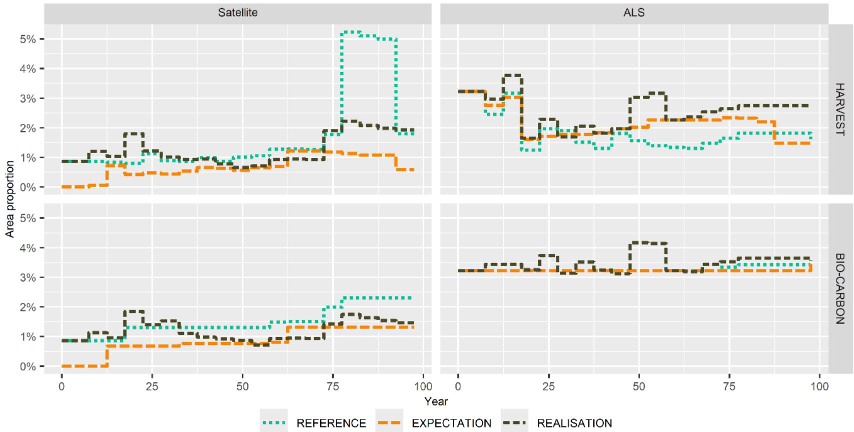

Figure B3. The area proportion of mature broad-leaf forests according to the three outcomes (REFERENCE, EXCPECTATION, and REALISATION) and the two problems (HARVEST and BIO-CARBON). Satellite refers to optical satellite imagery, and ALS to airborne laser scanning.

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This thesis examines how forest information uncertainty affects long-term forest planning and how that uncertainty is (and potentially could be) considered in the planning process at forest companies. The results show that forestry today employs only rudimentary strategies to cope with the effects of using uncertain forest information, and that there is an untapped potential for using analytical methods in the planning process. One promising method is stochastic programming, which this thesis evaluates from both theoretical and user-oriented perspectives.

Patrik Ulvdal received his doctoral education at the Department of Forest Resource Management at the Swedish University of Agricultural Sciences in Umeå. He holds Master of Science degrees in Forest Management and in Forestry from the same university.

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