Forest harvesting operational planning tools: a systematic review of optimization, simulation, and spatial decision support systems

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REVIEW PAPER

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ABSTRACT

Sustainable forest management relies on effective operational planning to ensure that harvesting practices support long-term objectives. Operations research methods have largely been used to support operational decision-making in forest harvest planning but the broader strengths, limitations and barriers to adoption remain unclear. This review addresses this gap by synthesizing existing research on operational planning tools for forest harvesting. Using PRISMA protocols, we conducted systematic searches in Scopus and Web of Science and identified 23 peer-reviewed studies published between 2005 and 2024. The included studies employed diverse approaches across geographic regions, most commonly being mixed-integer programming and geographic information systems (GIS). Results show that while these models provide valuable insights and demonstrate technical expertise, they are often hard-coded to specific sites, lack reproducibility and are rarely open-source. Developing modular, transparent and user-centric tools could strengthen the existing connection between research and practice, enabling forest planners to manage uncertainty and improve efficiency while aligning with broader sustainability goals. Our findings highlight the importance of designing adaptable frameworks that embed site-specificity as a structural element rather than a limitation. We synthesize findings into a practitioner checklist, covering inputs, constraints, solution approach, validation, user experience and openness to guide tool design and evaluation.

KEYWORDS

Systematic review; forest operational planning; optimization; simulation; decision support; scheduling.

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1 Introduction

Sustainable forest management (SFM) is critical to ensure that forests provide social, economic and environmental benefits for generations to come. Forest management planning is often presented in three hierarchical planning levels: strategic, tactical and operational. Strategic objectives like sustained yield and climate resilience are planned in terms of hundreds of years but the success of achieving these objectives depends on the day-to-day operational decisions and actions that occur in the forest. Sustainable forest operations are the day-to-day steps and processes that can implement strategic long-term forest management goals (Marchi et al. 2018). Operational planning and scheduling determines when, where and how these operations are carried out (Bettinger et al. 2016). Good operational planning aligns these processes with long-term sustainability targets to ensure that short-term actions do not compromise long-term goals. However, poor operational planning can compromise strong strategic plans, affecting all three pillars of sustainability (Schweier et al. 2019). Effective operational planning must account for the ecological and social components of sustainability, as poor planning can lead to environmental degradation, loss of biodiversity and negative social impacts within the communities that depend on these forests (Tampekis et al. 2024). Consequences can include reduced yields, uneven timber flow, higher costs and emissions, environmental damage, loss of certification and erosion of public trust. Strong sustainable forest operations and planning are critical for achieving SFM in practice as these decisions have immediate cost and sustainability impacts (Davis and Martell 1993).

The scope and complexity of forest operational planning has evolved alongside advances in forest operations technology and computational capabilities (Heinimann 2007). Early approaches supported motor-manual operations with pencil-and-paper planning. The transition and adoption of mechanized forest harvesting practices as well as improved road infrastructure increased operational capacity and productivity but also increased the scope of planning, requiring more advanced modelling approaches. These advances as well as changes in societal values around forest management have added complexity to decision-making and modern operational planning must now account for a wider range of environmental, economic and logistical factors than in the past (Brown et al. 2020). Shifting trends in objective functions, model types and the embrace of multi-criteria decision analysis tools reflect the evolution of forest operational planning, moving from sustained-yield timber-centric goals towards more complex, spatially-explicit and ecosystem-based objectives, and the value of these tools in assessing planning effort viability (Labarre et al. 2025). These developments have also been supported by the increase in computational power and increasingly sophisticated models and data collection processes, which expands the information available to decision-makers during planning (Janová et al. 2024). Technology advancements have increased the level of spatial and temporal data available, expanding the granularity of decisions that can be made and supported.

As these changes have occurred across forest operations and its planning, operations research (OR) has shown to be a continued and effective means of tackling these complex decision-making processes. Operations research (OR) methods to support decision-making in forestry are commonly used because they are closely matched with the business decisions needed in forestry (Rönnqvist et al. 2023). These methods support planners across the different planning levels in evaluating alternative management strategies, improve resource allocation and reduce costs, as demonstrated in landscape-level applications such as Quebec's provincial forest planning system (Beaudoin 2017). There are still challenges though. Rönnqvist et al. (2015) describes the open problems forestry faces such as integrating harvesting and transportation decisions, handling uncertainty in operational conditions and ensuring that the models are both operationally and computationally feasible. Recent work like Audy et al. (2023) has investigated the timber transportation planning component of these problems but moving a step earlier in the planning process, operational harvest decision-making systems aren't as systematically examined.

This review aims to address that gap by conducting a systematic review of optimization and simulation tools for operational-level harvesting planning and decision support. For the scope of this review, operational planning refers to sub-annual (one year or less) decision-making that determines when, where and how harvesting happens (Weintraub and Cholaky 1991). We consider choices across multiple operational scales, from individual machines to broader operating areas or districts, including how to deploy and coordinate equipment and crews, sequence and schedule work, plan access and landings and adjust plans as conditions change. Our emphasis is on optimization, simulation and other decision-support system approaches that use operational data to guide action, rather than stand-alone productivity studies or longer-term strategic models. Our objectives are to synthesize the current state of research in this area, identify key strengths and recurring attributes of existing operations researched-based methods, and highlight limitations and opportunities for innovation. We aim to inform both researchers developing future planning models and forest practitioners seeking to improve their operations.

The structure of the review is as follows. Section 2 describes the systematic review method. Section 3 presents the results, which are discussed in Section 4. Section 5 concludes with recommendations for advancing forest operational planning.

2 Materials and Methods

2.1 Systematic Review

A systematic review is defined as an explicit, reproducible method that uses pre-defined search terms to collect, synthesize and analyze available studies to answer specific research questions (Lasserson et al. 2019; Ahn and Kang 2018). This systematic review was guided by the Cochrane Handbook for Systematic Reviews and Interventions Chandler et al. (2019) and was reported on using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) (Page et al. (2021)) reporting guidelines. This protocol uses detailed checklists to guide the systematic review process to support overarching objectives of accountability, transparency and reproducibility of the study (Page et al. 2021). The movement of studies through the stages of study identification, screening, eligibility and inclusion are documented using the PRISMA workflow Figure 1.

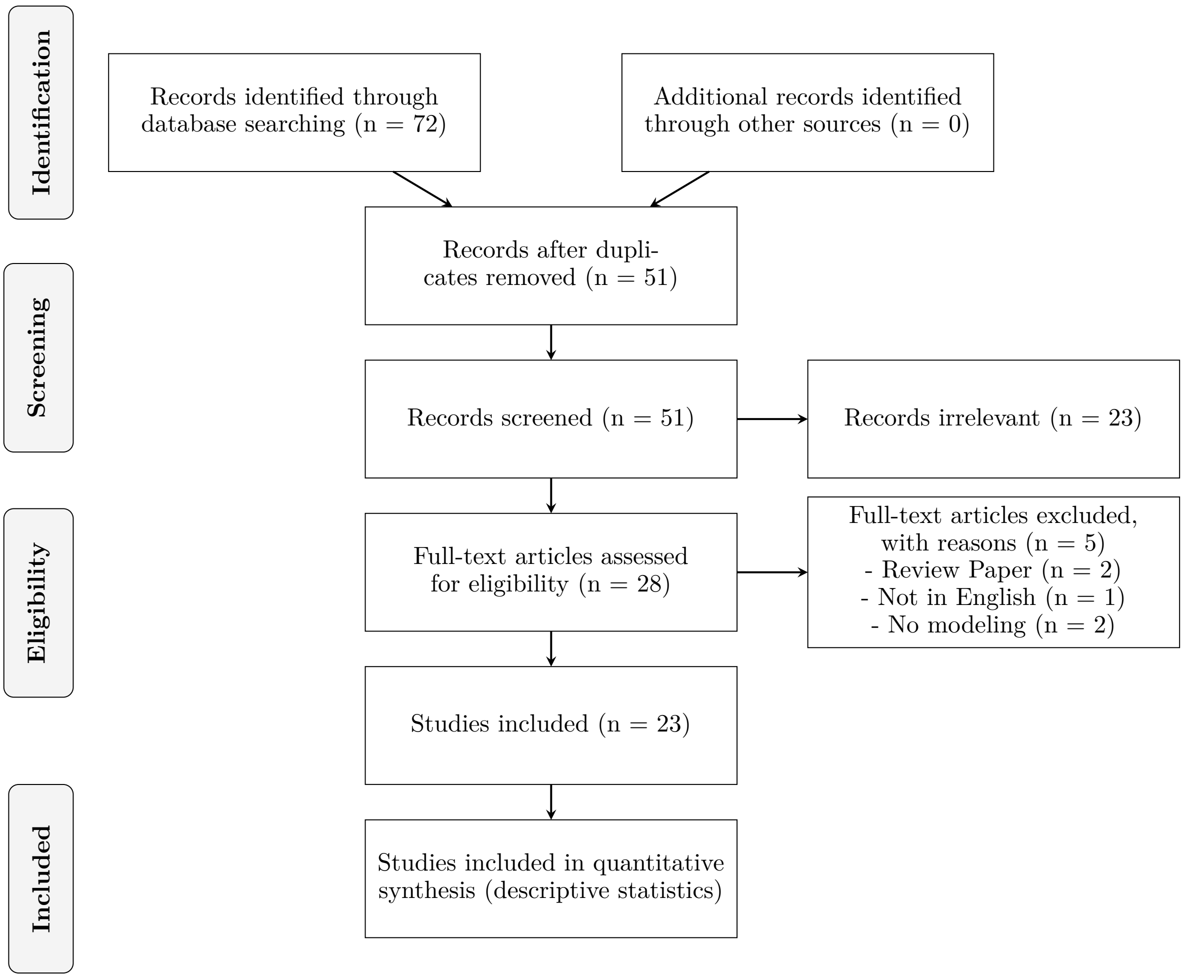

Figure 1.: Workflow outlining movement of studies through selection process, adapted from PRISMA 2021 guidelines

2.2 Search Method

This systematic review included peer-reviewed, scientific journal articles hosted within the Scopus and Clarivate Analytics Web of Science (WOS) databases. These databases were chosen because of ease of access and wide range of represented journals. We acknowledge the importance of other forms of publications like conference proceedings, gray literature and theses and the valuable information they provide on this topic. However, we chose to exclude everything but peer-reviewed journal articles to increase reproducibility and minimize bias from double-counting results. The data selected for inclusion was informed by the Cochrane Handbook for Systematic Reviews Interventions (Table 7.3.a: Checklist of items to consider in data collection) Chandler et al. (2019), with adaptations necessary for the forest operations context. The inclusion criteria focused on studies that examined operational forest planning tools or models. The studies addressed operational time frames (i.e. planning horizons of one year or less) or had an undefined planning horizon. Eligible studies employed methods such as optimization, simulation, decision support systems or other modeling tools aimed at supporting decision-making. No restrictions were placed on geographic location or publication date. Despite ongoing technological advances and differences in policies and operational environments, the fundamental mathematical approaches underlying forest operational planning are largely consistent over time and space. The search was limited to articles published in English. Studies that had limited focuses on bucking decisions, growth and yield modeling and timber transportation were excluded. Initial and iterative scoping searches were conducted when developing each of the database search strings. Final queries conducted on June 9th, 2025 yielded 34 results for Scopus and 38 for Web of Science. On September 2nd, 2025, we repeated our key searches in Google Scholar. No additional eligible peer-reviewed journal articles were found. Items encountered were theses, conference proceedings, or duplicates so PRISMA-recorded 'other sources' remains zero.

In Scopus, we searched TITLE-ABS-KEY for the conjunction harvest AND operation and combined this with any of (movement OR location OR scheduling OR allocation), (program OR design OR model OR decision), (forest OR wood OR timber), and (machine OR equipment OR worker). We excluded records containing (bucking OR productivity OR efficiency). Results were filtered for English and document type of article. Truncation captured word variants (e.g., harvest, harvesting; program, programming).

In the Web of Science Core Collection, we queried All Fields for harvest AND operation, and Topic for any of (movement OR location OR scheduling OR allocation), (machine OR equipment OR worker), (program OR model OR design OR decision), and (forest OR wood OR timber), while excluding Topic terms (bucking OR productivity OR efficiency). Results were filtered for English and document type of article. Truncation captured word variants (e.g., harvest, harvesting; program, programming).

The full query strings are available in the Appendix (Table 2).

2.3 Search Outcomes

Queries for each database were downloaded using .ris file format and uploaded into Covidence software. Covidence is a web-based screening platform for systematic reviews that allows for collaborative review processes and supports PRISMA protocol adoption (Innovation 2024). Covidence identified 21 studies as duplicates, and they were removed from the screening process. To ensure consistency in the screening process, two independent reviewers assessed the titles and abstracts of the retrieved studies against predefined eligibility criteria. The reviewers classified each study as Yes, No or Maybe for inclusion based on the outlined inclusion and exclusion criteria, using the Covidence management platform. Disagreements were resolved by consensus. We quantified inter-reviewer reliability using Cohen's κ, which corrects for agreement expected by chance given each reviewer's inclusion/exclusion rates. This is preferred over simple percent agreement in imbalanced screening sets, where high raw agreement can arise trivially from both reviewers selecting 'No'. We report κ with 95% confidence intervals at the title/abstract stage, alongside raw percent agreement and each reviewer's decision proportions. Following the title and abstract screening, full-text reviews were conducted to confirm the relevance of these studies against the outlined inclusion and exclusion criteria. At the full-text stage (n=28), one reviewer conducted the primary screening, and a secondary reviewer independently verified all inclusion/exclusion decisions as a quality control measure. Any discrepancies or uncertainties flagged during verification were discussed and resolved by consensus. This approach is consistent with recommendations for transparent and replicable coding practices in resource-intensive systematic reviews (Belur et al. 2021). Our search of Scopus and Web of Science returned 72 records, with no additional sources identified elsewhere. After removing duplicates, 51 unique articles remained for title and abstract screening. We excluded 23 as irrelevant, leaving 28 for full-text review. Five full texts were excluded, including two review papers, one non-English article, and two studies without a modeling component. In total, 23 studies met the inclusion criteria and were retained for synthesis, and all 23 were included in the descriptive quantitative analysis. The full-text review was completed on June 11th, 2025 and 23 studies were retained.

2.4 Data Extraction

Each reference was subsequently imported into Mendeley Reference Manager (Mendeley Ltd. 2024). A database using a tabular format was created to organize all necessary information for analyzing the included studies and findings of the systematic review. Key information extracted included the study design, type of modeling and solution approaches used, planning horizon, geographic location, availability of model and reproducibility. Key strengths, limitations and gaps were identified across the studies with an emphasis on how findings could improve future model development and practical implementation in forest operational planning. In line with PRISMA transparency, we note that although we critically analyzed all included studies and synthesized results across multiple dimensions, no formal study quality or risk of bias assessment tool was applied, as our review focused on descriptive synthesis rather than evaluation of intervention effects.

2.5 Data Processing and Analysis

We used the bibliometrix package (Aria and Cuccurullo 2017) and associated biblioshiny app in RStudio (Posit team 2025) to produce descriptive statistics on the dataset. Results are presented qualitatively to describe the necessary components of the models, their applications and limitations as presented in their studies. The data was synthesized narratively, with studies grouped according to main themes. We used ChatGPT (OpenAI, GPT-5 Thinking) to assist with coding during data processing and analysis and improve code readability. All code and outputs were independently reviewed and verified by the authors who take full responsibility for the integrity and accuracy of the work.

2.6 Data Availability

The study-level extraction table will be deposited in an open repository (OSF) under a CC BY 4.0 license (DOI link). The permanent DOI will be replaced at proof.

3 Results

A total of 23 studies were selected for detailed analysis in this systematic review of forest harvesting and operational planning models and decision-support tools. These studies were published between 2005 and 2024, with an average document age of 7.65 years. Although the search strategy did not include temporal restrictions, all included studies fell within the past 20 years. There is an observable increase in publications over time, particularly after 2020 with the highest number of publications in 2023 (n=8). However, given the small numbers and uneven year coverage, no formal statistical test of significance was conducted . The most frequently used keywords are "optimization" (n=5) and "system" (n=3).

3.1 Inter-Rater Reliability

Two reviewers independently screened records. Of the 51 articles assessed during the title and abstract screening phase, both reviewers agreed on 44 instances (24 for inclusion, 20 for exclusion). Disagreement occurred in 7 cases (6 one way, 1 the other). The observed agreement was 86.3%, while the expected-by-chance agreement due to chance was 49.8%. The resulting Cohen's Kappa coefficient was 0.726 with a 95% confidence interval of 0.538 to 0.915, indicating substantial agreement between viewers (Landis and Koch 1977). This consistency suggests a replicable study selection process.

Table 1.: Inter-rater agreement between reviewers during abstract screening

Reviewer A \ Reviewer B	Yes	No	Row Totals
Yes	24	6	30
No	1	20	21
Column Totals	25	26	51

Metric	Value
Observed Agreement (P_o)	0.862
Expected Agreement (P_e)	0.498
Cohen's Kappa (κ)	0.726
95% Confidence Interval	0.538–0.915
Interpretation	Substantial agreement

3.2 Citations and Authorship

The included papers were authored by 69 unique authors from 10 countries. When examining country of authorship, the most common affiliations were Canada (n=10), Sweden (n=10) and the USA (n=7), followed by Brazil (n=6), Chile (n=4), and Iran (n=4). Approximately 61% (60.87%) of articles involved international co-authorship. Several European countries (Austria, Germany, Norway, Portugal, Slovakia, Slovenia, and Switzerland) each contributed a single study through authorship. It should be noted that authorship country did not equate to study location.

With respect to first authorship, all but four authors contributed a single paper; Ezzati, Arora, Zamora-Cristales and Li each contributed two papers. The total number of citations of all papers included in the systematic review is 339 citations. The countries with the most citations are the USA (n=90) and Chile (n=80), followed by Sweden (n=71) and Iran (n=45). The paper with the most citations to date is Epstein et al.'s (2006) study that presented a *Combinatorial Heuristic Approach for Solving Real-Size Machinery Location and Road Design Problems in Forestry Planning* with 59 total citations.

The studies varied in terms of model type and solution, planning scope, data sources, objectives and reproducibility.

3.3 Model Type and Solution

A range of model types were presented within the review. To simplify, we grouped methods by how decisions are made and used. Each study is assigned one primary class, with secondary tags if needed:

(1) Math programming (MIP, IP, MP): optimization models solved with exact solvers or custom decomposition

(2) Simulation: discrete-event/agent or process simulations; optionally hybridized with optimization for scenario testing

(3) GIS/Spatial DSS: GIS-centric decision support to not only visualize but also solve

(4) Artificial intelligence and machine learning (AI/ML) and Computer Vision: machine learning or computer vision for perception/prediction in workflows

(5) Statistical/analytical: closed-form, econometric or probabilistic models

Under this scheme, the 23 studies are distributed. Eleven models employed mixed-integer linear programming (MIP) or integer programming models (IP) (Corner and Foulds 2005; Ezzati et al. 2015; Arora et al. 2023a,b; Bredström et al. 2010; Viana et al. 2023; Zamora-Cristales et al. 2013; Legües et al. 2007; Epstein et al. 2006; Jonsson et al. 2023; de Lima et al. 2011) (Figure 2). Where planning horizons have been defined (n=8), they ranged from two hours (material reception logistics in Marques et al. (2014)) to one year (annual harvesting allocation in Bredström et al. (2010)). Only one paper (Arora et al. 2023a) presented a rolling-horizon approach. Solution approaches frequently used commercial solvers such as CPLEX or LINDO (n=8), while some studies employed algorithms, heuristic or metaheuristic methods (n=8). Three models employed simulation approaches (Zamora-Cristales et al. 2013, 2015; Rukomojnikov and Sergeeva 2024) and Marques et al. (2014) employed both simulation and optimization in their model. Two papers employed statistical or analytical approaches. Five models directly employed Geographic Information Systems (GIS) in their model (de Lima et al. 2011; Epstein et al. 2006; Labelle et al. 2018; Shabani et al. 2020; Phelps et al. 2021) while the remaining works (n = 18) applied GIS primarily for spatial data presentation, dataset validation or visualization. GIS is the only identified user interface with the exception of Legües et al. (2007) and Marques et al. (2014) who presented prototype DSS/GUIs.

3.4 Planning Scope

Differences in scope of operational planning was evident. Four papers focused on individual machine behaviour while five papers included machine interactions as components of their models. Although models focused exclusively on log transportation and logistics were excluded, five models integrated harvesting and transport within a single model or decision-support system. Across the included studies, there was substantial variation in both the number of machines and the number of blocks used for model analysis. For machines and blocks, 16 of the 23 studies had discrete counts. The number of machines assessed ranged from 1 to 135, with a median of 3 (IQR is 45). While most studies reported small counts, the right tail is driven by outliers 120 and 135. The most frequent machine counts were 1 (n=4) and 4 (n=3). In addition, machine counts for seven models were either undefined or not applicable. The number of blocks assessed ranged from 1 to 1044, with a median of 4 (IQR is 9). Similarly to the number of machines, two higher values of 968 and 1044 contributed to a right-skewed distribution. The most frequent block counts were 1 (n=5) and 30 (n=2). One study presented itself as landscape-level, rather than providing a discrete value (Ezzati et al. 2016). In addition, block counts for seven models were either undefined or not applicable.

3.5 Data Sources

Most studies (n = 17) were developed and tested using real-world case studies (Figure 2). These case studies represented multiple forest types, including boreal, hardwood, coastal and mixed forests. There was a notable presence of various plantation types including eucalyptus and pine plantations (n=4), as well as a heavy presence of boreal forest types (n=6). The most frequent study regions were Sweden, Canada, USA, Iran and Chile, with smaller contributions (n=1) from New Zealand, Uruguay, Portugal, Brazil, Poland, and Finland. One paper did not specify a location.

Empirical operational data (site-specific data) was used in works such as Zamora-Cristales et al. (2013) and Phelps et al. (2021), whereas others used synthetic data for scalability and robustness testing (e.g. Jonsson et al. (2023)). Of the 23 studies presented, four (Corner and Foulds (2005), Bredström et al. (2010), Rukomojnikov and Sergeeva (2024), Li and Lideskog (2021)) identified their models as general.

3.6 Objectives

Of the 23 studies assessed, cost was the most dominant objective specified (n = 10). Time and downtime (n = 2) were also common while other objectives like discrepancies between log locations (Li and Lideskog 2023) and damage caused by timber felling (Shabani et al. 2020) were specific to individual models presented (Figure 2).

3.7 Reproducibility

Explicit validation was not reported in our extracted set. No reviewed model presented fully open-source artifacts however, one publication (Viana et al. 2023) provided data publicly on GitHub (see Appendix, Table 3. This includes full parameter values for the case study including contractors and harvesting sites. Reporting on deployability is limited: several articles reference prototypes or GIS workflows but packages and reproducible pipelines are generally absent.

3.8 Synopsis of Results

The deployment-relevant information is summarized below:

- **Primary model type counts:** math programming 11; simulation 4; spatial DSS/GIS 3; AI/ML 3; analytical/statistical 2.
- **Solution styles:** uses commercial exact solvers 8; heuristic/meta-heuristic 8; simulation/-analytical without optimality claims 7.
- **Interfaces:** prototype DSS/GUI explicitly mentioned in 2 studies (Legües et al. 2007; Marques et al. 2014); GIS workflow UIs in some studies; otherwise not recorded.
- **Independent validation (separate test data or third-party replication):** 0 explicitly reported in the extracted set.
- **Site-specific parameters required:** at least 19/23; *general* models declared in 4/23.
- **Open artifacts:** open code 0/23; public datasets 1/23 (Viana et al. 2023); parameter sets disclosed inline but no machine-readable in several case studies (few artifacts beyond PDFs).

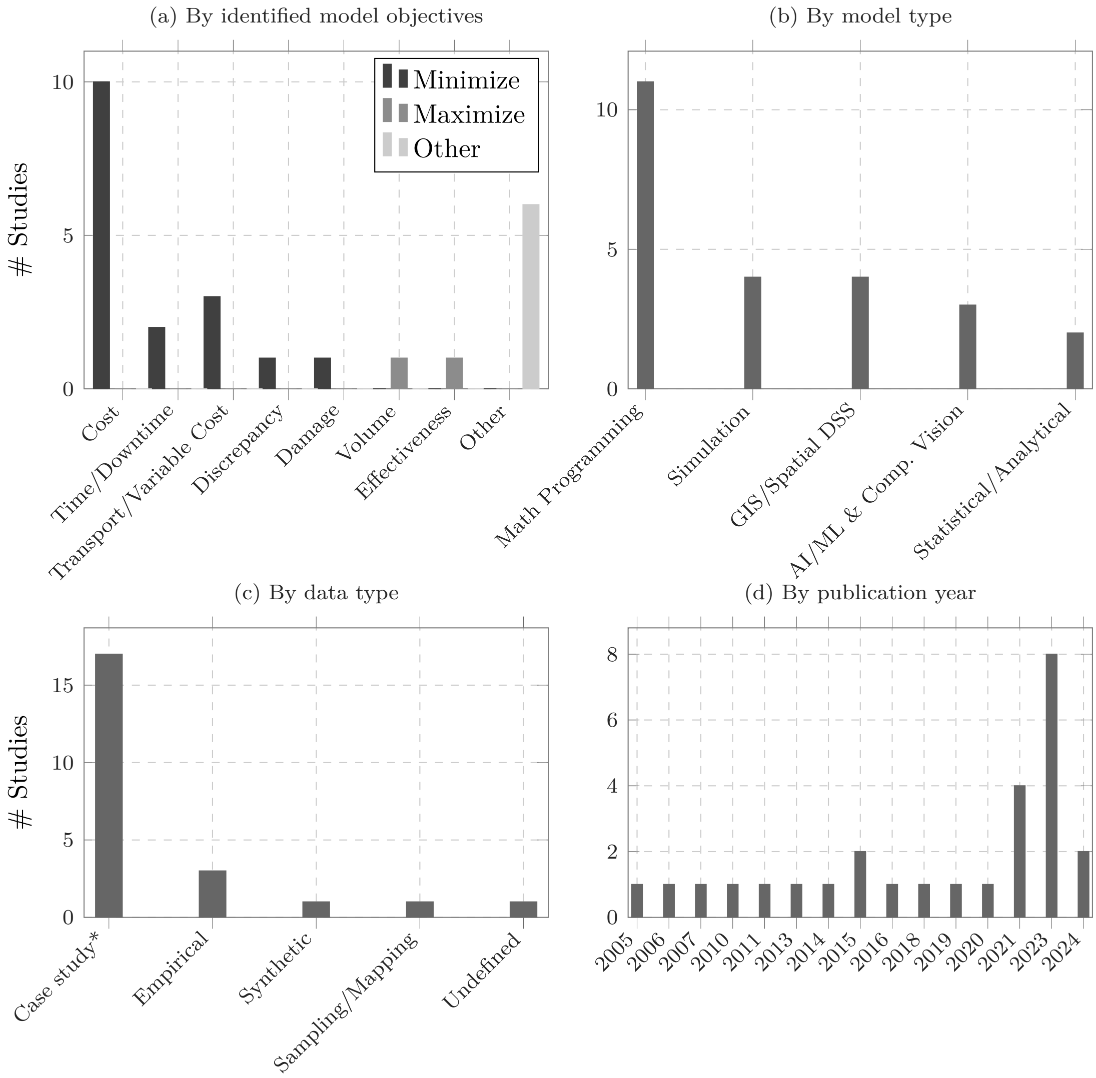

Figure 2.: Summary of studies by (a) model objectives, (b) model type, (c) data type, and (d) publication year. In (c), "Case study*" includes comparison, realistic scenario, and validation variants.

4 Discussion

This paper systematically explores the available literature on forest operational planning models and synthesizes the work into design guidelines for operational tool development. We translated recurring findings into practical recommendations that can support the realities of forest operational planning. The definition of 'forest operational planning' varies across the literature, which results in a wide range of models and tools. All with the goal to improve decision-making, these models function at different levels from an individual machine-level, to machine-to-machine interactions, to scheduling operations across multiple cut blocks. Across these levels, studies converge on three recurring themes: (i) forest operations are inherently site-specific, (ii) feasibility and agility often matter more in practice than mathematical optimality and (iii) clear, open tools help support managers in their decision-making. In this discussion, we will first present on common patterns identified in the geographic relationships and search terms of this systematic review before presenting a three-part evaluation framework to support both developers and users of forest operational planning models. The framework is organized around three key stages:

- 1. Model Design or Selection
- 2. Model Application and Use
- 3. Open-Source Solutions

For each stage, the findings are organized by themes. For each theme, we highlight key components, limitations and guiding questions that designers or users can ask themselves when developing, selecting or applying forest operational planning models. These guiding questions function as a practical evaluation checklist to help ensure that tools are accessible to intended users and operationally feasible and usable in the real world. In short, the framework synthesizes current practice and offers a decision-support tool for improving accessibility, agility and feasibility of forest operational planning models.

4.1 Systematic Review Findings

4.1.1 Geographic Relationships

The studies included in this systematic review were conducted across a wide range of countries. When comparing study location versus countries of authorship, study sites appeared more concentrated in a smaller set of countries whereas authorship was more internationally distributed. Canada and Sweden dominate in both countries of authorship and study sites. USA also appears strongly in both categories, although slightly more in authorship than study location. Interestingly, Brazil contributes high authorship but only is represented in one study site, suggesting that Brazilian researchers are contributing internationally to studies conducted elsewhere. In contrast, Iran and Chile appear more prominently as study sites than with authorship affiliation, reinforcing the cross-border collaboration in this field. This is heightened with several European countries that have affiliated authorship but no study sites listed. Overall, this indicates cross-border collaboration with certain countries providing both infrastructure and personnel, while others primarily offer scholarly support.

Unsurprisingly, the forest types represented in the reviewed materials are consistent with the geographic regions of study (i.e. the Scandinavian research is done on Boreal and the South American studies is done on plantations). Based on the geographic region and forest type specified in the model, different operational environment characteristics have been hard-coded into the model making it specific to that region or even as specific as that case study. As noted in Venanzi et al. (2023), different countries have different variability in forestry contexts. The USA for example has high variability whereas Chilean forestry is dominated by plantations. The presence of some geographies over others can also be explained by where the forest operations tend to be. There is higher adoption of technologies where those technologies meet the operational constraints of the terrain of that area.

4.1.2 Search Terms

Interestingly, the search terms used in this systematic review did not yield any results published earlier than 2005. It can be hypothesized that the search criteria excluded earlier papers because of changes in technology or terminology in the field. GIS software maturing in the early 2000s (Grigolato et al. 2017) and surges in OR popularity (Rönnqvist et al. 2023) as well as a decrease in computer costs may have increased papers with these search terms in this post-2005 timeline. It could also be likely that the search terms are more aligned with the terminology used nowadays whereas more basic logistics studies may be excluded using these terms. For example, there was a notable increase in the use of the terms optimization and systems in keywords, titles and abstracts over time, which could support the shift towards more computationally advanced approaches in forest operations modeling. The emergence and increasing prevalence of the word <system and optimization>, in line with the network paradigm presented in the Heinimann (2007) as the ongoing phase of development in forest operations engineering and some working to fill the gap Heinimann identified in mathematical models that need to link optimization models to on-the-ground conditions by making them spatially explicit. More GIS shows alignment with spatially-explicit modeling as called for by Heinimann (2007). While the standards and consistent modeling remains basically the same, the computational capabilities have advanced and may be more pressing in forest operational planning terminology. We see a similar trend in the post-2020 included articles with the incorporation of technology advancements like artificial intelligence (AI), machine learning (ML), and real-time sensing.

4.1.3 Study Limitations

The databases searched required institutional access, which presents a significant limitation to forestry practitioners who may not have access to these resources. Although many of the articles included were open-access, the accessibility of scientific literature remains a challenge for practical implementation. Guldin (2021) highlighted similar concerns in their review of small domain estimation research, underscoring disparity of access between researchers and practitioners. The review was restricted to journal articles written in English, potentially excluding relevant literature published in other languages. This could result in a bias towards research from English-speaking countries, which may leave out findings that would be helpful in a global forestry context. To mitigate potential biases in data screening and extraction, a consensus-based approach was used. Clear documentation outlined the workflow of the screening process. Two reviewers independently reviewed all titles and abstracts with high inter-rater reliability statistics. We did not calculate inter-rater reliability statistics at the full-text stage because our process involved verification rather than independent screening. In the full-text review stage, a primary reviewer screened full-texts and the secondary reviewer verified these decisions as a quality assurance measure. As emphasized in Belur et al. (2021), inter-rater reliability is influenced by human factors including prior knowledge and fatigue. We acknowledge that some reviewer discretion is inherent in systematic reviewing and have transparently reported our processes to support confidence in our findings. The nicheness of the topic could explain any directional bias, given the limited set of articles. However, the breadth and depth of literature covered here is likely sufficient to provide insights.This review did not apply a formal quality appraisal or risk of bias tool, which limits the ability to assess methodological rigor across studies. However, this decision was aligned with the descriptive aims of the review, which prioritized mapping themes, modeling characteristics, and research trends over evaluating intervention effectiveness.

4.2 Model Design or Selection

When developing or selecting a forest operational planning model, the first priority is to ensure that the model's intended outputs are aligned with the operational realities and needs of the user. The guiding questions in this first stage are focused on evaluating the fit between model design and user needs.

4.2.1 Planning Scope

Forest operations are inherently site-specific because unlike standardized industrial processes, this work depends heavily on the natural environment, which varies widely across sites. Operations must be planned and implemented with careful consideration of local conditions to balance productivity, cost, and environmental sustainability (Bettinger et al. 2016). Depending on the goals and objectives within operational planning, different information is needed to guide decision-making. This has led to a wide range of tools and models being developed within operational planning that all target specific parts of this decision-making. Given this variability in granularity, this review captured a range of models and tools. These function to improve decision-making across scales such as individual machine basis, machine-to-machine interactions and all the way to generalized block scheduling within an operational time frame. Even with their differences in granularity, however, in each of the papers the site-specific nature of forest operations is emphasized with each model tailored to the case in which it was developed.

4.2.2 Individual Machine-Level

The operational environment, including site conditions, terrain and machine availability, is fundamental in shaping the planning scenario (Lahrsen et al. 2022). On an individual machine-level, these variables are translated into operational thresholds like slope limits and productivity parameters that define when, where and how machines can operate. With advancements in technologies and changes in forest equipment and increased support of automated processes on these machines (AI, obstacle detection, etc), there is an increased attention to individual machine behaviour and how it can be optimized to improve overall planning. In Prinz et al. (2021), a detailed analysis of harvester performance illustrates how specific these operational thresholds can be, down to the saw blade. Each threshold can hold importance in maintaining environmentally-sound, safe, and economically-feasible operations. Deciding where to deploy equipment without considering the operational constraints and conditions of that area would bring significant risk to operations. The work of Epstein et al. (2006) and Labelle et al. (2018) support the idea that deployment and allocation decisions must be made with knowledge of individual site constraints, including physical constraints, infrastructure constraints and operational dynamics. Li and Lideskog (2021) investigated obstacle detection for harvested forest land to assist operators in their work, utilizing new technology to improve one's knowledge of individual site constraints. Terrain is a critical component in this, being the focus of three included studies (Ezzati et al. 2016; de Lima et al. 2011; Shabani et al. 2020). Shabani et al. (2020) used machine learning to develop maps that assess the susceptibility of different forest management areas to erosion and environmental impacts of harvesting. Ezzati et al. (2016) evaluated existing terrain conditions of forest management areas to find suitable areas for harvesting, and Phelps et al. (2021) that assesses and clarifies operability on steep slopes and poor soils for mechanized harvesting. This greater integration of terrain data also highlights the role in technological advancements to improve machine coordination (Venanzi et al. 2023).

4.2.3 Machine Interactions

A number of studies have focused on machine-to-machine-level interactions, investigating how scheduling and coordination of individual machines affect productivity and cost. Corner and Foulds (2005) highlighted the importance of interchangeability of workers and equipment, as well as the influence of time lags on operational efficiency. Arora et al. (2023a,b) demonstrate how sequencing constraints shape feasible harvesting schedules, using multiple machine assignments (Arora et al. 2023a) and precedence relationships (Arora et al. 2023b). Viana et al. (2023) modeled groups of equipment as 'harvesting fronts' moving from block to block and demonstrated the value of joint planning between contractors to minimize idle time and cost. Bredström et al. (2010) focused on annual planning of harvesting resources in Sweden, handling a pretty large dataset and minimizing production, travel and relocation costs. These studies show that harvest productivity doesn't only depend on individual machine performance but also how machines interact with each other. This can also be expanded to how machines interact with other systems, like transportation, for example. Other studies have expanded their scope to focus on the interactions between the harvesting phase and the transportation phase, connecting forest operations into the broader supply chain.

4.2.4 Integrated Harvesting and Transportation

The search criteria explicitly excluded models solely focused on timber transportation and log logistics. However, several of the included studies linked harvesting decisions with transportation and broader supply logistics, demonstrating the inter-dependencies between these planning stages (Santos et al. 2019). In conventional timber transportation, Legües et al. (2007) examined the role of machine mobilization points in shaping truck-machine interactions, while Epstein et al. (2006) proposed simultaneous optimization of machine locations and road designs. Marques et al. (2014) used discrete-event simulation to test the impact of different harvesting scenarios on material reception at a sawmill. Their visualization and quick computation time provides a tangible solution to strengthening the connection between the planning and operations sides, allowing for quicker communication and response.

Integration is noted to be particularly complex for biomass supply chains, where variability in moisture content, weight, quantity and spatial distribution is greater than in conventional timber. Zamora-Cristales et al. (2013) found that interference between grinders and trucks reduced utilization rates and increased costs (wait times making up up to 15 % of grinding cost). Like Viana et al. (2023) in machine to machine interactions, Zamora-Cristales et al. (2013) reiterates the role of idle time as a key driver in increasing operational costs. Building off of these findings using modeled truck-machine interaction delays, Zamora-Cristales et al. (2015) showed that integrating biomass processing and transportation decisions can lead to decent cost savings of 3 to 34 % in Pacific Northwest operations.

These studies reinforce the value of linking operational decisions in harvesting with transportation logistics, as seen in broader reviews like Audy et al. (2023), focused on timber transportation. Labelle et al. (2018) provides a different avenue of integration, suggesting that silviculture should also be incorporated to improve and support more holistic planning to improve supply chain inter-dependencies. However, solidifying these connections are often difficult in practice given computational availability, disaggregation of decisions because of contractor bases or accessibility of tools. Challenges can also arise around interoperability especially when the supply chain itself isn't as clearly linked or connected or when the models themselves don't have aligned inputs and outputs. This can also be amplified by challenges in data availability throughout the system (Labarre et al. 2025). This is also a recognized challenge when linking proprietary software together because of input/output alignment from different software which limits actual operational usability by forest decision-makers (i.e. logging contractors, forest professionals, etc). This challenge in interoperability poses a significant opportunity for future design, designing with interoperability in mind.

4.2.5 Design Implications

- Interoperability
  - What other models do you need to use?
  - How well do they work with others?
- What is the model's scope and horizon?
  - Do you need machine-level, machine interactions or block-level?
  - How can you validate that the scope covers the real decisions being made?
  - What is the planning horizon and time-steps?

4.3 Model Application and Use

Once the model has been selected for use or has been developed, the challenge shifts to its application in operational environments. This stage is focused on the model's performance in practice and how accessible and usable they are for decision-makers.

4.3.1 Generalized Models

Some models presented partial generalizability with specifics that made them applicable to similar sites and similar topography. Legües et al. (2007) and Epstein et al. (2006) show models that can be applied to similar sites with dynamic forest sectors and similar topography whereas, Depending on the design of the model, this partial generalizability extends to different scopes. In Ezzati et al. (2016), there is built-in flexibility for it to be applied to other operational systems.

The Planex model, a system used to identify landing locations, design road construction and allocate machine locations across thousands of hectares of forested land, is presented by Epstein et al. (2006) and later, revisited by Legües et al. (2007) with alternative solution methods that emphasize machine location decisions and road/exit intersections. This model is applied to large-scale forest management areas and can be extended to regions with comparable infrastructure and terrain. Similarly, Ezzati et al. (2015), Ezzati et al. (2016) and Phelps et al. (2021) proposed models presented with generalized applicability for mountainous terrain. In Phelps et al. (2021), for example, their framework allows for different criteria to be swapped in or altered, allowing for more specific analysis of forest management in mountainous terrain. However, in Ezzati et al. (2015), the model's application to hardwood forests in hard-coded into the model, which made it as Contreras and Chung (2011) described, 'difficult' to adapt to conditions beyond its original hardwood case. These examples highlight the partial generalizability problem. Across different forest types and terrain, operational complexity can increase, making it difficult to apply generalized solutions that are operationally feasible. Models can often be framed as general but their assumptions and embedded parameters tie them to specific operational environments. Flexibility varies across models of this type but finding an operationally feasible solution requires at least some level of site specificity.

As highlighted by Rönnqvist et al. (2015), this variability complicates efforts to generalize forest operational planning models. However, it also reinforces the need to design models that embed flexibility and adaptability as structural features. With the models presented as 'general', we see the role of parameter flexibility in allowing these models to meet a variety of contexts. However, they cannot be applied to every context because they were designed for specific objectives and components of forest operations. There are some hard-coded assumptions within the model that allow them to meet their specific cases effectively. For example, Rukomojnikov and Sergeeva (2024) is designed for harvester productivity but if you were to apply it to different equipment types, the coefficients used would need changes. In the current format of the model, redesign would be required to make those changes. This is a noted lack of reproducibility, where models that are made to perform well at specific site and tailored conditions often have little reusable design built in. Feasibility can also be measured via validation. For models calibrated and validated on one dataset, their applicability may be limited or not tested fully whereas if these could be robustly tested, there may be a stronger argument for applicability more generally.

4.3.2 Design Implications

- List of objectives and constraint plug-ins.
- What assumptions are acceptable to keep the model usable?
- What hard-coded assumptions can be replaced with localized parameters?
- Can constraints be adapted when infeasible solutions occur?
- What evidence shows it transfers to similar operational environments?
- Develop a list of common operations situations for your operational environment.
    - Test datasets for these environments.
- How are spatial and topological relationships represented in the model?

4.3.3 Uncertainty

Managing uncertainty is a critical part of designing flexible and durable operational plans. The operational environment is dynamic and decisions made in plans need to remain effective amid dynamic conditions (e.g. weather, equipment, workforce, site conditions) (Ulvdal et al. 2022). Uncertainty management is not a new component of forest operational planning and with or without mathematical models, the general and time-tested approach for this is re-planning regularly (Martell et al. 1998). This ability to pivot quickly instead of favoring a rigid but 'optimal' solution is a necessary strategy for ensuring feasibility of the operations. Most models use deterministic approaches for productivity and travel time (mobilization) despite these high levels of uncertainty (Jonsson et al. 2023). Some models, however, have integrated flexibility into their designs to support producing more operationally feasible outputs. Labelle et al. (2018) and Shabani et al. (2020) use both machine learning and optimization to support dynamic adjustment of parameters in real time. Combinatorial models such as Epstein et al. (2006) are essential for real-time machine tasking, particularly in multi-site harvesting systems (Sessions and Yeap 1989). Zamora-Cristales et al. (2015) allows parameters like cost and productivity to vary to allow for easier adaptation to different cases or to test different scenarios. The reviewed studies highlight the emergence of flexibility, agility and uncertainty management as critical capabilities in forest operational planning tools. Many papers, in their discussions, focused on the broader conversation about usability of these models and the need to pivot quickly without losing efficiency. Having the ability to cater to this uncertainty and, as mentioned above, site-specificity within the framework reduces the need for significant reworking if and when critical parameters change as well as account for uncertainty.

4.3.4 Design Implications

- What inputs are uncertain?
- How is robustness represented in the model?
- How does the model account for uncertainty?
- What does the re-planning process look like for the model?

4.3.5 Data Quality

Forest planners are often working with incomplete or uncertain data (Labelle et al. 2018) so the model needs to handle ambiguity, as well as uncertain weather patterns and dynamic site conditions that can quickly change the trajectory of operations. Spatial resolution and data quality may be a challenge (Labelle et al. 2018; Shabani et al. 2020). Data demands may exceed what is available in operational contexts.

4.3.6 Design Implications

- What data does the model need to run?
- What data and data quality do we have access to?
- What consistent data quality can we reach?
- What are the minimum viable inputs for the model to run?
- How can missing data be handled?
- What input and output formats are required and available for use?

4.3.7 Computation and Processing Time

Feasible solutions are ones that can be realistically implemented given site conditions, resources and workforce/equipment constraints, whereas an optimal solution is one that mathematically achieves the minimized or maximized objective function. In many operational settings, feasibility is prioritized over mathematical optimality. Both Epstein et al. (2006) and Hosseini et al. (2023) used heuristics and simulation-based approaches as a means of generating practical solutions under real constraints, where exact optimization would have limited the solution. Where planning horizons have been defined (n=8), they ranged from two hours (material reception logistics in Marques et al. (2014)) to one year (annual harvesting allocation in Bredström et al. (2010)). In the one paper that included it, rolling-horizon (Arora et al. 2023a) was explained as a means of reducing the computational complexity of the problem while maintaining operational feasibility. This is one approach in model development to keep the model operationally feasible while staying computationally reasonable. In Bredström et al. (2010), an annual planning model is tested.

Many models explicitly frame themselves as decision-support systems (DSSs) and emphasize their role in supporting, rather than replacing human decision-making. These systems alongside multi-criteria decision analyses (MCDAs) are valuable in supporting managerial decisions with strong visualizations (Marques et al. 2014) and their ability to improve one's capacity to evaluate or assess planning efforts more quickly (Seely et al. 2004). For example, Epstein et al. (2006) noted the value of exploring the solution space faster, allowing the forest manager to spend more time on analysis rather than generating maps. For a 1000 ha area, the model can produce multiple solutions with an average processing time of 15 minutes on a standard computer. This allows for testing of evaluation of alternative scenarios and assessment of the viability of different planning tools to decide machine location and road construction needed based on two heuristic solving approaches. Rukomojnikov and Sergeeva (2024) used simulation to investigate math regularities of harvester operations so that labor costs could be calculated quickly across multiple logging operations, again utilizing advances in technology to speed up the more time-consuming processes through automation. As presented in Frayret and Perrier (2016), simulation tools can be an effective means in exploring agility in forest operational planning.

4.3.8 Design Implications

- What run-time, hardware is acceptable for operational use of the model?
- What computing capacity does our team have? Does it match the needs of the model?
- What modeling experience does our team? How may this impact the output and insights?
- what does the model require (time, computing capacity)?
- How does the model find the solution?

4.3.9 Objectives and Multi-Criteria Trade-offs

The studies assessed in this systematic review largely reflect the traditional concerns that have been echoed in operational planning throughout time(Rönnqvist et al. 2023): efficiency, cost, and feasibility while also adapting to emerging pressures and changes in the operational objectives (multiple objectives, digitization, climate change, biomass demand) (Labarre et al. 2025). A core objective of minimized cost remained consistent across the studies, although occasionally phrased differently like reduced personnel resource allocation. Given that economic feasibility ultimately determines whether a solution can be adopted in practice, this objective remains prominent in operational planning models (Beaudoin 2017). While cost generally makes the adoption decision for different plans, there are still other important objectives and criteria that can influence decisions, as seen in the need for multi-criteria decision analyses in forest operational planning. We also see the emerging work on readiness and safety (Kozlowski et al. 2024; Li and Lideskog 2021) that expands the decision space beyond scheduling. Kozlowski et al. (2024), for example, uses predictive maintenance information so that schedules can be updated more readily.

4.3.10 Design Implications

- What objectives does the model solve for?
- Does the model address multi-criteria trade-offs?
- How are the objectives weighted? How can the users change the weights of the objectives?

4.3.11 Operational Feasibility

We also see emphasized need for operational 'realism' (e.g. terrain, equipment constraints) to be integrated with optimization techniques. Optimization techniques are widely used in this field but operational feasibility is just as critical. Many studies emphasize the need for 'feasible' solutions rather than 'optimal' solutions. Barriers may include mismatched data requirements and availability, limited training and computational resources. Model development can overcome some of these challenges, using increased interface between OR and planner as shown in Bredström et al. (2010) and Epstein et al. (2006) where it can emphasize the value of operationally feasibility, help expose model decisions that do not align with operational reality, and help adjust the outputs to become usable and useful insights. Alongside the technical math, the authors argue for the critical and iterative dialogues between the OR specialists and forest planners in order to translate this math into usable operational solutions. There is a need for alignment between models and the actual workflow of planners and foresters. This was attempted or achieved in different ways in the studies looked at. For example, in (Zamora-Cristales et al. 2015) and (Phelps et al. 2021), there was a heavy use of case-study based validation to check and validate field applicability. Jonsson et al. (2023) expands Bredström by contrasting different solution designs and stresstesting assumptions (e.g. initial team allocation, equipment availability) to further refine the operational feasibility of these solutions.

4.3.12 Design Implications

- What operational constraints might the math miss? How can we account for them?
- What is an acceptable level of error?
- How is feedback looped back into the model?
- What benchmarks define 'good' for a specific operational environment?
- What validity and feasibility checks are present within the model?
- What are the assumptions in the model? How are they audit-able for practitioners?
- What format are the outputs and how do they need to be translated to be usable for practitioners?
- What level of user expertise is assumed?

4.4 Open-source Solutions

Open-source modular solutions, as proposed in related fields (Moon and Howison 2014), could bridge the gap by combining adaptability with transparency and collaborative development. With none of the reviewed papers presenting as open-source, this offers an opportunity for expansion. The increasing recognition that forest planning systems must be user-centric and transparent aligns well with the open source pathos and the broader conversations of open science and collaboration gaining traction in environmental management. These models and tools can enhance capacity without undermining experience and allow for faster, more comprehensive exploration of the solution space. Future work should focus on building open-source reproducible tools that can flexibly respond to changing conditions while supporting practitioners in their daily decision-making. Specifically, we plan to examine the validity and applicability of a generalized tool for machine scheduling in forest operational planning. Aligning similar strategies employed in a strategic forest planning level model by Nguyen et al. (2022), forest operational planning models could benefit from open licensing, modular subsystems and the adoption of open-source technology as a means of improving collaboration and lowering cost.

4.4.1 Design Implications

- Is the code for the model open-source?
- Is there a plan for continuous updating and version control?

- How accessible is the code?
- How accessible are the datasets?

4.5 Adoption Checklist

Based on the framework presented above, we developed an adoption checklist for forest operational planning tools, outlining eight key criteria, verification points for each and the minimum acceptance levels required to ensure that the tools meet practical decision-making needs (Figure 3).

Adoption checklist for forest operational planning tools

Criterion	What to verify	Minimum acceptance
Inputs	Required datasets (blocks, roads, machines, shift rules, product specs) are defined with units and formats.	All inputs exist in your system; mappings to the required schema validated on a pilot block.
Constraints	Legal, safety, terrain, seasonality, shift and move-up rules are representable.	$\geq$95% of binding rules encoded or approximated; exceptions documented.
Solution approach	Model/algorithm fits problem scale and re-plan cadence.	Instance solves within X minutes for daily re-plans; stable across seeds.
Validation	KPIs and baselines are defined (cost, volume, utilization, move-ups, delay).	Back-test on $\geq$1 historical week; KPI deltas vs. baseline within agreed tolerance.
Re-planning & UX	Rolling-horizon or quick re-solve; user can lock assignments/overrides.	Re-plan without full rebuild; partial locks/overrides available in UI or config.
Generalizability	Parameters externalized; site-specific constants isolated.	New area on-boarding requires configuration, not code changes.
Openness & maintenance	Code/data access, license, and support path are clear.	Repo or escrow; explicit license; versioned releases; change log.
Compute & deploy	Hardware/OS requirements and containerization documented.	Runs on available infrastructure; container or reproducible environment provided.

Figure 3.: Checklist for adoption of forest operational planning tools.

5 Conclusion

This review shows that forest operational planning models have achieved considerable success in addressing specific challenges at individual sites and multi-site operations, particularly where models are tailored to local operational environments. This effectiveness is also supported by improvements in data availability, computational capacity and geospatial technology, however, these models fall short in reproducibility and broader applicability. Our review indicates that the majority of existing tools are difficult to reproduce or transfer beyond their original context or design case.

The current literature is well-established and advancements in technology are expanding the opportunities for the field. More complex and precise models are now feasible with advanced solutions approaches, but they are not always usable in practice due to barriers in accessibility and adaptability. Many existing tools are proprietary, technically complex or poorly documented which limits how effectively they can be applied in real-world operational forestry.

Many models are designed with hard-coded parameters, pushing the need for planning tools that can adapt to multiple sites and operational environments without rebuilding the models from scratch. Rather than using site-specificity as a limitation of these models, it should be incorporated as a structural and foundational design element in flexible and adaptable frameworks. This would allow for decisions to be driven by site-level data, as seen in the many models presented in this review, without sacrificing general utility. Framing models in this way allows for operational planning systems that are responsive to local conditions and structured enough to be reused across contexts with minimal going back to the drawing board. This is especially helpful given the uncertain conditions faced by forest managers throughout their daily plans.

5.1 Actionable Recommendations

Ultimately, forest operational planning should aim to support the real-world decisions that professionals are making every day. Connecting the dots between what is produced to improve forest operations and what is implemented in actual forest operations is critical to ensure the sustainability of the field. Therefore, we put forth three actionable recommendations in the development of these models

- Parameterize site-specificity and avoid hard coding it into the models.
- Mandate validation transparency in both datasets and performance metrics.
- Publish minimum viable open artifacts to maintain transparency even if full source can't be released.

The site-specificity needed for forest operational planning lends itself to the consistent development of bespoke solutions that can get the job done. By embracing site-specificity as a structural input instead of a barrier, however, forest operational planning research can evolve from isolated technical solutions towards more replicable and flexible planning systems that can better support forest professionals in their managerial decisions.

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7 Appendix

Table 2.: Search criteria used in Scopus and Web of Science databases

Database	Search Criteria
Scopus	(TITLE-ABS-KEY (harvest* AND operation*) AND TITLE-ABS-KEY (movement OR location OR scheduling OR allocation) AND LANGUAGE (english) AND TITLE-ABS-KEY (program* OR design OR model OR decision) AND TITLE-ABS-KEY (forest OR wood OR timber) AND TITLE-ABS-KEY (machine OR equipment OR worker) AND NOT TITLE-ABS-KEY (bucking OR productivity OR efficiency)) AND (LIMIT-TO (DOCTYPE , "ar")) AND (LIMIT-TO (LANGUAGE , "English")
Web of Science	harvest* operation* (All Fields) and movement OR scheduling OR allocation OR location (Topic) and machine OR equipment OR worker (Topic) and program* OR model OR design OR decision (Topic) not bucking (Topic) and Article (Document Type) and forest OR wood OR timber (Topic) not productivity OR efficiency (Topic) and Article (Document Types) and English (Language)

Table 3.: Open artifacts observed in systematic review

Paper	Open Artifact
Viana et al. (2023)	https://gitlab.fing.edu.uy/victor.viana/fhtp/