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Review Article

Towards precision forestry: A systematic review of optimisation methods for individual-tree decisions in forest management

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A R T I C L E I N F O

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A B S T R A C T

Societal demands for forest biodiversity and ecosystem services (BES) are growing and diversifying, which necessitates careful decision-making in forest management. Optimisation methods can support the decision-making process and resolve trade-offs between various BES objectives, and are successfully applied for forest management at the stand and landscape levels. However, there is an increasing interest in optimising management planning at an even finer resolution: the individual-tree level. This systematic review summarises the studies that optimise individual-tree decisions in forest management, taking individual-tree data as input and prescribing a management decision for every tree as the output. Tree-level management planning directly incorporates relevant tree attributes into the planning process - rather than relying on aggregated proxies - and complements developments in precision forestry, remote sensing and autonomous forest machines. We identified 47 relevant studies, which use diverse optimisation techniques such as heuristic algorithms, mathematical programming and machine learning. Several management targets and constraints (e.g., economic value, biodiversity and the structural features of the forest) have been addressed in the studies. Rich information about individual trees is available, although the attributes typically gathered during field inventory, like species, tree height and diameter at breast height, are still the most commonly used in decision-making. Identified directions for future research are to integrate natural disturbance risk predisposition, link tree-level optimisation with management plans at larger spatial scales and develop the real-world implementation of the individual-tree decisions.

1. Introduction

Forests are crucial for maintaining biodiversity (FAO, 2024) and provide innumerable ecosystem services. Globally, forests sequester around 3.5Pg C yr^{-1}, equivalent to nearly half of humanity's annual emissions from fossil fuel consumption (Pan et al., 2024). They also play a role in purifying water (Kreye et al., 2014; Zhang and Wei, 2021), improving air quality (Baumgardner et al., 2012; Nowak et al., 2014), and reducing the severity of natural disasters (Grima et al., 2020; Zhang et al., 2022), and are an important site for spiritual, religious, and cultural experiences (Nesbitt et al., 2017; Torralba et al., 2020; Williams, 2003). Forests additionally provide invaluable raw materials like fuelwood (Derebe et al., 2025) and timber for construction and industrial applications (Chauhan and Meena, 2021; Ramage et al., 2017).

Multifunctional forest management (MFM) is defined as managing forests for 'the provision of multiple ecosystem functions and services simultaneously', paying close attention to 'the interactions among them' (Caicoya et al., 2023), and has been widely embraced by policymakers in recent decades (Lanchberry, 1996; Parson et al., 1992). Implementing MFM is challenging, largely due to the existence of trade-offs between the biodiversity and various ecosystem service (BES) (Felipe-Lucia et al., 2018). In particular, there is typically a trade-off between timber production versus biodiversity and ecological goals (Mazziotta et al., 2023). To successfully implement MFM, synergies and trade-offs between BES

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should be characterised, so that a reasonable compromise between the desired forest services can be defined and identified. This calls for careful multifunctional management planning. The use of optimisation methods can support the planning process (Kaya et al., 2016). If the BES objectives can be combined and weighted, then optimisation methods can help to find the best available management actions. Varying the weights can also allow the decision-maker to explore and characterise the synergies and trade-offs between BES (Mutterer et al., 2025; Pascual, 2021a).

At the level of forest landscapes, optimisation for multifunctional management planning typically entails designing a portfolio of management activities for small spatial units, typically a few hectares each, that collectively maximise the management objectives (Blattert et al., 2022; Bont et al., 2025; Caicoya et al., 2023; Vergarechea et al., 2023). An example is Bont et al. (2025), who divide a mountainous forest into stands and assign to every stand one management approach between close-to-nature forestry, clearcut, or no management while targeting multiple BES objectives. At the level of forest stands, optimisation often involves choosing the best timing for a particular silvicultural intervention (Płotkowski et al., 2016) or optimising the parameters that determine a set of thinning regimes (Pukkala and Miina, 1997). However, instead of the landscape or stand scale, this literature review addresses optimisation methods at an even finer precision: the individual-tree scale.

Tree-level management planning prescribes a specific management decision for every tree. Recent literature reviews of adjacent topics in forest management have suggested that management planning at the tree level is less common than at the stand or landscape levels, which can be attributed to the difficulties in acquiring the necessary individual-tree inventory data (Kaya et al., 2016; Keefe et al., 2022). There are arguably four main motivations to take interest in management planning at the individual-tree level. The first motivation is that stand- or landscape-level management optimisation problems can be viewed as a restricted version of the corresponding tree-level problem. Stand- and landscape-level silvicultural planning limit the decision space by aggregating trees into coarser units. The decision space of the larger-scale problem is therefore a subset of the decision space of the tree-level problem, so the optimum at the larger scale cannot exceed (and may fall below) the optimum achievable at the tree level.

The second motivation is that individual-tree characteristics are necessary to determine the provision of BES. For example, microhabitats are most common in large, dead trees (Vuidot et al., 2011); the preservation of dead trees is important for local biodiversity (Löfroth et al., 2023); characteristics like diameter at breast height (DBH) (Damnyag et al., 2025) and stem defects (Knoke et al., 2006) significantly affect a tree's economic value; and trees directly adjacent to water are most important for regulating the aquatic ecosystem (Keleş, 2019). Tree-level management planning directly includes these characteristics in the decision making rather than relying on aggregated proxies at the stand or landscape levels.

The third motivation is that recent advances in remote sensing make it ever more feasible to collect rich individual-tree data to enhance tree-level management planning. Technologies like Terrestrial Laser Scanning (TLS) (Calders et al., 2020; Liang et al., 2016; Maeda et al., 2025) and Aerial Laser Scanning (ALS) (Vauhkonen et al., 2014) can provide rich 3D geometrical information. Meanwhile, photogrammetry (Iglhaut et al., 2019; Krause et al., 2019) and videogrammetry (Hristova et al., 2025) enable the capture of textural information about the forest environment, although do not yet perform as well as TLS at capturing accurate 3D point clouds in complex forest conditions (Kükenbrink et al., 2022). Individual-tree detection algorithms can be applied to the raw point cloud data (Laino et al., 2024; Roussel et al., 2020; Wielgosz et al., 2024) to extract 3D digital reconstructions of the individual trees or canopy, from which many tree attributes can be estimated, such as tree position, DBH, and height (Gollob et al., 2021; Liang et al., 2016; Marzulli et al., 2020), biomass volume (Singh et al., 2022), stem taper (Calders et al., 2020; Liang et al., 2016) and tree-related microhabitats (Frey et al., 2020). Although TLS has proven especially accurate for individual-tree data collection (Calders et al., 2020), in larger areas ALS presents the biggest opportunity to operationalise tree-level management planning due to larger scale data collection potential and easy handling. Hyyppä et al. (2024) demonstrated that ALS can be used to estimate the tree height, diameter, volume, and biomass of 100 million trees, and presented a roadmap for how this can be scaled to the entire country of Finland. Combining TLS and ALS can provide complete information from the ground and aerial perspectives (Dobre et al., 2021). Although co-registering these data sources has historically been a challenge, recent studies have presented new approaches that achieve high accuracy, even in complex forest environments (Ghorbani et al., 2024; Kushwaha et al., 2023).

The fourth motivation is that tree-level management planning algorithms complement the research into autonomous harvesting machines. The development of autonomous machines for forestry is an active field of research, often included in 'Forestry 4.0′ roadmaps (Visser and Obi, 2021). In particular, developing autonomous harvesting robots has been identified as a major opportunity to improve the health and safety of foresters (Jelavic et al., 2021). Foresters have one of the highest vocational accident rates among all professions (Janocha and Hopler, 2018; Sygnatur, 1998) and often suffer health problems due to the intensive physical labour of the job (Kim and Chung, 2024). Delegating dangerous or strenuous labour to a robot could help avoid some of these problems. While there remain technical challenges to the operational deployment of autonomous robots, such as navigating uneven terrain and achieving cost efficiency, new methods for autonomous forest navigation (Li et al., 2020), the recent development of a semi-autonomous harvesting robot (Jelavic et al., 2022), and the development of an autonomous forwarder (La Hera et al., 2024) amount to real progress in this field. Individual-tree planning methods can eventually be integrated as software to support the decision-making of autonomous machines.

In this study, we have conducted a systematic review of optimisation methods for tree-level decision support in forest management. The review has four research objectives, which situate the studies within the emerging paradigms of multifunctional management and digitalisation in forestry:

- Summarise the methods available for tree-level decision support in forest management;
- Assess which BES objectives are addressed in the existing studies;
- Assess the use of individual-tree data;
- Assess the optimisation techniques used to support the decision-making.

2. Methods

2.1. Literature review

We performed a systematic literature search to identify the tree-level optimisation studies (Fig. 1). Our criterion for including a study in the review was that the study must involve a method that: (a) takes in individual-tree attributes as input data, (b) outputs management decisions for individual trees, and (c) includes a computational procedure to determine the management decisions (as opposed to, say, consulting a forester, which is not conducive to optimisation).

A search query was constructed to reflect these criteria, with the additional requirement that the manuscript must be written in English:

TITLE-ABS-KEY (("tree-level" OR "tree level" OR "tree selection" OR "tree-selection" OR "single-tree" OR "single tree" OR "individual-tree" OR "individual tree") AND (optimi OR "heuristic" OR "decision support") AND ("decision" OR manage* OR "harvest") AND forest*) AND (LIMIT-TO (LANGUAGE, "English"))*

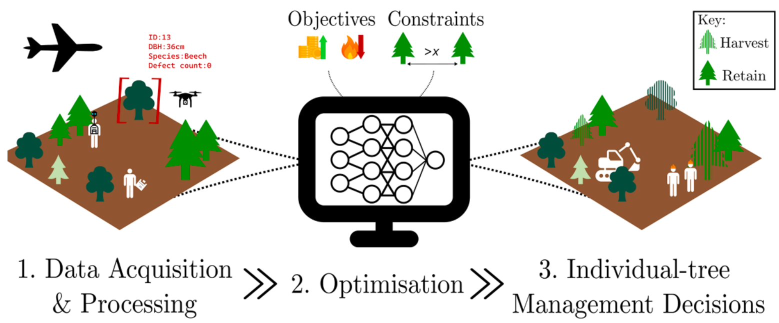

Fig. 1. Conceptual illustration of individual-tree optimisation methods. The optimisation takes in individual-tree data, user-specified objectives and constraints, and outputs individual-tree decisions such as which trees to cut and which trees to leave in a thinning treatment.

We submitted the query to Scopus on 8th July 2025 and received 398 manuscripts. All 398 of their titles and abstracts were screened, which led to 320 manuscripts being rejected and 78 manuscripts being retained for a full-text reading. After reading the full manuscripts, 42 were rejected and the other 36 were retained for the literature review.

For all rejected studies, the reason for rejection was determined with the following logic (Fig. 2). If the study was not related to forest management, then it was deemed 'off-topic'. For example, our search query returned many off-topic studies about the random forest machine learning model or about trees in urban areas. If the study relates to forest management but does not include a decision-making component, then it was categorised as 'no management decision-making'. For example, many studies described individual-tree growth models without prescribing management decisions. If there is a decision-making component but not on the individual-tree level (e.g., with stand-level decision variables), then the study was deemed 'not individual-tree scale'. Finally, three studies were rejected as 'other' after passing the screening criteria because the main language was not English ($n = 1$), there were issues accessing the manuscript ($n = 1$), or the study concerns individual-stump harvesting as opposed to individual trees ($n = 1$). The predominant reason for rejection during the abstract and title screening was 'No management decision-making', whereas during the full-text screening it was 'Not individual-tree scale' (Fig. 2).

To account for potential limitations in our search query, we also conducted a 'forwards snowball search' (Wohlin, 2014) – i.e., we read the title of every reference in the studies from the systematic search, and where the title seemed relevant, we read the full text – and we included studies from the authors' prior knowledge. This allowed us to identify an additional 11 studies which resulted in a final total of 47 manuscripts being included in the review. For all included studies ($n = 47$), key details like the publication year, main purpose of the study, optimisation technique and data acquisition method were collected into a table to be used for further analysis (Appendix A).The details about the 47 studies were collected by a single author but the final table was approved by all co-authors.

2.2. Mathematical framework

To facilitate description in the results section, we propose a mathematical framework that describes the individual-tree decision-making problem. Our notation is adapted from the multi-objective optimisation textbook of (Miettinen, 1998).

In every method there is a fixed treatment unit containing N individual trees that we index by $i = 1, 2, \ldots, N$. There is a set of M individual-tree management decisions $D = \left\{d^1, \ldots, d^M\right\}$, and we let $\boldsymbol{x}_i = \left(x_i^1, \ldots, x_i^p\right)^T$ denote the available attributes for the i'th tree, such as allometric measurements, health status, or economic value. A management intervention is an ordered[1] sequence of management decisions and is denoted as $\boldsymbol{h} = \left(\left(i_1, d^{i_1}\right), \ldots, \left(i_N, d^{i_N}\right)\right) \in \mathscr{H}$ where i_j is the index of the j'th tree in the sequence and d^{i_j} is that tree's management decision. There are also $K \geq 1$ objective functions $f_k(\boldsymbol{h}, \boldsymbol{x}_1, \ldots, \boldsymbol{x}_N) : \mathscr{H} \times X \rightarrow \mathbb{R}$ corresponding to the management objectives in the treatment unit. Additionally, the decision-maker can impose constraints on which management interventions are acceptable, like constraining the harvest intensity between a lower and upper bound. Let $\mathscr{H}_{permitted} \subseteq \mathscr{H}$ denote the subset of the possible management interventions that additionally satisfy the decision-maker's constraints.

The goal in every method can then be formulated as maximising the objective functions over the space of permitted management interventions:

$$\max_{h \in \mathscr{H}_{permitted}} \{f_1(\boldsymbol{h}, \boldsymbol{x}_1, \ldots, \boldsymbol{x}_N), \ldots, f_K(\boldsymbol{h}, \boldsymbol{x}_1, \ldots, \boldsymbol{x}_N)\}$$

In other words, the goal is to make the best (sequential) decisions on the individual-tree level such that the overall forest management intervention maximally attains the specific management objective(s) for the treatment unit, without violating any constraints. If $K = 1$ then a global optimum intervention may be sought. However, if $K \geq 1$ then there is likely a trade-off between some of the management objectives, and the goal is instead to identify solutions that acceptably balance the different objectives $f_k(\cdot)$.

3. Results

3.1. Description of the studies

3.1.1. Management decisions and number of interventions

We identified that the set of forest management decisions D in each study depends on the time period addressed. There are three distinct cases in the literature. In the first case ($n = 28$), only a single, immediate management intervention is optimised. For every tree, there is then a binary decision ($M = 2$) of whether to cut the tree or to retain it in the forest: $D = \{\text{cut, leave}\}$. In the second case ($n = 17$), there are instead multiple management interventions at different times. The decision is to which intervention every tree should be assigned: $D = \{\text{intervention 1}, \ldots, \text{intervention M}\}$. For example, in an uneven-aged management regime where two thinnings are planned, the possible assignments for a tree are: (a) cut the tree in the first thinning, (b) cut the tree in the second thinning, or (c) do not cut the tree. In the third case ($n = 2$), there are no pre-scheduled interventions, and the management decision is the individualised cutting year to assign to the tree: $D = \{\text{year 1, year 2}, \ldots\}$. For example, deciding to cut every tree in the year that it reaches its economically optimal diameter, and using optimisation to solve for

[1] It is also possible to make decisions in parallel for every single tree, in which case the order of $\boldsymbol{h}$ does not matter.

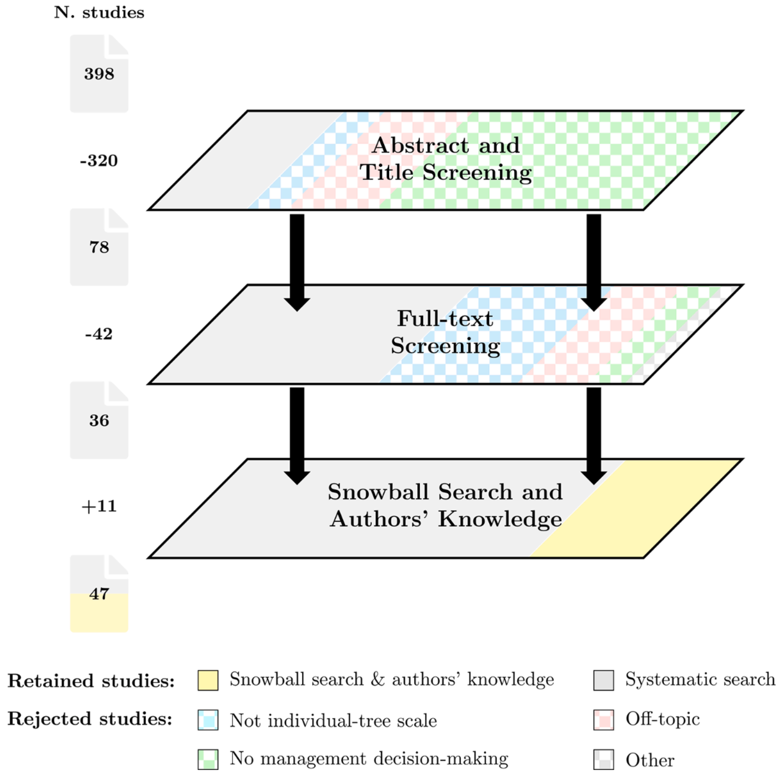

Fig. 2. Identification of the 47 studies included in this review. The shading of the rectangles is the proportion of studies retained/ rejected at each step. Studies were either identified from the systematic search or from the subsequent snowball search.

those optimal years (Lohmander, 2018). The rarity of individual cutting years in the literature reflects that in forest management, interventions are typically several years apart as opposed to every year.

3.1.2. Case study characteristics

For every study in the review, geographic data were recorded about the case study area (Fig. 3). This refers to the forest location where the optimisation method was applied. Europe was the most represented continent with just under half (n = 21) of the case studies. There were

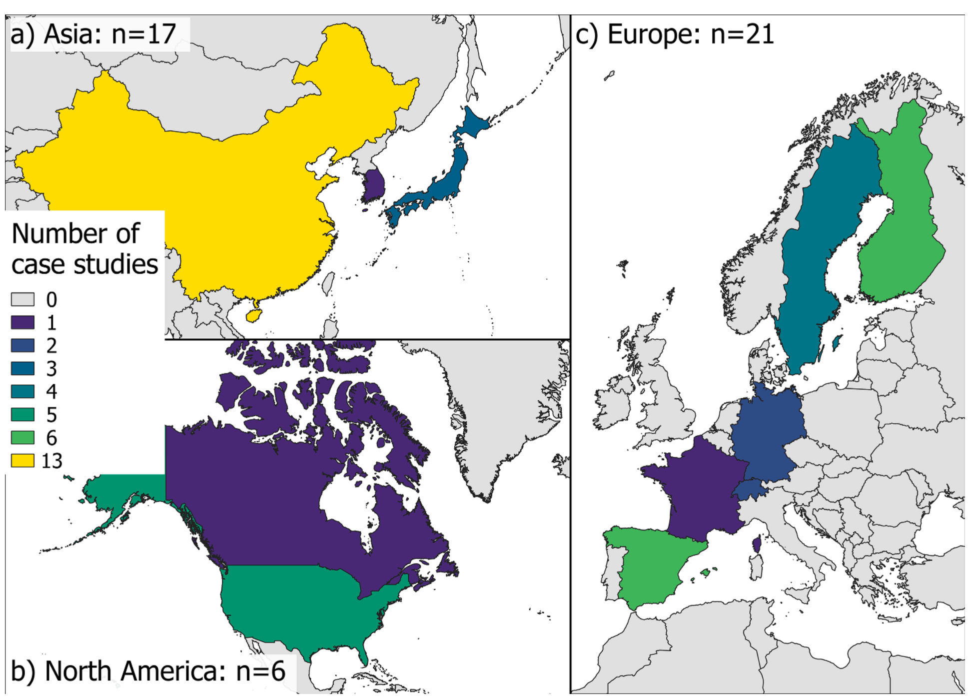

Fig. 3. Geographic distribution of case studies. All case studies using real-world data were either based in Asia, North America, or Europe. Country information for individual studies is available in the Supplementary Information. Three of the studies are not plotted because no specific country was mentioned (Daume and Robertson, 2000; Koster and Fuchs, 2022; Lohmander, 2018).

also 17 case studies in Asia, and the remaining 6 studies described an application in North America. In a further 3 studies the data were not clearly associated with any country because the authors used simulated individual-tree data and did not report the geographic location upon which their simulation was based (Daume and Robertson, 2000; Koster and Fuchs, 2022; Lohmander, 2018). The lack of geographical context makes it harder to interpret their results in real-world forestry, but optimisation methods developed on simulated data can still be transferred to real data. As well as a broad range of countries, the case studies covered a broad range of forest conditions, such as metasequoia plantations in China (Chen et al., 2023), hardwood forests in New York State, USA (Foppert and Maker, 2024), and uneven-aged mixed forests in Central Europe (Sforza et al., 2024). This reveals that optimising individual-tree decisions is a generalisable concept, not limited to any biogeographic region or forest type. The studies are written by 34 different lead authors, which also signals a broad interest in the individual-tree planning topic. Although no filter was applied on the publication year during the literature search, the studies were all published between 1998 and 2025.

In nearly all studies ($n = 42$), the spatial extent of the case study area was either explicitly reported or could be estimated from the other reported forest site properties (Fig. 4). The median extent was found to be 1.40 ha, with sizes ranging from 0.09 ha (Sun et al., 2022) up to 162 ha (Wing et al., 2019). Only 6 studies had a spatial extent exceeding 10 ha. In most studies ($n = 37$), the number of individual trees included in the optimisation was also reported or could be estimated. The median number of trees was found to be $N = 1119$, ranging from a case study with only 20 trees up to 17,734 trees. Relative to conventional forest management optimisation, the spatial extents considered in individual-tree optimisation methods are therefore extremely small. The sizes of the case study areas reflect the typical size for a single forest stand. Yet stand- and landscape-level optimisation procedures usually consider tens or hundreds of stands (Pohjanmies et al., 2019) which makes their spatial extent orders of magnitude larger than the typical extents of individual-tree optimisation. This reflects that on the one hand, collecting individual-tree data for a large area is onerous, and on the other, performing optimisation on a large dataset can be computationally challenging. There was also a wide range in the density of stems per hectare, with the minimum being 102 stems/ha, the maximum 7570 stems/ha, and a median of 882 stems/ha, which again highlighted the diversity of the forest conditions under investigation.

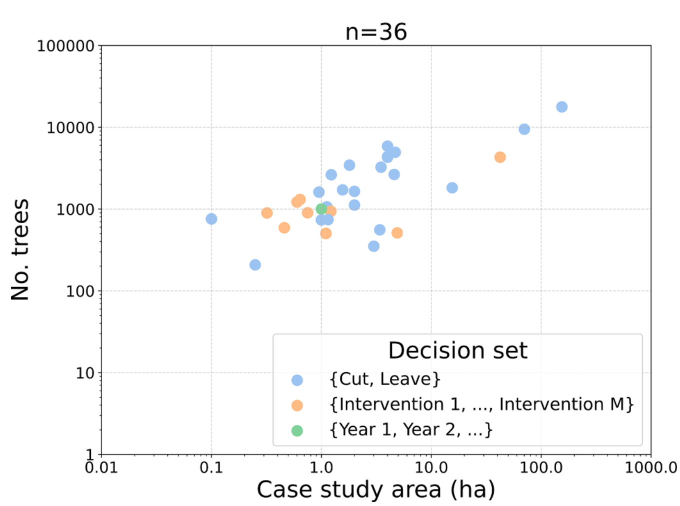

Fig. 4. Spatial scale of case study areas. Only the studies where both the number of individual trees and the spatial extent of the case study area were available ($n = 36$) are plotted. Both axes have a logarithmic scale.

3.2. Problem formulation

3.2.1. Objective functions

Diverse objective functions $f_k(\cdot)$ were identified across the studies (Fig. 6a). Roughly half of the studies ($n = 22$) included multiple objective functions, while the other half ($n = 25$) included just one objective function. Objectives pertaining to economic value ($n = 21$) were the most common and typically involved the calculation of the soil expectation value or net present value (Heshmatol Vaezin et al., 2009; John D Foppert, 2019; Pukkala et al., 2015, 1998) - two closely related quantities from forest economics that assess the expected, future-discounted economic return from managing a stand with a particular management regime. Equally common as economic value objectives were spatial forest structure objectives ($n = 21$), where the goal is to perform the intervention(s) while imposing a particular spatial pattern. For example, (Wing et al., 2019) clustered the harvested trees in order to implement group-selection silviculture, while (Pascual and Guerra-Hernández, 2022) created a spatial corridor of harvested trees to facilitate a cut-to-length operation. Spatial patterns are also used to promote the stability of the stand, such as by minimising competition between standing trees (Li et al., 2017; Qiu et al., 2023; Zhao et al., 2024). Non-spatial forest structure objectives appeared frequently ($n = 17$), involving the manipulation of forest properties that do not depend on the tree coordinates, like the DBH distribution (Pukkala et al., 2023), species mingling (Bettinger and Tang, 2015; Pang et al., 2023), and vertical stratification (Zhao et al., 2024). Biodiversity objectives sometimes featured ($n = 11$), which includes fostering species diversity (Sun et al., 2022) and the protection of deciduous trees (Vestlund et al., 2005).

We distinguish between 'operational costs and revenue' ($n = 7$) and 'economic value' ($n = 21$) to reflect that these are two different ways of considering economic return. Economic value objectives are characterised by a long-term and holistic perspective, considering features like how the tree's economic value increases as it grows (Lohmander, 2018), the rates of return available from alternative investments (Vauhkonen, 2020) and the opportunity costs of allocating limited growing space to old trees rather than faster-growing younger trees (Koster and Fuchs, 2022). By contrast, 'operational costs and revenue' are the direct financial outcomes from a forest operation, such as the costs for logging and the income from selling the timber. The remaining objectives were only tackled by a few studies each, reflecting limited research interest: imitating the decisions of foresters ($n = 5$), promoting high-quality wood ($n = 3$), mitigating risk ($n = 2$), improving landscape amenity ($n = 1$) and maximising seed production ($n = 1$). Appendix B provides a detailed list of the objectives.

3.2.2. Clusters definition

Based on the identified objective functions $f_k(\cdot)$ the studies were partitioned into four clusters corresponding to the priorities of forest management. The clusters are: (a) profit-driven forestry ($n = 17$), where the objective functions relate solely to economic value or operational costs and revenue; (b) nature conservation ($n = 16$), where the objective functions relate solely to the ecological properties of the forest; (c) balanced management ($n = 9$), where economic and ecological objective functions are addressed in parallel, and finally (d) imitating foresters ($n = 5$), where one uses historic data about which trees a forester has selected during past thinnings to teach an algorithm to select the same trees. As articulated by (Daume and Robertson, 2000), methods in (d) are essentially about approximating the cognitive decision-making process of the forester. There was also some correspondence between the cluster of the studies and their case study country. Nature conservation studies were particularly prevalent in China ($n = 11$), whereas profit-driven forestry studies were particularly prevalent in the boreal forest countries of Sweden, Finland and Canada ($n = 7$). Balanced management studies appeared in many countries but were most prevalent in Spain ($n = 4$).

Overall, the number of individual-tree decision-making publications has steadily increased in recent years. Although the first publications on this topic were released in 1998 (Pukkala et al., 1998; Pukkala and Miina, 1998), over half ($n = 26$) of the publications were released between 2020 and mid-2025. This acceleration has been driven by a sharp increase in the number of publications addressing ecological objectives, i.e., belonging to the 'balanced management' or 'nature conservation' clusters. Most ($n = 13$ out of 18) publications prior to 2019 belong to the 'profit-driven forestry' or 'imitating foresters' clusters, having no ecological objectives, whereas the majority since 2019 ($n = 21$ out of 29) belong instead to the 'balanced management' or 'nature conservation' clusters. Meanwhile, interest in profit-driven forestry has remained consistent over the years: the $n = 17$ studies in that cluster are quite evenly spread between 1998 and the present day. Finally, the 5 publications about imitating foresters' decision-making all appeared between 2000–2008. This implies that developing algorithms to replicate foresters' decisions is no longer a priority in the literature. Rather, the priority is to make optimal decisions, with less emphasis on mirroring current silvicultural practices. However, three of the five 'imitating foresters' studies were written by the same author (Minowa, 2008, 2005, 2001) which reflects that the topic only ever received modest attention.

3.2.3. *Constraints*

Constraints are often employed alongside objectives to achieve multiple management objectives simultaneously during an optimisation procedure. Almost all identified constraints could be described as 'ecological', restricting the decision space $\mathscr{H}$ as a means to limit ecological deterioration of the stand during the management interventions (Fig. 6b). This includes imposing limits on the harvest intensity of the interventions ($n = 19$), e.g., (Dong et al., 2020; Lee et al., 2025; Packalen et al., 2020), ensuring that the diameter distribution in the stand remains sufficiently diverse ($n = 12$), e.g., (Nanos et al., 2024; Pascual, 2021a; Qiu et al., 2023), and ensuring that a good species mixture remains in the stand after the intervention ($n = 8$), e.g., (Sheng et al., 2023; Xuan et al., 2023). Of course, some of these same constraints can promote future economic value too. Maintaining a healthy and dense stand helps to ensure that there will be enough high-quality trees in the future so that future revenues are not compromised. Some studies went beyond preventing ecological deterioration and imposed the constraint that any management intervention must *improve* stand structural indices ($n = 4$), e.g., (Chen et al., 2023; Dong et al., 2022). In such methods, individual-tree decisions would not be allowed if they worsened any of the measured ecological properties of the stand. This constraint is compatible with managing forests in protected areas and nature reserves, where management interventions are typically only scheduled if ecological benefits are anticipated. In one study, an economic constraint was applied, requiring that the mean relative value increment of the harvested trees should be less than in initial conditions (Pascual and Guerra-Hernández, 2022).

3.3. *Use of individual-tree data*

3.3.1. *Data collection*

We screened the studies for how the individual-tree data $\boldsymbol{x} \in X$ were acquired. In total, eight unique data acquisition methods were identified (Fig. 5, legend) which includes standalone methods like 'Field inventory' and '[Light detection and ranging] LiDAR (ALS)' but also hybrid acquisition methods like 'Field inventory & LiDAR (ALS)'. More than half ($n = 28$) of the studies relied on field inventory data alone, and a handful of studies ($n = 5$) used only simulated individual-tree data. As for remote sensing, ALS LiDAR was the most popular technology ($n = 8$) followed by unmanned aerial vehicle (UAV) LiDAR ($n = 2$), with backpack LiDAR ($n = 1$) and UAV images ($n = 1$) also featuring in one study each. The key difference between ALS and UAV is that ALS employs high-altitude aircraft (typically at least 120 m above ground), whereas UAV employs unmanned vehicles at lower altitudes (typically <120 m above ground). ALS typically achieves a larger spatial coverage at lower point-cloud resolution compared to UAV, which usually achieves a higher point-cloud resolution for a smaller region (Feigl et al., 2025; Liang et al., 2016; Puliti et al., 2020). ALS acquisition incurs higher fixed costs than UAV but can achieve lower costs per m^2 due to its larger spatial coverage. Where remote sensing was employed, the data was sometimes combined with field inventory data to obtain ground-truth labels for estimating the individual-tree attributes from the remotely sensed data (Pascual, 2021a; Sforza et al., 2024). One study was deemed 'Unclear' ($n = 1$) because it was inconclusive how the data was acquired (Lohmander, 2019).

While manual field inventory was still the most common method of data acquisition in recent years, there has been a surge in the use of remote sensing data acquisition since 2019. Between 1998–2018, only 1 out of the 18 published studies included individual-tree data from remote sensing (Contreras and Chung, 2013). Yet between 2019 and mid-2025, 10 out of the 29 published studies included data from remote sensing. A driving force behind the increase is the improving availability and quality of nationwide ALS datasets. The studies based in Switzerland ($n = 2$) used ALS data acquired by the Swiss Federal Office of Topography between 2019–2020 (Sforza et al., 2025, 2024), with a point density of 15–20 pt/m^2. Likewise, (Pascual, 2021a) used the ALS data from the National Program of Aerial Orthophotography in Spain, which has run three nationwide collection campaigns since 2009 with increasing point density and altimetric accuracy. None of the included studies explicitly compare whether the data acquisition method impacts optimisation outcomes. However, as argued by (West et al., 2021), different technologies achieve different accuracies in individual-tree feature estimation, and the errors during data acquisition can in turn affect the optimal solution.

3.3.2. *Individual-tree attributes*

For every study, we recorded all the mentioned individual-tree at-

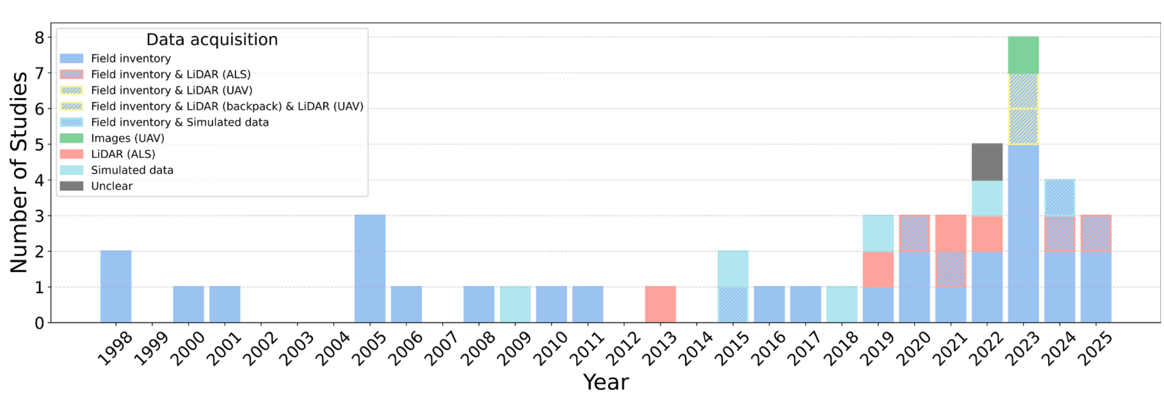

Fig. 5. Number of studies with each data acquisition method.

tributes $(x^1, \ldots, x^p)$. After de-duplication and grouping similar attributes together, we identified 26 distinct attributes across the literature (Fig. 6c). Every attribute was tagged as 'measured' if it describes a measurable property of the tree, or 'modelled' if it must be calculated from the measured attributes (e.g., future growth or economic value). The most common attributes were those traditionally measured during a field inventory: DBH ($n = 44$), tree species ($n = 42$), coordinates ($n = 39$) and tree height ($n = 37$), with $n = 28$ studies including all four of these attributes in the decision-making. Among the 'modelled' attributes, the most common were individual-tree growth ($n = 18$), spatial indices ($n = 18$) and non-spatial indices ($n = 15$). Individual-tree growth is predicted to enable planning interventions in the future (Lohmander, 2018) and as a step to predict a tree's future economic value (Pukkala et al., 2015). Meanwhile, the spatial and non-spatial indices were typically calculated based on the properties of a tree and the properties of its nearest neighbours, and were particularly common in the China case studies (Dong et al., 2022; Pang et al., 2023; Xuan et al., 2023). Spatial indices are those that explicitly depend on the tree coordinates, e.g., the average angle between neighbouring trees. Non-spatial indices depend on the average characteristics in a defined spatial area, such as the tree species diversity in a microstand of trees. There are also several attributes that appeared in only a handful of studies, which reflects that individual-tree decision-making is sometimes applied to very specific forest management problems where specific data are required. For instance, (Nanos et al., 2024) estimated seed production ($n = 1$) for every tree with the goal to select a set of seed trees for retention during final felling that will maximise stand regeneration. Similarly, $n = 3$ studies estimated individual-tree risks from fire in order to tailor their interventions towards improving forest fire resistance (Contreras and Chung, 2013; Dong et al., 2020; Pascual, 2021b).

When separating the attribute frequencies by the clusters defined in Section 3.2, some patterns emerged (Fig. 6c). Studies in the profit-driven forestry cluster were disproportionately likely to include present economic value and harvest costs in the decision-making (Härtl et al., 2010; Lohmander, 2018), which reflects their interest in maximising economic returns. Studies in the nature conservation cluster frequently used spatial and non-spatial indices. An illustrative example is (Dong et al., 2020) who combined four spatial indices and two non-spatial indices into an individual-tree thinning index which, for every tree i, determines the probability that the tree is selected to be cut in a thinning treatment. The attributes that appeared in the balanced management studies are diverse, such as whether the tree contains a bird's nest (Martín-Fernández and García-Abril, 2005), predicted felling time (Sforza et al., 2025), and individual-tree fire risk scores (Pascual, 2021b), reflecting that practitioners in this cluster were interested in a wide range of specific features about the forest management. Finally, the studies about imitating foresters were disproportionately interested in tree health and wood quality, with several of these studies recording the

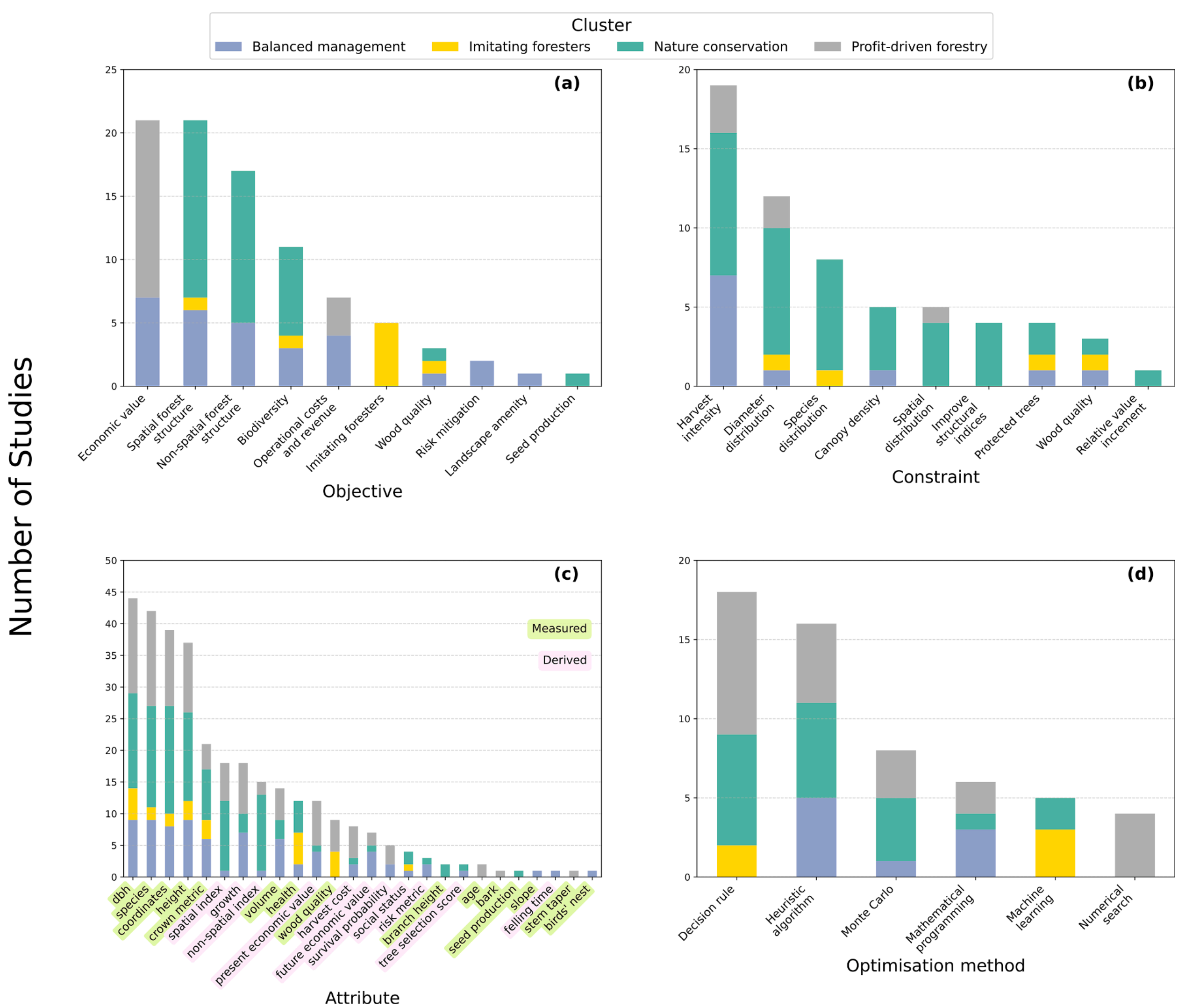

Fig. 6. Frequency plots of (a) the objectives, (b) the constraints, (c) the individual-tree attributes and (d) the optimisation techniques in the studies, with separation by cluster.

stem defects for every tree (Minowa, 2001, 2005, 2008). Stem defects are among the easiest tree attributes to visually assess in the field and have been shown to influence the economic value of the resulting timber (Akay et al., 2015; Čakša et al., 2021), so they may be a key consideration in foresters' decisions.

3.4. Optimisation techniques

The studies were screened for the optimisation techniques they used in the decision-making. Some studies used multiple optimisation techniques, in which case all techniques were recorded (Minowa, 2008; Pukkala and Miina, 1998; West et al., 2021; Zhao et al., 2024). Decision rules were the most popular technique ($n = 18$). A decision rule is a sequence of logical conditions to determine, for every tree, which management decision it should be prescribed. In some cases, the decision rule includes parameters that are optimised from the data (Pukkala et al., 1998; Pukkala and Miina, 1998), which allows decision-makers to fine-tune the decision rule to a particular dataset or environment. In other cases, the decision rule includes hard-coded scalar parameters (Vestlund and Hellström, 2006), which gives the decision-maker exact control over the decision-making logic. The next most common techniques were heuristic algorithms ($n = 16$) such as simulated annealing (Kirkpatrick et al., 1983), genetic algorithm, differential evolution and threshold accepting. Heuristic algorithms are search strategies to achieve good solutions in a reasonable runtime (Murray and Church, 1995; Pukkala and Kurttila, 2005). Their popularity reflects that many authors explicitly wanted to keep the computational runtime low (Pukkala et al., 2023; Sun et al., 2022; West et al., 2021). Monte Carlo methods ($n = 8$), which involve randomly generating many solutions and retaining the best ones, were also common. A smaller number of studies included mathematical programming ($n = 6$), machine learning ($n = 5$), or numerical search procedures ($n = 4$).

3.4.1. Relationship to clusters

The optimisation techniques and the cluster of the study correlate (Fig. 6d). Studies in the profit-driven forestry cluster were particularly fond of decision rules ($n = 9$). Their decision rules often involved applying financial mathematics to optimise the timing of individual-tree harvests, which amounts to a decision rule based on the DBH and/or age of the trees (Härtl et al., 2010; Heshmatol Vaezin et al., 2009; Lohmander, 2019). This is essentially a tree-level application of conventional stand-level forest economics, where the goal is to optimise the rotation length of an even-aged stand (Helmedag, 2018). By contrast, none of the studies in the balanced management cluster used decision rules ($n = 0$), with these studies instead preferring mathematical programming and heuristic algorithms. The latter approaches are particularly suitable for analysing trade-offs between competing management objectives, since one need only vary the weights of the different objective functions and re-compute the solutions to construct a Pareto frontier of management alternatives (Pascual, 2021a; Sforza et al., 2025). Studies in the nature conservation cluster used a broad range of optimisation techniques, while studies for imitating foresters made particular use of neural networks ($n = 3$).

4. Discussion and future directions

The studies show that tree-level optimisation methods are generalisable to myriad BES objectives and forest conditions. Tree-level management planning has therefore the potential to enhance multifunctional management across a wide range of biogeographical contexts. As remote sensing increases the availability and quality of individual-tree data, tree-level management planning will become ever more operationally feasible. Yet management planning at this precision is still a nascent field of research due to the difficulties in acquiring timely, high-resolution data about individual trees, and there is scope for improving the existing approaches to support forest management. The real-world implementation of tree-level management plans also introduces additional operational considerations that must be addressed.

4.1. Tree-level management planning

The existing studies have mostly applied their optimisation routines on case study areas of just a few hectares, which is a typical size for a single forest stand. Yet in forest management, the management plans for individual stands must be integrated together in order to meet management objectives at larger scales, such as regional and national objectives (Baskent et al., 2024; Heinimann, 2010), which remains an unresolved challenge in the field. One approach to bridge tree-level optimisation to larger spatial scales is to simply optimise the decisions for every tree across the entire large spatial extent. The major bottleneck is that the size of the management intervention space $\mathscr{H}$ scales exponentially in the number of trees (N). Applying individual-tree optimisation to a large number of trees thus requires a careful choice of the optimisation technique to ensure that the problem is computationally tractable. Heuristic algorithms are typically preferred over exact methods when computational runtime is important (Murray and Church, 1995). In this review, the largest recorded number of trees ($N = 17{,}734$) is in (Packalen et al., 2020) who used the cellular automaton heuristic algorithm, although that study does not indicate whether the solution is close to the global optimum. Active research into reinforcement learning (RL) for environmental decision-making suggests that RL may be another suitable algorithm for big individual-tree datasets, since it is scalable to large state and action spaces and has performed well on tree-selection (Zhao et al., 2024) and other environmental decision-making tasks alike (Chapman et al., 2023). Instead of simply scaling one decision method to a larger area, an alternative approach is to manage larger forest areas as a mosaic of small-scale individual-tree optimisations. The challenge is then aggregating and combining the local management plans to ensure that collectively, the localised plans serve the global management objectives - a task which is similar to hierarchical planning (Eyvindson et al., 2018) and composing landscape-level forest plans for forest areas under multiple private ownership (Kurttila et al., 2001).

A variety of management objectives have been addressed in the studies, including economic value from timber and biodiversity. Nevertheless, there remain important forest services that have not been included in the individual-tree framework, possibly due to the challenges of tree-level management planning and relative novelty of planning at this precision. A conspicuous absence is water protection, in which forests play a vital role. Forests have a purifying effect on water because their root networks reduce soil erosion and pollution runoff (Kreye et al., 2014), and it has been found that cutting and removing trees can increase the flow of soil and sediment into the water (Webb et al., 2012) to the detriment of aquatic ecosystems (Wood and Armitage, 1997). Removing trees adjacent to water can remove the shading effect of the trees, leading to increased temperatures which may also harm the aquatic ecosystem (Keleş, 2019). Careful individual-tree planning could limit the damage of forest operations in riparian zones, e.g., by customising buffer zones of trees around water bodies, or prioritising trees to leave standing that are situated on slopes near water. There has also been very little consideration for cultural, spiritual, and recreation values – the 'cultural ecosystem services' (Romanazzi et al., 2023) - with only one study considering these explicitly via the assessment of landscape amenity (Niemi et al., 2025). Recreation is an important forest function for members of the public (Abate et al., 2025) and people generally have aesthetic preferences for old, vertically layered forests with irregular spaced trees and diverse tree species (Giergiczny et al., 2015). The individual-tree framework could incorporate these preferences to enhance the management of forests in recreation areas. Their absence to date may be explained by the difficulty in quantifying cultural value.

We found that 26 unique individual-tree attributes have so far been incorporated into the decision-making processes. Relevant attributes yet to be incorporated into the decision-making are individual-tree scores for the risk from some natural disturbances. While a few studies did address individual-tree fire risk, several other important risks were not yet considered. For instance, bark beetle populations depend on individual-tree attributes like species and tree volume, as well as the spatial arrangement of the trees (Gohli et al., 2024; Müller et al., 2022), so it is feasible that individual-tree planning could help control the population, at a time when the overall forest destruction from bark beetles is rising in some parts of the world (Patacca et al., 2023). Similarly, wind and snow risk calculations that are available on the individual-tree level (Peltola et al., 1999) have not yet been integrated into an individual-tree decision procedure. Wind is particularly relevant because the thinning procedure increases overall wind risk: once some trees have been removed, wind can penetrate deeper into the stand (Peltola, 1996), and trees on the edge of a clearing are especially vulnerable.

The tree-level data can be further enriched by also considering other remote sensing technologies for the data acquisition. To date, nearly all the remote sensing studies used LiDAR. Although LiDAR is apt for collecting 3D structural information, there is ongoing research into complementing LiDAR with hyperspectral and RGB imaging, which have performed well in identifying key parameters like tree species (Ballanti et al., 2016; Dalponte et al., 2012) and assessing tree health (Bahe et al., 2021).

The most common optimisation techniques used were decision rules, heuristic algorithms and monte carlo methods. This suggests that the authors preferred to use computationally efficient and easy-to-implement methods rather than methods with greater flexibility (e.g., deep learning) or guarantees about the optimality of the solution (e.g., mathematical programming). In this regard, the individual-tree methods differ from the spatial forest planning applications at larger spatial scales presented in a recent review (Baskent et al., 2024), where the most popular optimisation methods were 'exact' methods like integer programming rather than heuristic algorithms. Some studies compared different algorithms for tree-level optimisation and reported mixed findings about whether the choice of algorithm affects the optimality of the resulting solution (Minowa, 2008; Pukkala and Miina, 1998; West et al., 2021; Zhao et al., 2024). A systematic comparison of optimisation techniques for tree-level management planning could help clarify the implications of these methodological choices.

In all the studies identified in this review, the decision was about harvesting – either which trees to harvest, or when the trees should be harvested. Although harvesting decisions are a crucial part of forest management, we emphasise that the mathematical framework developed in Section 2.2 can accommodate any generic management decisions, and that moreover, there are many other forest management activities that might benefit from careful decisions on the individual-tree level. For instance, the careful placement of tree guards to protect specific trees from ungulate browsing (Bianchi et al., 2021; Hardalau et al., 2024) or to provide a favourable microclimate for growth (Lai and Wong, 2005; West et al., 1999; Zellweger et al., 2024); selecting specific trees to act as trap trees for pests (Holuša et al., 2017; Laidlaw et al., 2003); the application of fungicides (Opoku et al., 2007) or fertiliser (Fernández et al., 2009); and trunk girdling (Goren et al., 2010) are all examples of individual-tree decisions undertaken in forest management. These decisions could also be subject to optimisation by changing the decision variables, objectives and constraints, so that the planning process is broadened from just end-of-life harvesting decisions to decisions throughout the tree's lifetime. Naturally though, practitioners should anticipate that the optimisation problem becomes more complex when more decision alternatives are available and when the temporal decision horizon is lengthened.

4.2. Real-world implementation

The optimisation procedures presented here essentially output a list of tree ID-decision pairs. However, in order to implement the management decisions in practice – and particularly if integration with autonomous harvesting machines is envisioned - methods are needed to match the tree IDs from the dataset with the physical trees standing in the forest. A classic approach to identify individual trees is to physically tag the trees with a unique ID - e.g., by applying spray paint (Hall, 1936) or using radio frequency identification (RFID) tags (Björk et al., 2011). The downside is that this precludes using remotely sensed data or autonomous machines, whereby the trees are not physically visited during the data acquisition. If the data are georeferenced, another option for identification is to use the tree's coordinates as a unique identifier and provide the forester with global navigation satellite system (GNSS) information on site (Lee et al., 2023). A key challenge is ensuring continuous GNSS coverage, even in dense canopy or remote areas obscured from satellite coverage (Fauzi, 2016). The ongoing research into individual-tree traceability presents other ideas for identifying the trees: for example, using computer vision to identify trees based on the structure of their branches (Yrttimaa et al., 2025). To make in-situ tree identification even easier, the management decisions could also be integrated with Augmented Reality platforms for forestry (Kushwaha et al., 2025), although such technologies require further field validation before operational deployment becomes realistic.

Implementing optimised tree-by-tree decisions would also require closely engaging with professional foresters, because it represents a departure from the status quo of forest operations. During thinning treatments for example, foresters are typically given instructions and targets for a stand. Within the bounds of these instructions and targets, they have the autonomy to make tree-selection decisions, for which they consider multiple factors like the estimated future growth of the trees, the terrain, and the presence of microhabitats (Cosyns et al., 2020). Expert foresters tend to develop highly personalised tree-selection preferences, such that when two expert foresters are given the same thinning instructions, their choices of which trees to cut are often very different (Pommerening and Grabarnik, 2019; Spinelli et al., 2016).

The studies examined in this review implicitly reimagine the role of the forester, from *making* the individual-tree decisions to *interpreting and applying* the optimised tree-by-tree decisions. If interpreting computerised decisions would indeed become a regular part of the forester's job, then many foresters would need to be trained in using digital technology and interpreting optimisation outputs. Processes would also need to be developed to manage situations where the judgement of the optimisation routine and the judgement of the forester on the ground diverge. On the one hand, the forester can spot obstacles and tree attributes that are not visible in the data, so he can perform corrective action when the optimisation routine errs. On the other hand, the forester may be subject to cognitive biases, so his decisions may be suboptimal compared to those of a computer. Hybrid solutions that combine algorithmic recommendations with expert judgement may allow practitioners to combine the best of both worlds.

5. Conclusion

Careful tree-level management planning has the potential to enhance forest management, especially when there are multiple complex biodiversity and ecosystem service objectives. This review synthesized the existing methods for optimizing the management decisions for every individual tree. The studies to date have been applied in European, Asian and North American forests, focused exclusively on harvesting decisions, and looked at small spatial scales (a few hectares) and a small number of management interventions (mostly one) at a time. Diverse ecosystem services have been addressed, many attributes of individual trees are integrated in decision processes, and the studies have mostly preferred simpler, heuristic, and interpretable optimisation techniques over techniques with better optimality properties and flexibility.

Several limitations in the existing literature were identified. For one, there is a lack of attention towards integrating tree-level management plans with management planning at larger scales, which is crucial for the achievement of regional and national policy goals. Additionally, the existing studies only focused on harvesting decisions, whereas forest management is concerned with many other decisions at the individual-tree level that could also be optimised in the same framework. Furthermore, the consideration of all types of natural disturbance risk and some critical ecosystem services, such as water protection, is missing. Addressing these limitations is a promising direction for the further development of tree-level management planning algorithms. Finally, in order for tree-level management planning to be implemented in the forest, methods for in-situ tree identification are needed, and it will be important to work closely with the foresters that perform the manual work of implementation. As forest management becomes increasingly multifunctional and data-driven, tree-level planning provides a framework for translating forest data into decisions at the highest possible resolution.

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Declaration of competing interest

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

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.tfp.2026.101226.

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