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Improving forest decision-making through complex system representation: A viability theory perspective

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ABSTRACT

Forests are complex adaptive systems (CAS) featuring dynamics that can take centuries to unfold. Managing them for multiple objectives (e.g. financial performance, climate regulation, biodiversity conservation, watershed protection) in the face of multiple risks (e.g. market fluctuations, illegal logging, natural disturbance) involves making decisions under deep and pervasive uncertainty. Through a systematic literature review, we explore quantitative approaches for integrating uncertainty and complex-systems theory into forest management planning and examine common challenges like dimensionality, tractability and realism. In addition to comparatively well-studied techniques from operations research and portfolio theory, we highlight a largely-overlooked framework known as viability theory. Whereas approaches like stochastic programming and robust optimization seek to maximize performance given predefined outcome probabilities and uncertainty spaces, respectively, viability theory aims to identify executive rules that can delineate the boundaries of the safe-operating space based on system dynamics. We discuss the potential utility of this novel approach to capturing uncertainty and examine potential barriers to improving forest decision-making and management.

1. Introduction

Forests play a crucial role in climate change mitigation and adaptation strategies (Kim et al., 2017; Fischer, 2018). However, growing human and natural pressures threaten the future stability of forest ecosystems around the world (Rönnqvist et al., 2015; Reyer et al., 2017). Forest management seeks to promote the provisioning of vital ecosystem services like timber, carbon storage, watershed protection, and recreation under profound environmental and economic uncertainty (Yousefpour et al., 2012; Morin et al., 2015; Blanco et al., 2017; Ontl et al., 2018). Despite the immense challenges involved in balancing multiple objectives in the face of numerous risks under accelerating global change, there is a strong demand for management approaches designed to provide portfolios integrating ecosystem services while also enhancing the resilience of forests to an uncertain climatic future (Rönnqvist et al., 2015; Hashida and Lewis, 2019).

Navigating these challenges requires understanding forests as complex adaptive systems (CAS) featuring dynamic interactions between human and natural components (Ostrom, 2009; Rammer and Seidl, 2015; Messier et al., 2016; Findlater et al., 2022) that cannot be considered separately (Rosa and Dietz, 2012; Equihua et al., 2020). They contain nested feedback loops encompassing social, economic, and environmental processes that are often individually and collectively sensitive to environmental change (Folke et al., 2005; Aubin et al., 2011; Radke et al., 2017; Fischer, 2018), while also shaping environmental processes. For example, forests act on the climate system (e.g. by heat radiation exchanges with atmosphere and by storing carbon) while also being affected by it (e.g. by becoming more vulnerable to disturbances) (Walther, 2010; Rammer and Seidl, 2015).

While forest managers typically neglect feedback that operates across such drastically divergent spatial scales (e.g. by treating climate as exogenous), they regularly deal with nonlinearities working across comparable divergent temporal scales. Tree harvesting (or losses to fires) can occur in minutes, with most complete information about current market prices and disturbance risk. However, the effects of a thinning treatment, for example, can take years or even decades to

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materialize. Replanting and reforestation—are investments that take place over even more extended periods and may not generate profit for a century or more— and are performed in the face of profound uncertainty about the climatic and economic conditions (Gray and Hamann, 2011; Keenan, 2015). This interplay of immediate and delayed effects, compounded by global change, makes forest management problems increasingly ill-defined, which complicates effective application of standard decision-making techniques. While physical and engineering systems are more likely to be optimally controlled, those involving living organisms are influenced by identified actors, predictable regulations, or rare, unforeseeable disturbances (Aubin et al., 2014). Uncertainty in forest management outcomes spans a spectrum ranging from complete knowledge to complete ignorance (Knight, 1921; Courtney et al., 1997; Walker et al., 2003; Kangas and Kangas, 2004; Pasalodos-Tato et al., 2013; Radke et al., 2017; De Pellegrin Llorente et al., 2023).

As a discipline, forest management planning seeks to structure such problems by combining models from the natural sciences – such as forest-dynamic or ecosystem models – with various mathematical decision tools, many of which have their roots in operations research (Radke et al., 2017; Castro et al., 2018). The large variety of forest ecosystem models provides insights into ecophysiological processes, forest management alternatives, and system sensitivity to actions and external drivers like climate change (Landsberg, 2003). However, as Wolfslehner and Seidl (2010) noted, there is a lack of methodological research to effectively integrate these natural science models with decision-making tools. They highlight that simplified models, often limited to describing forest growth, are commonly used, which limits the ability to capture the full dynamics of forest ecosystems across various scales. In fact, in operations research, modelling and solvability of a management problem are closely connected. This explains why modelling is constrained. Thus, planning problems involve uncertainties related to the simplified biophysical models used and the data that feeds them. This is true for each module, of each model, that is used to generate the input data for the decision tool. Despite this, decision tools often fail to account for uncertainty and instead provide prescriptions that implicitly assume a deterministic and well-behaved system. This is a well-documented problem because failing to consider uncertainty can have profound and far-reaching impacts on forest management (Ben-Tal et al., 2009; Hoganson and Meyer, 2015).

To help fill this gap, we surveyed the literature for recent advances in accounting for complexity and thus uncertainty in the context of forest management planning. In keeping with previous reviews, we find that the most prominent approaches are stochastic programming and robust optimization, which have their roots in operations research, economics, and finance (Hildebrandt and Knoke, 2011; Yousefpour et al., 2012; Castro et al., 2018; Eyvindson and Kangas, 2018). Stochastic methods maximize expected utility within defined scenarios, while robust methods seek good-enough solutions without probability distributions (Ben-Tal et al., 2009; Alagador and Cerdeira, 2022). Other increasingly popular techniques use tools like fuzzy logic, Bayesian belief networks, and agent-based modelling (Bingham et al., 2023).

Regarding this aspect, viability theory, though often disregarded, may offer a promising alternative in capturing system complexities for forest decision science. Viability theory explores how dynamic systems can evolve without compromising their ability to persist in a subsequent iteration (Aubin and Frankowska, 1991; Aubin et al., 2011). Instead of optimizing or satisficing an objective function in traditional decision-making tools (De Lara et al., 2015; Rönnqvist et al., 2015), the main objective of viability theory is to find a safe operating space—a set of initial states—wherein plausible environmental changes would not be so disruptive as to preclude intervention or control to restore the integrity of the system itself. This is done by evaluating the dynamic properties of a system to determine the extent to which a system can, and should be, subjected to exogenous control. Viability theory is appealing because it imposes few constraints on modelling, allowing it to align closely with descriptive sciences. However, the method also suffers from the curse of dimensionality related to the organization of data in high-dimensional spaces. Although potential applications to natural resource management have been highlighted in past work (Oubraham and Zaccour, 2018), the located attempts to reconcile viability theory with the unique challenges that characterize forest management remain scarce (Rapaport et al., 2006; Andrés-Domenech et al., 2011; Bernard and Martin, 2013; Andrés-Domenech et al., 2014; Mathias et al., 2015; Houballah, 2019). Thus, we framed the end of this article with a critical assessment of the potential applicability of viability theory to the management of forest systems. Its inherent flexibility in modelling and representation allows for a more comprehensive exploration of complex ecosystem dynamics and uncertainties. By examining viability theory in the context of forest management, we aim to shed light on its potential utility and encourage further exploration in this area, setting the stage for a more nuanced approach to decision-making under uncertainty.

This paper explores ways to better integrate complex systems into decision-management problems in forestry, drawing on viability theory. Although previous research reviewed decision-making tools to reduce uncertainty and suggested adaptive management recommendations, our focus is directed towards understanding how management problems are represented and formulated (Question 1). We hypothesize that more integrated system representations can enhance our understanding of system behaviors, facilitating enlightened control and management. First, we explore the historical evolution of operations research and viability theory in response to growing climate-change concerns. We highlighted their convergence for complex and adaptive forest management. Building upon this shared basis, we then undertake a systematic literature review to understand how existing decision-making methods in forestry and viability theory complement each other in addressing uncertainty and complexity in forestry (Question 2). Our analysis spans a diversity of management situations, planning horizons, and scales from single-objective management of individual stands to multifunctional dynamics at the national forest level. Specifically, we shed light on three main approaches currently applied in forest-decision-making: stochastic methods for managing risks, robust methods, and adaptive frameworks for handling deep uncertainty. Despite limited applications of viability theory in forest decision science, examples from natural resource management under uncertainty show that its dynamic system representation and identification of ideal forest states could complement or support existing decision-making methods in complex forest management. To address the specificity and complexity of forest management within today's context, our study focuses on the emerging challenges of multiple risks, climate change, and volatile markets. Drawing inspiration from viability theory, we aim to explore how its resilience, viability, and adaptability principles can inform adaptive strategies and guide decision-making in response to evolving environmental conditions and market dynamics through comprehensive CAS modelling (Question 3). Finally, we conclude by discussing the opportunity emerging from the viability framework when applied to CAS as well as areas of future research on this topic.

2. Historical development of decision-science from forest management to social-ecological systems

Recent achievements in forest management decision-making (Fig. 1, Fig. S1) have shifted from management prescription towards studying complex systems to better advise decision-makers in the face of uncertainty (Albert et al., 2015; Blanco et al., 2017; Nocentini et al., 2021). Historically focused on timber harvesting, modern forest management now requires understanding the functioning of evolving systems while optimizing resource allocation and trade-offs between conflicting goals (Raum, 2017). Meanwhile, viability theory has emerged as an approach that more closely aligns with descriptive system analysis, though it is not strictly a descriptive method. It offers avenues to facilitate adaptive decision-making amidst uncertain system evolution, potentially holding relevance for forest management.

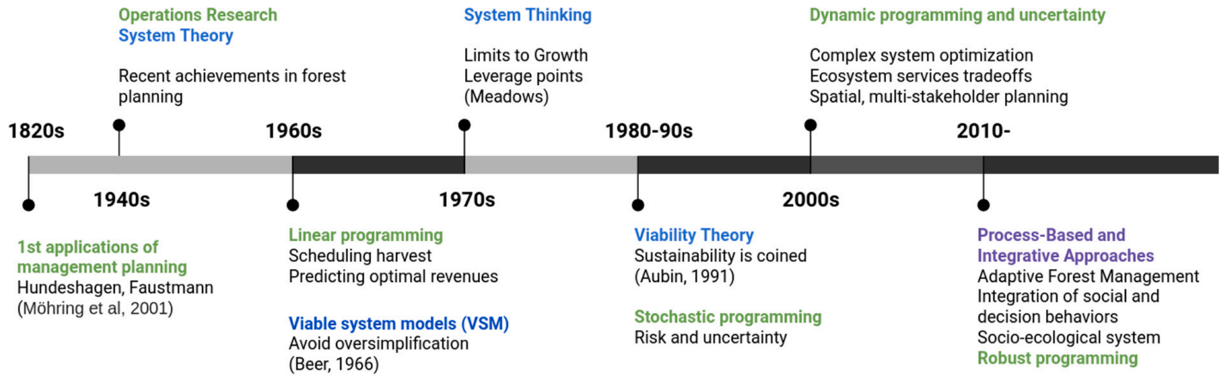

Fig. 1. Parallel evolution of forest-management decision-making and viability theory towards uncertainty integration. This timeline contrasts the evolution of system approaches (blue) and operations research, which have led to divergent views and developments (Viability Theory vs Optimization) before converging around the consideration of uncertainties related to the changing environment within which forest management operates (purple) (Beer, 1966).

Decision science explores the process of making choices by gathering and organizing information and assessing alternative solutions to an identified problem. In the 1940s, disciplines such as operations research and systems theory sought to develop quantitative techniques for solving problems involving objectives like minimization and maximization, including efforts to capture satisficing behaviors (Horning, 1942; Wiener, 1965; Bare and Weintraub, 2015). Optimality is reached when the chosen alternative allows the best use of available resources to achieve a desired outcome or goal (Kaya et al., 2016). In forestry, linear programming in the 1960s helped schedule harvest operations, often to maximize the net present value of different sequences of costs and revenues (Bare and Weintraub, 2015). Like all modelling, these decision techniques entail various degrees of simplification, and researchers were cognizant of the risk that oversimplified representations of such complex systems could lead to mismanagement (Beer, 1956).

Since the 1960s, operations research has expanded to address various considerations regarding forest harvesting problems. It covered applications from trade-off analysis between potentially conflicting ecosystem services (Alvarez et al., 2017; Baskent et al., 2020), to integrated problems *from land to the mills* (Shahi and Pulkki, 2013; Varas et al., 2014; Baghizadeh and Zimon, 2021). Operations research also included spatial (Malchow-Moller et al., 2004; Belval et al., 2015; Orlowsky et al., 2017) and multi-stakeholder planning constraints (Paradis et al., 2013; Gautam et al., 2017; Xavier et al., 2017; Etongo et al., 2018). Models increased the number of considerations promoting environmental, biodiversity, and social perspectives that aligned with the Sustainable Forest Management (SFM) practices as described by the United Nations General Assembly in 2007 (McDonald and Lane, 2004). SFM aims to maintain and enhance the value of all forests for present and future generations. The uncertainties surrounding climate change accelerated the development of stochastic and robust programming, (Ben-Tal et al., 2009; King and Wallace, 2012), driving urgent efforts to mitigate its impacts (Biesbroek et al., 2009).

The 1990s saw the integration of stochastic optimization into stand management (Valsta, 1992), as well as the formalization of viability theory. The need to understand how complex systems could effectively respond to a changing and unpredictable environment spurred the emergence of viable system models in 1959 (Beer, 1959). Viability theory formalized this approach in 1991, offering tools and algorithms (Aubin and Frankowska, 1991; Aubin, 2010; Aubin et al., 2011) to study how living systems adapt and thrive amidst uncertainty. This theory builds upon Jacques Monod's concepts in "On Chance and Necessity"(Monod, 1974). Monod posited that evolution operates based on chance and necessity. In this evolutionary system, initial states are associated with subsets of evolutions governed by inherent constraints. "Chance" suggests that natural processes emerge from random interactions within the environment, while "necessity" dictates that evolutions must adhere to viability constraints to maintain desirable states. Thus, Aubin used viability theory to operationalize sustainability, offering mathematical tools that explore the compatibility of environmental, economic, and social variables to validate sustainable management (Brundtland, 1987; Aubin et al., 2011). While still not widely applied in forest management, viability theory provides valuable insights into CAS resilience by identifying a safe-operating space where systems can evolve effectively and avoid irreversible disruptions. This safe-operating space is bounded by viability constraints that cannot be violated, ensuring CAS's long-term survival and dynamic stability. Viability constraints encompassing flexibility, stability, and more arise from forest management goals, policy objectives, and conservation principles. They act as reference points to avoid, no matter how and when the system would evolve. Viability theory thus focuses on the potential evolutions which comply with these pre-specified constraints, rather than seeking an optimal solution.

As for operations research, optimization, including an increase in a system's entropy, were introduced in 2000 through dynamic programming (Majumdar et al., 2013). More recently, social and decision behaviors and attitudes have emerged in process-based and integrative approaches (Fontes et al., 2011) to support Adaptive Forest Management through the iteration of decision-making based on experimentation and scientific learning updates (Yousefpour et al., 2012).

3. Methods

3.1. Selection and review of studies

We systematically reviewed the literature from three scientific databases (Web of Science, Google Scholar, and Scopus) for articles published in English and to some extent in French[1] from 1990 to 2023 using search terms related to three organizing concepts: ecosystem management, uncertainty, and decision science. The concepts and the research terms linked to them are presented in Fig. 2. Each key concept individually yielded millions of results and helped construct the following research combination that would first focus on forest decision-making contexts ("Forest management" OR silviculture*) AND (uncertain* OR risk OR "climate change") AND ("decision-making" OR optimization OR "control theory" OR viability OR robust OR stochastic). The initial research yielded 1,262 results (duplicates excluded). After manually identifying the papers that were off-topic, 731 were selected for abstract screening. Subordinate references were also considered during the screening to complete the database. Since viability theory recently

[1] We included papers written in French because Viability Theory (which is the main focus of this review) was first developed in France, and a non-negligible part of the references used were originally written in French.

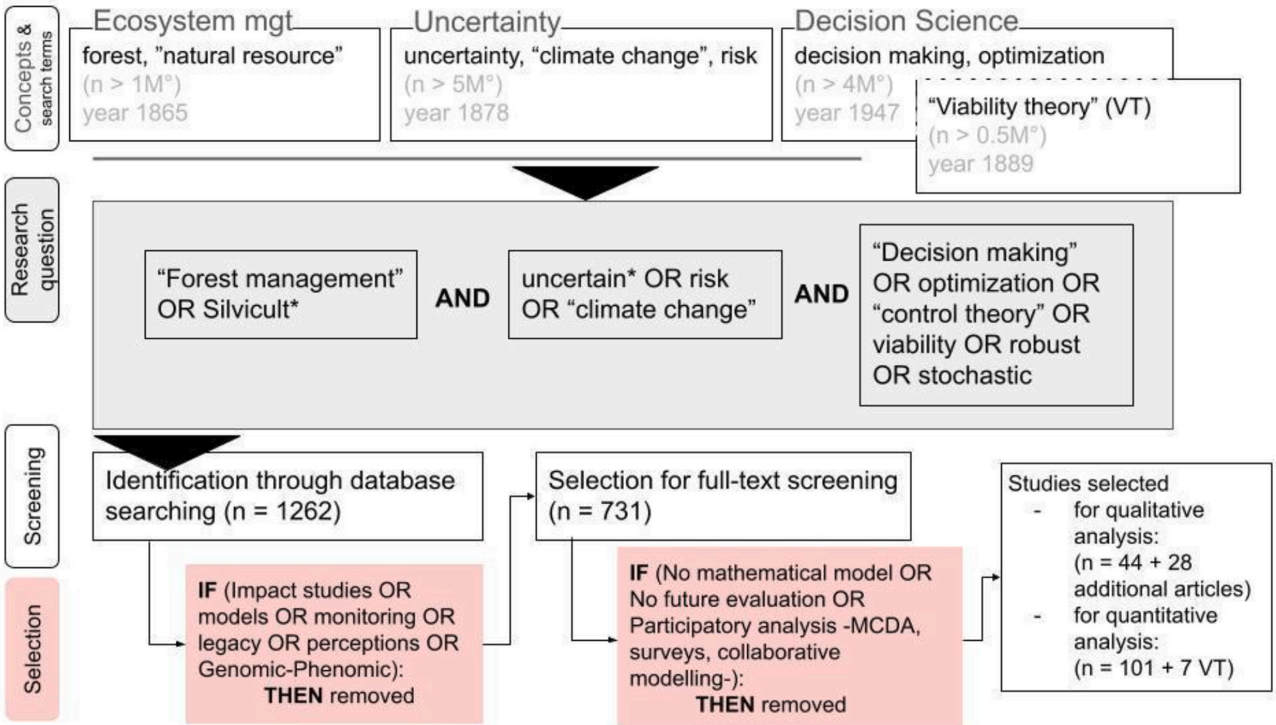

Fig. 2. Flow diagram showing queries and final selection of research articles used for the analyses (n = 180). Each key concept was defined by a list of keywords. For each list, we noted in light gray the number of references in Millions (M°) and the year of the earlier article found in the database. The set of articles identified for each key concept was combined and yielded 1,262 references. Two successive filters (in pink) were applied before screening the final selection (n = 152), from which 72 articles were used for qualitative analysis and the remaining 108 for quantitative analysis. The qualitative analysis was supplemented with 28 additional articles found during the screening process.

emerged to formalize problems related to nature and social phenomena, we extended the scope of the viability-theory applications used in our paper to include the field of natural-resource management. Doing so allowed us to add ten more articles to the list (Oubraham and Zaccour, 2018). Articles describing, comparing, or using numerical decision-making tools applied to future projections were selected for the study and scanned to determine whether they fit our topic. From the selected list, we excluded articles dealing with multi-criteria decision analysis (MCDA), sensitivity analysis, scenario comparisons, perception analysis, and participative modelling because these concepts are commonly used to understand decision-makers' preferences, rankings, beliefs, and goals under uncertainty.

While these methods are essential to refine decision-making tools, we focused on how problems are formulated to represent the dynamic evolution of forest systems by considering various drivers before service-provision preferences come into play. We excluded papers dealing with monitoring, remote sensing, genomic evaluation, impact analysis, mapping methods, projections, and models not directly utilized as input or integrated into the decision-making processes. We screened the full texts of the remaining 180 articles. 180 articles published in English or French between 1990 and 2023 remained for exhaustive and thorough reading. Peer-reviewed articles and reviews, handbooks, and book chapters constituted a base to compare numerical tools for forest or natural resource management decision-making under uncertainty. Finally, 108 references presenting numerical applications were selected to compare the different problem formulations and uncertainty representation in forest decision-making (Fig. 2). The 72 remaining articles served as a supplementary foundation for conducting a meta-synthesis of past conceptual frameworks and optimization approaches, which allowed us to enhance the description of the methods presented. This foundation was utilized to establish the criteria presented in Section 3.2. to outline a basic comparison between the numerical applications.

3.2. Description of the database and network analysis

The bibliometric indicators included authors' names, the names of authors citing them within the selected list of articles, the year of publication, the journal in which the article was published, the keywords, and the study case area. Each of the 108 studies included in the numerical analysis was categorized according to two criteria (Table 1). The first criterion dealt with uncertainty considerations. Complex decision problems inherently involve uncertainty stemming from the multitude of interacting elements. Outcome uncertainty typically increases with complexity (Floricel et al., 2016). We classified articles by the source of uncertainty (e.g. climate change, market price, etc.), the technique used to represent this uncertainty (e.g. scenario trees, fuzzy sets, etc.), and how it is integrated into decision models (e.g. stochastic programming, robust optimization, etc.). This classification aids in understanding how insights derived from descriptive models inform decision-making within a context of uncertainty. The second criterion delved into the essential aspects of decision science in forest management, including management objectives to maintain, minimize, or maximize decision rules, constraints, number of decision-makers, or objectives involved. For both criteria, categories were non-mutually exclusive, with some articles analyzing different decision tools at the landscape and stand level (Table 1). Based on this classification, co-occurrence and uncertainty network maps were built using VOSviewer V 1.6.19 and Excel to comprehensively examine how complex systems are addressed within decision-making processes, considering the diverse objectives, rules, and constraints inherent in forest management. By integrating key sources of uncertainty and common features of complex adaptive systems, we presented a generic adaptive forest system. We created a table comparing a stylized forest harvesting problem (Table 2), informed by the paper screening, to assess optimization and viability theory concepts. Lastly, we evaluated these approaches based on their ability to

Table 1
Description of both categorical criteria (uncertainty and forest management) collected from the screened studies used for comparison in the quantitative numerical analysis (n = 108).

Criteria	Criteria category	Category description
Uncertainty	Source of uncertainty	Climate, growth, price, disturbance, risk, inventory, belief, policy, flexibility
	Approach to evaluate uncertainty	Set of mathematical tools
	Decision-making numerical model	Stochastic programming, dynamic programming, robust programming, DSS, simulation, non-linear programming, hierarchical, spatial, viability theory, process-based approach, adaptive programming, portfolio
Forest management	Objectives	Single vs multiple Minimize loss, shortfall, uncertainty, disturbance effect Maximize revenue (NPV, profit, LEV, benefit), utilitarian welfare, carbon, diversity, sustainable productivity (wood – non-timber products) Maintain employment, vitality, stability
	Number of scenarios explored	From 1 to 15, from 1 to infinity
	Temporal scale	Static, short-mid-long term, infinite
	Spatial scale	Stand, holding, forest, landscape, regional/national scale
	Decision level	One or multiple stakeholders
	Forest type	Structure (even-aged or uneven-aged) Type (plantation, regeneration, mixed species, monospecific)
	Area	Countries
	Decision variables or controls	Harvest schedule (type, species), regeneration (type, species), adaptation measures, rotation age, retention, resource provision
	Constraints	Production level, sustained management, spatial considerations, environmental targets, budget, functioning

Table 2
Illustrative example of generic forest management problem to compare optimization and viability theory.

Decision-making problem	Schedule harvest under unpredictable fire risk	
Method	Optimization approach	Viability theory
Planning horizon	Most of the time bellow 100 (Table S1)	Infinite timeline
Objective	Maximize the **timber revenue** obtained from what is harvested per period of 5–10 years.	Ensure sustainable timber productivity through successive steps until a dynamic equilibrium is reached.
Constraints	- Ensure harvest rate does not exceed the forest productivity - Achieve or maintain a balanced age-class distribution over the planning horizon - Ensure even flow - Operational constraints (workforce, time between treatments etc.) - Set the maximal surface that can be harvested	- Ensure that **timber revenue** across the timeline remains greater or equal to a defined threshold (current, feasible level, relationship function with other objectives i.e. ensure the timber revenue would not impede the productivity of the forest) - Operational constraints - Set the maximal surface that can be harvested
Uncertainty	The productivity can variate in an interval based on the standing volume under fire risk and no fire risk (robust approach) The probability of fire could be observed via stochastic scenarios.	
Treatment of uncertainty	Compare management alternatives that would lead to higher performance across the scenarios (robust approach) or higher expected outcome when averaging the scenarios (stochastic approach)	For each initial timber revenue rate and forest productivity, explore if there exists one trajectory that satisfies constraints with a high probability or that is also robust across scenarios.
Output	Presentation of the maximum timber revenue that is guaranteed (robust approach) and/or expected (stochastic approach)	Set of timber revenues and forest productivity rates that are compatible and ensure a guaranteed sustainable management over time (we shall refer to the 'guaranteed viability kernel', instead of 'viability kernel')
Infeasibility is described by	Infeasibility is described as the absence of a solution, meaning there is no possible action schedule that allows the system's properties to comply with the given constraints.	The system's properties, which evolve under the described controls and environmental drivers, cannot be sustained. In that case, the guaranteed viability kernel is empty.

capture uncertainty, support flexible decisions, and solve complexity.

4. Result and discussion

4.1. General overview of the database

We ran a preliminary analysis for each key concept which showed that "decision-making" and "uncertainty", followed by "forest" and "natural resources management", generated many results (Fig. 2). In contrast, keywords related to viability theory returned relatively few. Our study evaluated 108 decision-making applications published between 1990 and the beginning of 2023 representing a wide range of forest biomes (temperate, boreal, sub-tropical, and tropical forests; Fig. 3). Forest management decision studies were primarily concentrated in Fennoscandia, Western and Central Europe, and North America. Most applications from France in our sample size (n = 5) were related to viability theory. The classification of the selected publications presented in Fig. 3 highlighted that most of the ecosystems studied were boreal forests (n = 33) and temperate forests (n = 31). Six studies analyzed tropical or sub-tropical forests, which implies that more complex forest structures are less represented within our sample. Case studies mainly focused on pure stands (n = 61) and even-aged systems (n = 54). Forty-one studies explored uneven-aged systems. Plantations and regeneration systems were equally represented in the study (n = 38 each).

Viability concerns are of great interest to bioeconomics, environmental science, and conservation biology (Wei et al., 2013; Oubraham and Zaccour, 2018; Oubraham et al., 2022). Viability theory also has applications in engineering (Zaytsev et al., 2018), automatic control (Blanchini and Miani, 2015), and supply-chains (Ivanov, 2022). In the context of forest management research, viability theory has received marginal attention compared to other domains where optimization is present. To our knowledge, only six articles have applied viability theory to forest ecosystems and forest management (Rapaport et al., 2006; Andrés-Domenech et al., 2011; Bernard and Martin, 2013; Andrés-Domenech et al., 2014; Mathias et al., 2015; Houballah, 2019).

Network maps showed relationships between authors and commonly used keywords (Fig. 4). Author relationships (Fig. 4A) identified four sets of decision-making approaches further described in Table 3 and cited here according to the size of the sets: stochastic and dynamic methods, robust optimization (Knoke cluster), adaptive forest management (Jacobsen cluster), and viability theory. The latter is split into two sub-groups: one referring to the seminal formalization of the theory (e.g., Saint-Pierre and Aubin's work) and the other to its extended use (Doyen cluster). Stochastic and dynamic stochastic programming (Borges cluster) are closely related clusters. Eyvindson depicts the stochastic cluster, while Garcia-Gonzalo's cluster focuses on decision-support systems and dynamic programming. The network map of concept co-occurrence highlighted relationships between methods and uncertain external controls (Fig. 4B). Viability theory relates to

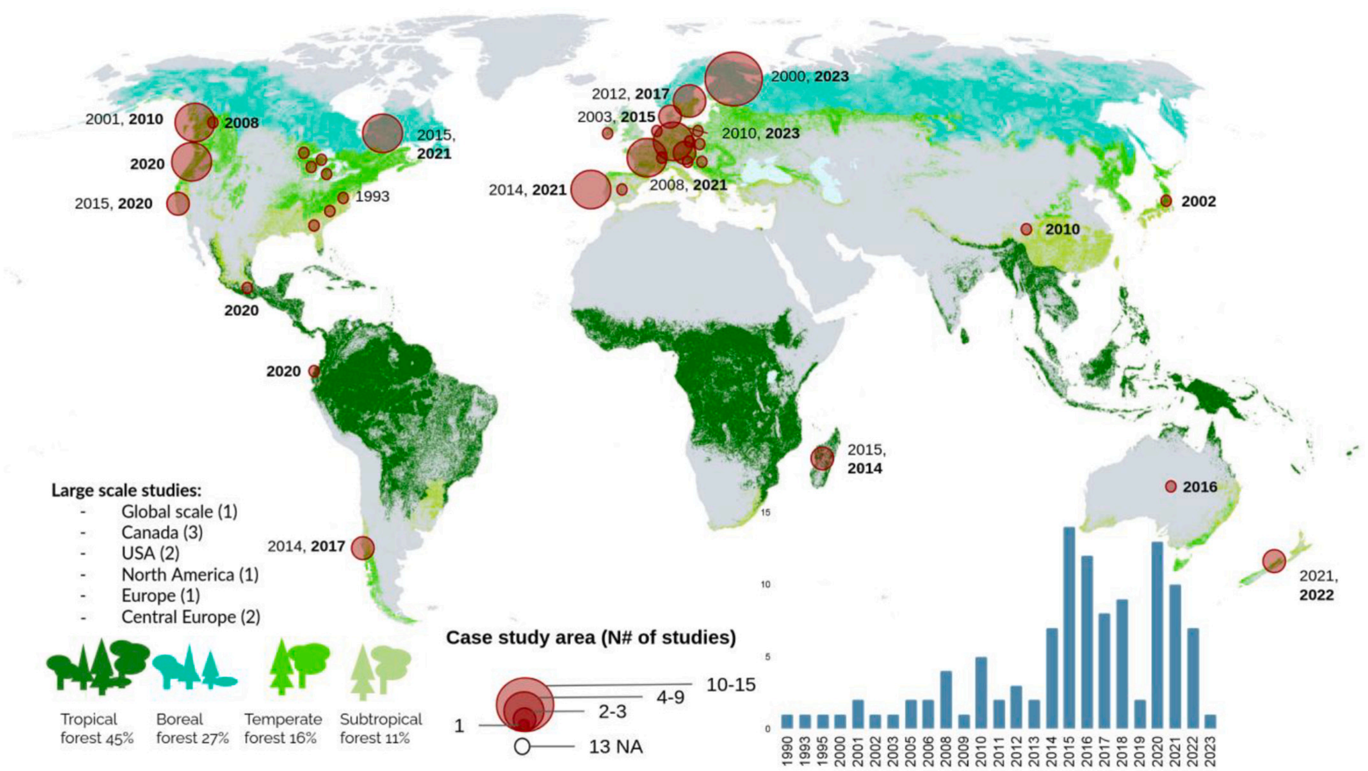

Fig. 3. Spatial distribution of the 108 research articles used in the comparative analysis of forest decision-making models sorted by region, forest type, and publication year. The forest ecosystems were categorized by biome type and color-coded accordingly (legend on the left). Above the forest-type legend, the number of large-scale studies was referenced. For the comparative analysis, case studies were grouped by location, and the respective numbers of studies (N#) were denoted by proportional red circles (legend at the center). The years of the oldest and most recent (bold) articles were highlighted near each set of circles. Thirteen studies were theoretical case studies and were noted as NA (not applicable). The histogram on the right illustrates the evolution of the number of articles published over the years.

flexibility, management of biodiversity, and ecosystem services. Socio-ecological systems connect to adaptive management, decision-making, and agent-based modelling. The connection between complex adaptive systems and these approaches thus remains to be explored.

4.2. Addressing complex interaction in decision-making

In reviewing forest CAS decision-making tools, key state variables include average height, diameter, density, and biomass (Table S1). These variables are influenced by silvicultural operations, global warming, and environmental disturbances. Decision-makers prioritize harvest schedules, forest composition, prevention measures, biodiversity conservation, rotation age, investment, and deforestation rates. This representation helps forest managers evaluate strategies for sustainable forest resource use.

Viability theory uses state variables such as forest surface, age-class distribution, tree density, population dynamics, deadwood, carbon sequestered, road infrastructure, timber demand, and local assets. Control variables involve managing deforestation and afforestation rates, timber removal strategies, monetary transfers, CO_2 emissions, resource demand, infrastructure maintenance, tax imposition, workforce proportion, and demographic rates. Viability constraints maintain current provisions and needs over time, such as revenue and timber supply, and impose tolerable bounds on state and control variables to represent physical, technological, or environmental constraints. Ensuring increased capital over time to maintain generational equity and managing tourism impact are also critical constraints.

Based on the literature review, we identified a challenge in integrating interactions and complex feedback loops into the problem representations used for forest-management decision-making. This requires a precise understanding of how system components interact. Some phenomena are too complex to describe with certainty and can be more effectively evaluated through an examination of their sources of uncertainty. In Fig. 6, we explored the sources of uncertainty considered in decision-making models. These elements depict external factors that vary in predictability and controllability by human activities. A significant portion of the applications studied considered uncertainty derived from growth projections and climate change, or growth projections and prices, jointly. While disturbances and risk attitudes received attention, uncertainties related to inventory, beliefs, and the discount rate were less emphasized in decision-making models. In conclusion, while progress has been made in addressing the compounding effects of external factors and increasing the complexity of capturing uncertain phenomena, there is still room for improvement in incorporating feedback between the different levels of uncertainties to achieve more realistic representations of forest ecosystems.

Forests are open systems often regulated by unpredictable external factors; interactions between external factors and the forest cannot be exhaustively imagined. As such, equations need to describe phenomena based on partial information. Differential inclusions is an extension of differential equations that maps the derivative of a function to a set of possible values[2]. Differential inclusions present a solution concept for discontinuous differential equations (Leine and Nijmeijer, 2004). It can capture complex dynamic interactions and potential future outcomes from a single initial state. This tool is commonly used in viability theory, but it has rarely been applied in optimization methods due to the challenges to operationalize it for practical management prescriptions.

[2] A differential inclusion can have the following form: $y^{\cdot} \in F(y, u, v)$ where F is a set-valued function. The set-valued function is parametrized by controls u and uncertainties v.

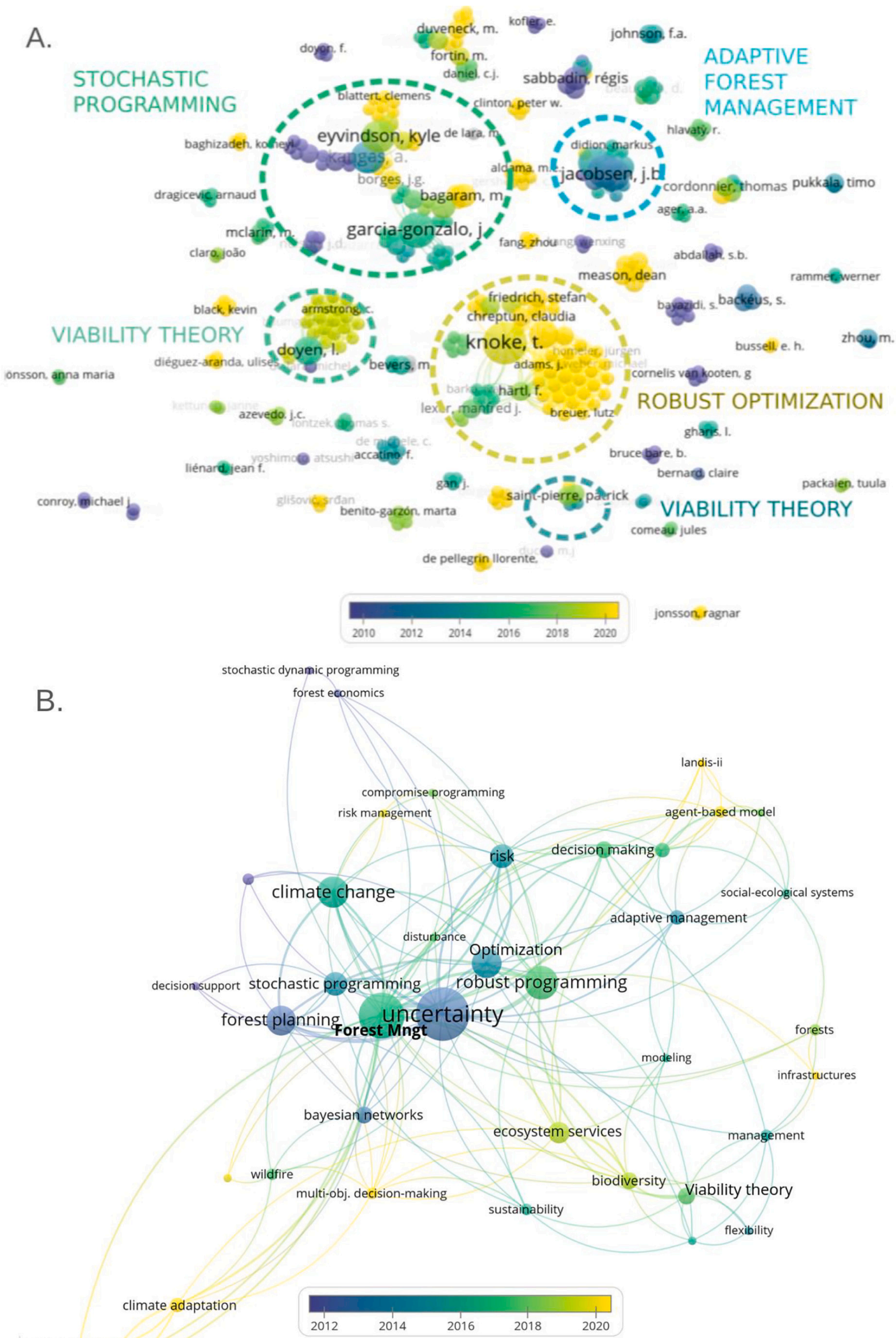

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Fig. 4. Co-occurrence networks visualization presenting relationships between authors (A) and keywords (B) among the selected 108 publications dealing with forest decision management under uncertainty (data visualization was performed using VOSviewer V 1.6.19, Leiden University, Netherlands). In A), each author was represented as a node, with the node's size being proportional to the number of citations received from the 108 publications. Authors were colored by years and grouped. The shorter the distance between two nodes, the more closely connected they are (based on their co-citation). In B), the node's size is proportional to the number of occurrences of a keyword. Keywords were colored by year and grouped. The distance between nodes is proportional to the frequency of keywords co-occurrence and indicates their relatedness.

Based on the literature review and the quantitative analysis we conducted, we identified the key components and properties essential for accurately describing CAS in forests, with the aim of supporting decision-making processes.

4.3. Description of CAS in decision-making numerical models

In this study, we utilize a typical complex adaptive forest system's (CAS) problem as the foundation for our analysis. This CAS scenario encapsulates the multifaceted dynamics of forest management, integrating ecological, economic, and social dimensions. Our examination revolves around operational methods and viability theory to inform effective decision-making within this CAS framework. The typical representation of CAS in decision-making approaches encompasses key components that highlight the degree of control decision-makers can exert (Castro et al., 2018; Krawczyk and Pharo, 2013). These components include forest state evolutions, external controls such as climate change and biotic crises (over which decision-makers have varying degrees of control), and management controls, including harvest, thinning, and regeneration strategies to comply with desired properties such as product demand, ecosystem functioning, and climate change mitigation. Incorporating local vulnerability assessments, dynamic climate change scenarios, and various disturbance risks, our objective is to sustain wood production while enhancing the resilience and sustainability of forest ecosystems amidst uncertain environmental and market dynamics (Fig. 6).

As a conceptual illustration, we use a case study of a CAS as a reference point, briefly describing how each decision framework would be applied. This analysis provides valuable insights into addressing provision demand, fostering forest functioning, and confronting external challenges such as climate change and crises within the context of forest management.

Forest CAS and viability theory operations tools often draw from control theory (Oubraham and Zaccour, 2018). Most of the time, this involves defining state variables, control variables, and their interrelationships. State variables describe the system's evolution. They must be sensitive to change, linked to management, or directly connected to targeted provisions. Controls include predictable and unpredictable human activities and external factors[3] that influence the evolution of state variables with fast or progressive changes. These interactions can be represented with varying complexity, from linear equations to difference inclusions, which portray non-deterministic evolutions and path divergence. The controls describing the actions to be taken on land are more specifically called decision variables. Control theory helps elucidate how various controls can be applied to influence the state variables and achieve desired outcomes. Constraints imposed on the state, the velocity of change, or the controls ensure decision variables adhere to necessary standards (technical, environmental, economical) and prevent system failure.

Optimization in forest management typically involves defining an objective function, decision variables, and constraints. The goal is to maximize or minimize the objective function subject to the set of constraints:

$$\textit{Maximize (or minimize)}\ f(x^*(t)) \tag{1}$$

$$\textit{Subject to} \tag{2}$$

$$x^*(\cdot) = g(x(t), u(t)) \tag{3}$$

$$u_i \geq a_i, \forall u_i \in U \tag{4}$$

$$u(x) \geq b_{u(x)}, \forall x \in X \tag{5}$$

$$K = \{k_1, k_2, \dots, k_n\} \tag{6}$$

Where the evolution of the state $x^*(\cdot)$ is described by the system dynamics $g(x(t), u(t))$, depending on the state of the system $x(t)$ and its admissible controls $u(t)$ at time t, we denote by X the state space and U the set of controls, also known as decision variables(Eq. 3). The model optimizes the objective function $f(x^*(\cdot))$ while ensuring that: 1) controls in U remain realistic i.e. greater than or equal to a specific constant a_u which depends on u (Eq. 4) or $b_{u(x)}$ which depends on the state x (Eq. 5); and 2) a set of constraints K is respected. The set of constraints K imposes conditions on state variables via constraints $\{k_1, k_2, \dots, k_n\}$ (Eq. 6). The objective and constraint functions can be linear or nonlinear, influencing the choice of the solving algorithm. The optimization method described here was not intended to incorporate viability elements. It is important to mention that control theory is a subfield of optimization that is particularly focused on controlling dynamic systems over time to achieve optimal performance.

In viability theory, the set of constraints Q specifies conditions on sustainable objectives to be maintained (Oubraham and Zaccour, 2018; Saint-Pierre, 1994) to identify the initial states from which the variable could evolve and remain in the feasibility set K.

$$S_D = x^*(\cdot) = g(x(t), u(t)) | u(t) \in U \tag{7}$$

The system S is described by a dynamic**s** D, which consists at time t on the set of potential evolutions $x^*(\cdot)$ driven by the controls $u(t)$ belonging to the set U. Given a set of admissible controls U, feasibility set K, of objective constraints Q, and dynamics D we define E_a the set of viable evolutions $x_a^*(\cdot)$ as:

$$E_a = \{x^*(\cdot) \in S \,|\, \forall t \in T, x(t)\ \textit{starting from}\ x(0) \in K\ \textit{satisfying}\ Q\} \tag{8}$$

$$K = \{k_1, k_2, \dots, k_n\} \tag{9}$$

$$Q = \{q_1, q_2, \dots, q_m\} \tag{10}$$

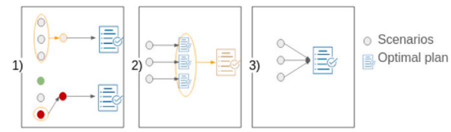
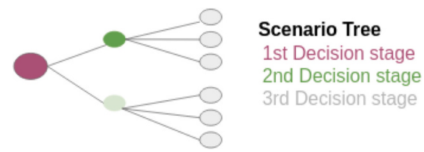
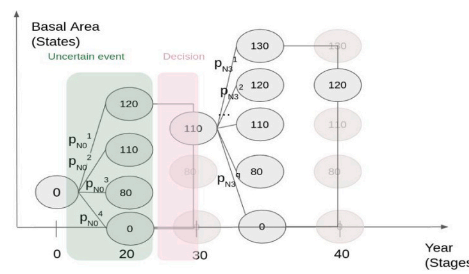
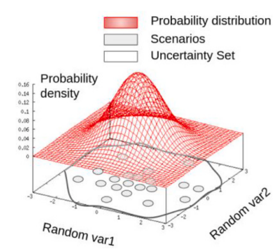
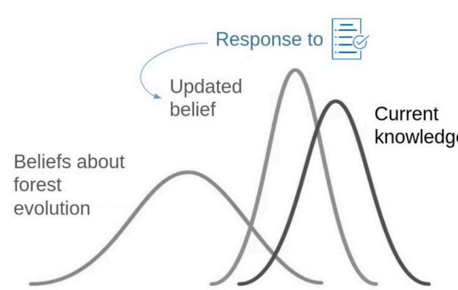
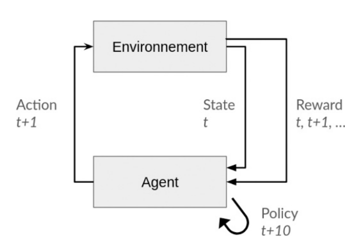
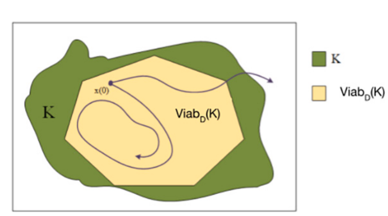
Viability theory evaluates if a trajectory $x^*(\cdot)$ of the system S, starting from an initial state $x(0)$ and influenced by admissible controls $u(t)$ e.g. $g(x(t), u(t))$, can remain within a feasibility set K for all t∈T and satisfy the set of constraints. In Viability Theory, K is usually associated to the state-space within which we need to stay ($\{k_1, k_2, \dots, k_j\}$ constraints in optimization). This space is closed and bounded.

$$\mathrm{Viab}_D(K) = \{x(0) \in X \,|\, x_a^*(\cdot)\ \textit{starting from}\ x(0)\ \textit{and} \in E_a\} \tag{11}$$

The objective of viability theory is to find the viability kernel $Viab_D(K)$ of initial states $x(0)$ for which at least one viable evolution $x_a^*(\cdot)$ exists, also referred to as viability kernel. In other words, $x(0)$ is viable if, there exists a trajectory in the state space, state $x(t)$ that starts in $x(0)$ and remains inside K forever. Interestingly, the viability kernel couples

[3] external factors are hardly or not at all controlled by human

Table 3
List of decision-making tools considered along with their mathematical formalism. The description provided is inspired by a comprehensive examination of decision-making tools in forestry. For further elaboration, Bakker et al. (2020), Castro et al. (2018), Yousefpour et al. (2014) include a detailed list of these tools, outlining their specific objectives and mathematical frameworks.

Method	Definition and decision aim	
Stochastic Programming (SP)	Optimization method that incorporates uncertainty by modelling various scenarios of CAS evolution, aiming to select the management with the most favorable and probable outcome. SP compares the worst and expected scenario (1), the averaged optimal solution (2), and the inclusion of all scenarios and their likelihood (3).	
Multi-Stage SP	Sequential decision-making method that resolves uncertainty in different decision stages, promoting adaptive management and flexibility. The waiting time for more information before intervention is evaluated. Scenarios are built in a scenario tree that is adjustable (N° stage, N° uncertain outcomes, N° decisions).	
Dynamic Programming	This method also breaks down complex problems into sequential decision steps, but the scenarios are represented in a network. All of the branches do not need to be explicitly defined allowing optimal management options to be defined at any state of the CAS.	
Dynamic Stochastic Programming	Evolves well-defined state space with transition probabilities that are possibly decision-dependent and subject to uncertainty. Defines an optimal sequence of actions at any state of the CAS, providing the highest provisions with sufficient success probability.	
Robust Programming	Optimization approach focused on finding good-enough solutions under various uncertain conditions, satisfying the constraints, whatever the uncertainties. Uncertainty is considered a space instead of defining a scenario with probability distribution. The selection of robust planning is based on satisficing metrics (satisfying and sufficing), regret measures (relative measure of choosing incorrectly or assuming the wrong future scenario), satisficing-optimizing, and the maximin rule. Satisficing-optimization selects the management decision that ensures compliance with the highest number of constraints.	
Non-linear Bayesian updating Decision-Making	Management focused on understanding system dynamics to inform decisions, considering the learning and perception of managers. Bayes' theorem is a valuable tool for experiential learning and updating beliefs concerning the future evolution and management of a system. This method is part of the Adaptive Forest.	
Non-linear Agent-Based Decision-Making	Simulation-based method that models individual agent interactions to assess their effects on system management. Part of the adaptive forest management concept.	
Viability theory	A mathematical framework that ensures systems remain within desired states over time, considering dynamic properties, constraints (constraint set K), and controls. It explores the link between the initial configuration of a system (x(0)) and the existence of strategies to prevent failure. Viability theory determines viable state spaces ($Viab_D$ (K)), highlighting the extent of control attainable over the system. By construction, viability theory cannot help maintain sustainable management beyond the viability kernel, because by construction the system is condemned to leave the safe space. The edges of the viable state spaces delineate the area of irreversible actions.	 taken from Zarch et al., 2021

the feasibility set K with the dynamics of the system which includes the admissible controls[4]. Under control theory, the system can be fully managed so that actions taken on the system would allow it to change direction. Control theory seeks the optimal time path of the system. Viability theory aims to find relevant management strategies (controls) to maintain the system within the viability kernel $Viab_D(K)$. Viability theory thus generalizes optimal control theory by exploring all of a system's possible management alternatives (Krawczyk and Pharo, 2013; Aubin et al., 2014).

It is important to note that these formulas describe the deterministic case of both approaches. Different options for integrating uncertainty will be further explored in the paper. Additionally, optimal regulation can be to "do nothing," allowing the state to evolve inertially.

Most optimization approaches focus on achieving specific management objectives by finding a sequence of decision variables that would best respect the constraints, while viability theory ensures that the system remains within viable bounds over time, providing a safe operating space[5]. To complement optimization methods, viability follows a backward approach (Durand et al., 2012), starting from a set of viability constraints and identifying the set of initial states which allow the system (though non-mandatory) to comply with these constraints. Viability theory resolution algorithm proceeds progressively eliminating points within the feasibility set K. For each selected initial state, which represents a point in the feasibility set K, the viability algorithm examines whether this point can be reached from a preceding feasible point, thanks to the dynamics of the system. When viability is not immediately achievable, the properties of the system are thoroughly examined to determine various factors: the time elapsed before constraints are violated, whether the system's viability is definitively compromised, strategies for restoring viability, and the duration required for such restoration. The "exit function" serves to gauge the maximum duration during which the system's evolution can maintain compliance with the constraints. Conversely, the "crisis function" assesses the minimum duration (denoted 'crisis time') an evolution, originating from a specific state, remains outside the viability kernel. The evaluation of regulatory policies can involve exploring three avenues: adjusting the system's dynamics D using viability multipliers, implementing impulse control to modify initial conditions, and relaxing constraints to change the feasibility set K. These changes will ultimately affect the viability kernel. In natural resource management, viability analysis often highlights the importance of minimal intervention to achieve sustainability, particularly when current practices prove unsustainable. In line with this, Andrés-Domenech et al. (2014) present the minimal conditions required to alter the system so that the current situation can be incorporated into the viability space, thereby restoring viability. Consequently, viability analysis allows us to understand the economic cost of change to achieve sustainable solutions and offers a complementary perspective to optimization methods by focusing on maintaining system viability over time. After exploring the extent to which the properties of a system can be controlled with this method, optimization can be used to determine the best strategies while keeping the system in a safe operating space.

In the following section, we will describe different approaches to forest CAS management planning, aimed at capturing a wide range of potential system evolutions. By exploring these methods, we aim to understand their differences and similarities with viability theory.

[4] As a metaphor, a point located in the feasibility set K is considered as *alive* but will only be able to *survive* if it is included in the viability kernel. Otherwise, its kinetics will inevitably lead it outside of the feasibility set K.

[5] By construction, leaving the safe operating space implies that we can no longer sustain the desirable properties of the system such as wood provision, economic returns or biodiversity preservation. Since the safe space is conditioned by the desirable properties we select, leaving this space does not necessarily imply deforestation.

4.4. Toolbox of decision-making methods for complex adaptive systems

To effectively manage complex adaptive forest systems (CAS) in forestry, decision-making tools must balance computational effort, the representation of uncertain phenomena, and decision-making flexibility towards change (Fig. 7). The diagram provided in Fig. 6 outlines an ideal CAS where forest dynamics are characterized by the number of trees per diameter class (y_i) over periods (k), incorporating elements like growth, uncertainty, and climatic dynamics. This section is needed as a reference to introduce viability theory in forest decision science.

In Fig. 6, forest dynamics are governed by a growth-transition matrix reflecting the general trend at the studied site. This aligns with stochastic programming approaches, where probability laws approximate continuous distributions of CAS future outcomes, such as tree growth and timber price variability, using discrete scenarios linked to probabilities (King and Wallace, 2012). By assessing the likelihood of success for different management alternatives under various conditions, stochastic programming evaluates the gain of introducing uncertainty and its impacts on the solution (Eyvindson et al., 2017).

The influence of climate change and hazards on tree biomass gain or loss indicate that forest systems might deviate from predicted growth. Stochastic programming uses quadratic functions to mitigate downside risks by introducing value at risk (VaR), which measures the potential loss at a certain confidence level, or conditional value at risk (CVaR), which calculates the average loss exceeding the VaR (Eyvindson et al., 2018). However, most applications are anticipatory, with decisions made at the planning outset, preventing reactivity measures.

The decision-making process is greatly affected by the decision-maker's capacity for management change. Multi-stage stochastic methods enable successive optimization of interventions as new information (e.g. price fluctuations) is disclosed to gauge the feasibility of preferences across scenarios and the value of waiting before intervention (Boychuk and Martell, 1996; Bagaram and Tóth, 2020). Due to coupled modelling, the use of continuous-stochastic processes for each optimization stage leads to high solvability complexity (Bakker et al., 2020). CAS dynamics are discretized to reduce the set of scenarios to consider. Methods are developed to solve problems with a wider range of scenarios (Kim and Ryu, 2011; Bagaram and Tóth, 2020) and better grasp CAS behaviors under climate change, changing product demand and decision-maker behaviors.

Dynamic programming addresses forest growth and climate disturbances by also breaking down complex-decision problems into sequential steps but representing a network of states in contrast to multi-stage programming, which focuses on decision timing (Ferreira et al., 2012; Yousefpour et al., 2014; Bakker et al., 2020). This way, the evolution of the forest can be visualized by a network of nodes symbolizing the forest stand's state or age, and arcs that define a decision to take, reach, or leave the node (Mohammadi Limaei and Mohammadi, 2021). Stochastic dynamic programming adds intermediate nodes before the decision node to reflect transitions between stages based on states and actions. The connections in the network are not predefined and can be adjusted based on the information that becomes available at each stage (Bertsekas and Tsitsiklis, 1991; Davis and Cairns, 2012). Despite its usefulness in forestry management for issues like wildfire prevention (Ferreira et al., 2012) and spatial considerations (Ferreira et al., 2016), dynamic programming can suffer from combinatorial complexity due to the network size. Furthermore, dynamic programming follows the memoryless rule, meaning past choices do not affect current decisions (Kreps and Porteus, 1979).

Uncertainty representation poses challenges due to the need for extensive observations and the unpredictable nature of rare events, referred to as crises in the diagram (Fig. 6). Examples of such crises are market crashes, storms, fires, and pests, all of which are exacerbated by global warming. Traditional probabilistic methods may prove insufficient since these crises can be considered unpredictable and rare events (Black Swans), which necessitates understanding the underlying mechanisms that lead to their occurrence (Dragon Kings) (Sornette, 2009). This may lead decision-makers to explore non-probabilistic approaches like robust optimization and adaptive management frameworks. Moreover, while prioritizing probabilities for optimal management may suffice at the regional level with acceptable loss probabilities, managers often favor resilient, adaptable, and effective strategies across all uncertainties.

Robust optimization aligns with the multifaceted nature of complex systems (Knoke et al., 2020). This framework accommodates manager preferences for satisfactory outcomes over optimized targets, acknowledging the interplay between objectives and uncertainties inherent in complex systems. By evaluating management alternatives across a defined uncertainty interval where CAS outcomes may change, robust optimization accounts for the dynamic nature of forest ecosystems and potential correlations between uncertainty sources. This enhances the realism of decision-making tools. However, constraints must remain achievable regardless of the CAS state realization, which complicates balancing robustness with solution performance. Additionally, the shapes of the uncertainty space affect the worst-case scenario and how robustness is defined and solved (Bakker et al., 2020). To address this, decision-makers can adjust the level of conservatism by enlarging the uncertainty set (Bertsimas and Sim, 2004). Existing forestry applications of robust analysis focus on multi-objective land-use and species allocation portfolio (Knoke et al., 2020), timber demand and supply (Varas et al., 2014), or impact of managers' perception on optimal management (Nelson et al., 2016). These applications remain static optimizations, keeping the same decision process throughout the optimization (Yanıkoğlu et al., 2019). However, applications of multi-stage robust optimization and robust-stochastic hybrid methods can be found in other research fields (Bakker et al., 2020).

Existing decision-making methods in forestry can use probabilistic laws or consider all possible future outcomes without specifying stochastic processes (Bakker et al., 2020). Probabilistic laws precisely characterize the future evolution of CAS but are limited by combinatorial problems, required data, and solving time. On the contrary, the other approach considering all possible outcomes allows the use of simpler algorithms for problem solving. The former evaluates the impact of uncertainty through a limited number of scenarios, while the latter relies on the uncertainty space and uncertainty magnitude to determine solution safety, but to our knowledge, applications so far have not integrated adaptive choices or decision-maker learning over time. In forest management, common optimization strategies to minimize risk explore growth drivers and stand vulnerability. However, current models overlook factors like canopy shape and tree selection, which are crucial for decision-making and forest dynamics. For example, Ferreira et al. (2016) and Marques et al. (2017) used stochastic dynamic programming to identify connections between controllable parameters (such as diameter class, density, and species) and the risk of wildfire, while Petucco et al. (Petucco and Andrés-Domenech, 2018; Petucco et al., 2020) found traditional metrics insufficient for capturing forest complexity and evaluated windthrow risk. These studies highlight the need for a more comprehensive approach to decision-making in forest management.

To ensure sustainable forest planning, describing the flow of information through interactions among management actions, environmental factors, and ecosystem responses is gaining interest in the adaptive forest-management (AFM) framework (Yousefpour et al., 2013; Buongiorno and Zhou, 2015; Radke et al., 2020). AFM promotes methods to explore possible management options and their lifespan under different scenarios. This dynamic framework involves continuous monitoring, learning, and adjusting management strategies to achieve sustainable forest health and productivity. AFM compares strategies like carbon sequestration, resistance and resilience management, biodiversity conservation, and production to achieve multiple objectives. This approach aligns with the ideal characterization of a CAS in Fig. 6, where AFM's components—forest dynamics, climatic dynamics, carbon stock, products, and controls—are interconnected to optimize forest management under uncertainty. Flexible and integrative decision-making approaches developed for and used by AFM can adapt to changing conditions and uncertainties. AFM utilizes both trend-stationary processes (stochastic modelling, transition matrices) and non-stationary processes (time-varying parameter models or Bayesian and Markov chain methods). By monitoring trends and fluctuations, AFM can better predict changes and adapt management strategies accordingly.

Stochastic AFM outline intrinsic system responses, including forest health decline, dieback, varying growth rates, regeneration success, mortality, genetic selection pressure, species composition, biodiversity, and soil development. Time-varying parameter models represent transitions from the current environment, growth, and risk dynamics to a new yet unknown climate with associated dynamics. The impact of these flow of control-responses influences the values derived from forest ecosystems by owners and society at large. Exploring the behaviors and beliefs of decision-makers is crucial since even if a solution appears optimal, decision-makers might not feel the urge to change their practices. Tools such as Markov chains (Liénard and Strigul, 2016) and Bayesian analysis (Yousefpour et al., 2014) help understand how decision-makers perceive and react to changes. These tools assist in updating the perceived probability of outcomes and the time needed to recognize environmental changes necessitating new decisions. Agent-based models (ABMs) extend these methods by integrating simulations of the actions and interactions of autonomous agents (individual entities such as trees or actors) within a system for decision-making purposes (Sotnik et al., 2022). Coupling social and ecological models is relevant since drastic impacts could be mitigated by social actions and preferences, both of which could be potentially influenced by environmental change.

Furthermore, AFM decision techniques can also take advantage of opportunities in addition to loss prevention. AFM explores the evolutions of natural[6] systems that provide rights or opportunities to achieve specific goals, enhancing flexibility (Pasalodos-Tato et al., 2013). In addition to its focus on management allocations that resist change, AFM also seeks to regulate the number of management alternatives according to uncertainty levels. These levels of uncertainty will increase in the future due to potential bifurcations and climate change impacts. Management options shall remain flexible and tuned to various possibilities. Other approaches like the Tolerable Windows (Bruckner et al., 1999; Petschel-Held et al., 1999) or information gap methods (Ben-Haim, 2006) consider the threshold before irreversible effects can take place and how much uncertainty can be tolerated before decisions must change. Thus, management is reduced to only necessary interventions to foster the ecosystem's functioning and avoid irreversible transition.

In this section, we explored the toolbox of familiar decision-making techniques for managing complex adaptive forest systems under uncertainty. We identified two key areas for improvement: integrating both gradual and extreme environmental changes into considerations and enabling adaptive decision processes. However, these opportunities present challenges in managing computational complexity within decision science. Due to great modelling freedom, viability theory provides a dynamic framework that enhances system representation in decision science (Fig. 7). This framework supports a variety of decision-making processes and has the potential to combine different representations of uncertainty, though not necessarily in all cases, which offer a possible bridge to address gaps in existing methodologies. Drawing on the literature review of viability theory applications in forest and natural resource management, the following sections investigate how this approach could enhance the formulation of problems in forest decision-making. This framework offers a way to inquire into our effectiveness in managing forest systems.

[6] The word "natural" can be assimilated to "not controlled management".

4.5. Viability theory's role in balancing representation trade-offs for CAS management

Analyzing the evolving demands on forest engineers, Schmithüsen highlighted that "a flexible, non-intensive management approach, closely aligned with natural conditions is likely the best foundation for preserving future options" (Schmithüsen., 1994, p. 690). This aligns with viability theory, as formalized by Aubin in 1973. Based on chance and necessity, viability theory orients systems towards desired trajectories when necessary, thus emphasizing the link between system configurations and strategies to avoid failure states. It introduces "viable" control strategies centered around the concept of the viability kernel, which determines the set of states within which the system can remain viable under a set of given constraints. These strategies allow the system to explore all possible actions and trajectories, ensuring it remains within the viability space and avoids non-viable states. This is precisely what Messier et al. (2016) call for in forestry, by emphasizing finding an "envelope of desirable future stand structures" in complex adaptive management under uncertainty.

Geographical distribution of forest decision-making models shows that most applications are concentrated in forested regions that have been managed for a long time, highlighting the importance of decision-making in these areas (Fig. 3) (de Jesus França et al., 2022). Additionally, applications of viability theory were also identified in tropical forests potentially extending the scope of decision-making analyses. The few applications of viability theory to forest management covered state variables like forest surface, age-class distribution, tree density, population dynamics, deadwood, carbon sequestered, road infrastructure, timber demand, and local population's capital. Control variables involved deforestation and afforestation rates, timber removal strategies, monetary transfers, CO_2 emissions, resource demand, infrastructure maintenance, tax imposition, workforce proportion, and demographic rates. Viability constraints maintain current levels of provisions and needs over time, such as revenue and timber supply, and impose tolerable bounds on state and control variables to represent physical, technological, or environmental constraints. Ensuring an increase in capital over time to maintain generational equity and managing tourism impact are also critical constraints. This approach emphasizes the description of potential forest evolution and self-regulation and incorporates the drivers of forest ecosystem failure to allow for more precise and necessary management interventions.

A key reason to explain the interest in viability theory when it comes to decision-making is its ability to analyze both non-deterministic and stochastic dynamic systems using differential inclusions (De Lara and Doyen, 2008; Krawczyk and Pharo, 2013; Rougé et al., 2014; Bates and Saint-Pierre, 2018). Differential inclusions encompass a range of potential system evolutions described by a series of differential equations, similar equations with uncertain parameters, or a combination of both (Krawczyk and Pharo, 2013). The first type addresses uncertainties in model dynamics, such as climate change scenarios, while the second deals with uncertainties in model parameters, akin to non-probabilistic approaches like climate crises. Note that the deterministic case is a specific case of differential inclusions having just one described dynamic in the set. Unlike differential equations that offer specific paths, differential inclusions outline all possible paths within state-path constraints, ensuring system sustainability. Considering different alternatives increases the chances that a desired outcome will eventually occur. This consideration gives decision-makers flexibility in solving decision problems dealing with complex adaptive forest systems (CAS) evolving with predictable dynamics and unexpected phenomena of various sorts. For instance, one might assert the current viable states that would ensure the CAS outlined in Fig. 5 can respond to evolving product

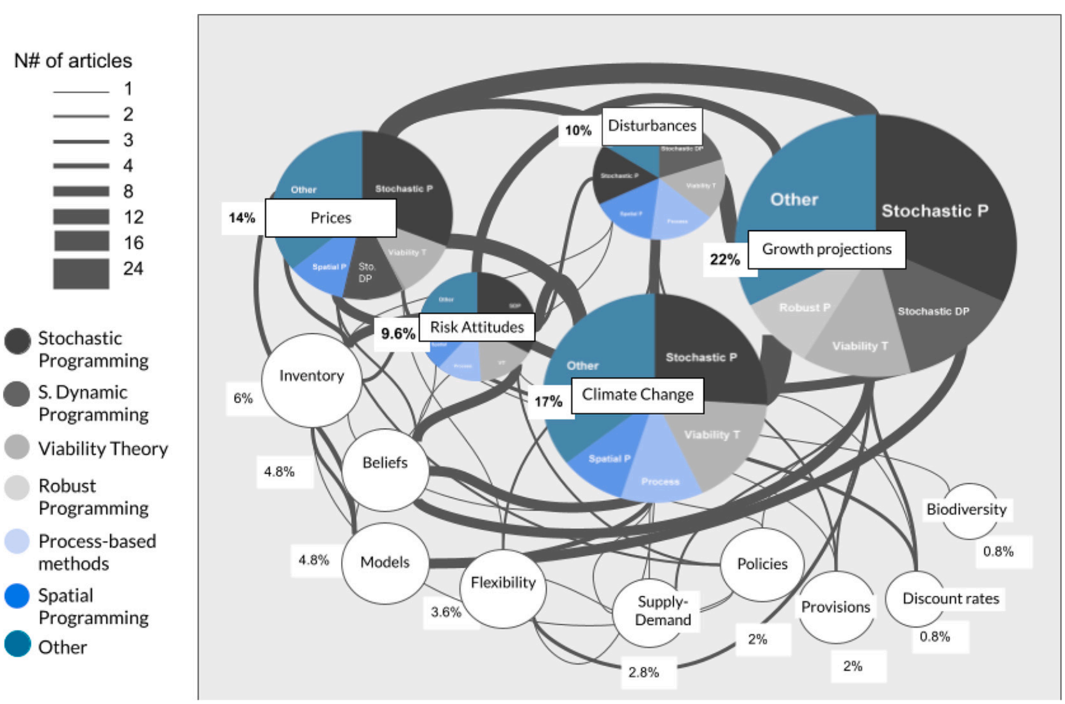


Fig. 5. Network and distribution by topics (pie-charts) of the decision-making numerical models used to predict uncertainty in forest management. Information was collected on the type of uncertainty for each decision-making method. Occurrence of each source of uncertainty was counted and then sources were classified by order of importance. Whenever a study included multiple sources of uncertainty, these sources were linked by an arc, with the size of the arcs differing according to the number of articles. We view the presence of multiple sources of uncertainty as a proxy for understanding the degree of intricate interactions tackled in the decision-making context. Five main topics emerged as sources of uncertainty considered in the models (and nine minor ones, represented by the white circles) from the 180 research references reviewed, with growth projections, climate change, and prices present in over 50% of all the studies. For each topic, the distribution of numerical models was represented by pie charts. The connections between pie charts signify the quantity of references that consider the topics jointly within the case studies.

demand and carbon storage requirements while preserving forest structures that could be resilient to a variety (in time, intensity, and damage) of compounding climatic crises, such as storms, droughts, and subsequent bark beetle pests.

Regarding stochastic approaches, the existence of a viability domain when uncertainty is included means that sufficient control exists to give the system a chance of remaining in the viability kernel for a 'given strength' of controls, but it may not necessarily happen (Krawczyk and Pharo, 2013). The viability kernel indicates an area of potential stability or sustainability. This theory is particularly relevant for complex adaptive systems, as it helps understand their potential to maintain, grow, or recover with sufficient management support (Hunsaker and Thomas, 2018). Viability theory thus complements robust optimization by seeking satisficing measures rather than resource-expensive optimality. Like robust optimization, which determines the most robust decision to change based on a defined range in which variables can change, viability theory defines feasible strategies evaluating a space of possible evolutions. However, most robust applications to forestry management have focused on designing an uncertainty space that would ensure more or less conservatism according to the risk attitude of decision-makers. Originally, robust optimization was developed based on a bounded representation of the uncertainty space, though recent advancements have allowed for dynamic uncertainty over time (Knoke et al., 2020). In contrast, viability theory does not explicitly define the uncertainty space; rather, it emphasizes the sustainability of the evolving system to a dynamic environment (Krawczyk and Pharo, 2013; Oubraham and Zaccour, 2018). It identifies critical constraints that enable systems to operate within safe boundaries, balancing various state variables. The viability kernel reflects on the control margins we have on the behaviors of a system. As the system approaches the viability boundary, flexibility diminishes, and only a set of limited control can ensure the properties of the system (Saint-Pierre, 1994). The more flexibility we model in control options and objectives, the more descriptive the approach will be; as flexibility decreases, it becomes more normative. For example, in forest management, the clear definition of viable constraints allowed to understand the underlying trade-offs in place and to clearly identify, which were the minimum necessary changes required to ensure a sustainable timber production without compromising desirable environmental quality or physical capital (Andrés-Domenech et al., 2014). These constraints outline desirable couples of initial state variables from which decision-managers can achieve and sustain objectives over time. In optimization, interactions between objectives would be examined through Pareto frontier research and trade-off analysis.

Based on the past applications of viability theory to natural resource management, the CAS in Fig. 6 (see comparison Table 4) could be captured by three state variables: 1) the risk level in terms of the percentage of forest impacted, 2) the biological productivity of the forest, 3) the income obtained from the forest or the relative difference between production and demand. The timing of harvesting, the thinning intensity, and the regeneration choice would influence the level of

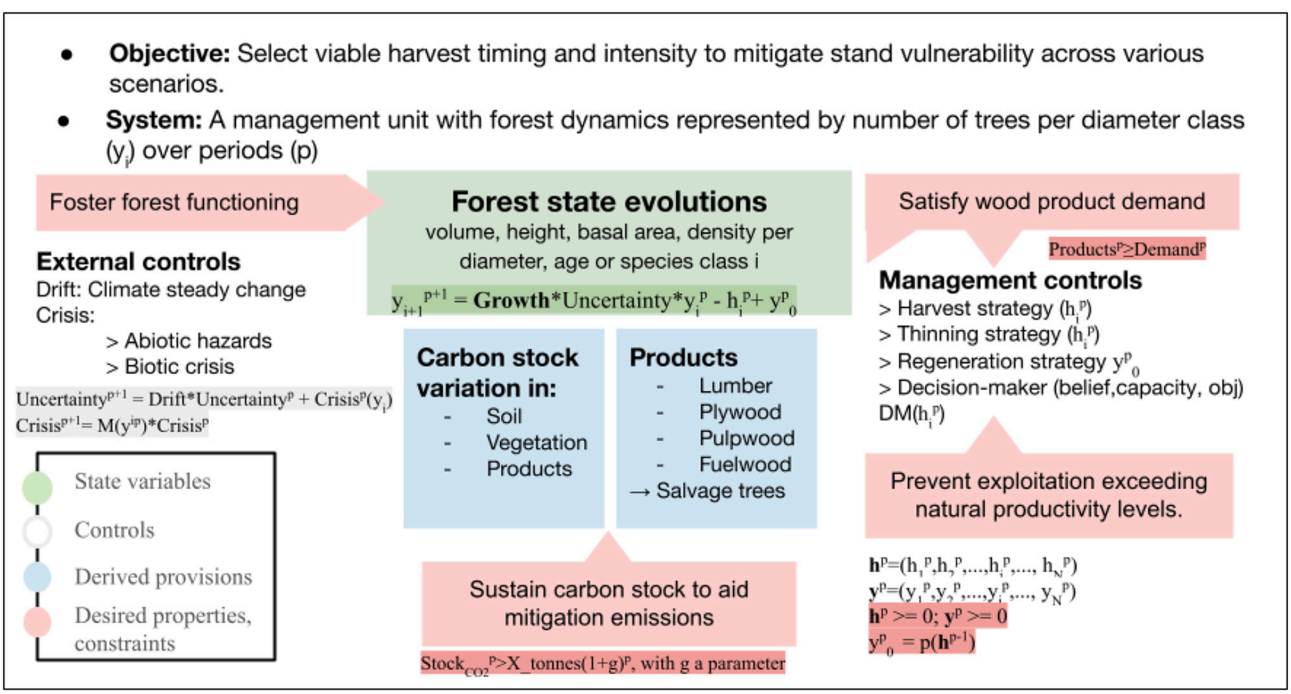


Fig. 6. Integrated forest complex adaptive system (CAS) management framework: Assessing wood production, socio-economic returns, and forest functioning. Based on the literature review and the work of Doyen (2018), we illustrated an ideal representation of forest CAS for decision-making, incorporating several key components: the objective, which describes the purpose of decision-making, the system, which delimits the study object arising from the decision problem; and the state evolutions of this object (here the forest, in green), defined by a non-stationary transition matrix (Pyy et al., 2017). Derived provision can be deduced (in blue). This transition matrix ideally integrates control parameters of two sorts. External controls influence the system and are regulated to varying degrees by human decisions. They include factors such as climate steady change (Drift) and abiotic and biotic shocks (Crisis). The latter depends on the state of the forest. Equations modelling uncertainty and crises are provided to illustrate these influences (dynamic climate change integration: Jacobsen and Thorsen, 2003, fire management: Gómez-Vázquez et al., 2014, windstorm management: Petucco et al., 2020; disturbances: Liénard and Strigul, 2016). The diagram includes an example of a time-inhomogeneous Markov chain to better approach the impact of dynamic disturbances on forests. A Markov chain is a stochastic process used to build transition matrices describing transition probabilities based on the current state, and time-inhomogeneous processes define transition probabilities that can change over time. The second type of controls relates to human action. These integrate forest treatments, decision-maker beliefs described using the Bayesian updating approach (Yousefpour et al., 2014-), and societal needs (product demand as modeled by Global Forest Products Model - Buongiorno and Zhou, 2015). Constraints on the system's functioning, production, and exploitation are applied (in red). This comprehensive framework provides an exploration basis for decision-making to better integrate dynamic environmental factors and human influences on forest management. If applied to a forest property, this CAS would help the manager evaluate the quantity of wood which can be safely extracted from their land under risk of disturbances.

Table 4
Comparison of decision-making methods for representing complex adaptive systems.

Systems components	Stochastic Programming	Multistage Stochastic programming	Dynamic stochastic programming	Robust optimization	Bayesian update (Adaptive Forest Management framework)	Viability theory
Forest dynamics	Probability laws	Probability laws	Probabilistic dynamics	Non-probabilistic representations	Process-based equations	Process-based equations, various ways of representing forest dynamics
Provision evaluation	Expected provisions	Expected provisions and value of waiting	Expected provisions	Satisficing level under every scenarios considered	Expected provision	Space of states that would allow specific provision levels
External controls	Probabilistic scenario tree (climate change, risk, timber price) Downside risk metrics	Probabilistic scenario tree, allows to consider new information (price fluctuation)	Probabilistic network of states, transition nodes between state nodes to represent uncertain events	Uncertainty space, non-probabilistic methods	Non-stationary process, comprehensive modelling	Uncertainty space, probabilistic dynamics
Management controls	Static decision strategies	Stages to allow change in decision strategies	Optimal management is defined based on considered forest states	Static decision strategies	Adaptive decision strategies	Adaptive decision strategies
Constraints	Hard-constraints or probabilistic guarantee	Hard-constraints or probabilistic guarantee	Hard-constraints or probabilistic guarantee	Hard-constraints, guaranteed performance or budget of uncertainty	Evolving constraints	Constraints are made explicit when the problem is solved

production that we could secure. Decision-maker beliefs and desire to adapt to climate change might be considered as well. The viability constraint would be to find acceptable risk damage that would still allow for enough productivity to comply with environmental requirements while simultaneously maintaining production at a level sufficient to support society. The uncertainty space is not precisely delineated. Instead the model allows for a represention of admissible states described by acceptable risk, biological productivity, and demand levels (Krawczyk and Pharo, 2013). Viability theory explores worst-case scenarios and broadly defines the viable state to reach or maintain based on what could be done with our current resources, guarding against all courses of uncertainty, from the worst to the best cases.

Additionally, risk-averse managers may believe that relying on a single trajectory to secure productivity is insufficient to address the various challenges associated with climate change. This concern involves exploring the flexibility of options at the edge of the viability kernel, for example, when balancing conflicting ecosystem services such as production and biodiversity conservation, when the system's sustainability is at stake (Mathias et al., 2015).

Existing literature on applying viability theory to forest management has explored several aspects: defining feasible forest area trajectories under sustainable policies (Andrés-Domenech et al., 2011), determining flexible harvest schedules that respond to timber demand and biodiversity recommendations (Rapaport et al., 2006; Mathias et al., 2015), and examining the impact of infrastructure on wood production, tourism, and nature conservation (Houballah et al., 2021). While most forest applications are deterministic, other sectors have embraced stochastic and robust representations (Oubraham and Zaccour, 2018). Similar to optimal control methods, viability theory suffers a dimensionality curse: models can have any number of control variables, but it is difficult to use more than four state variables because viability theory usually relies on graphical methods to determine the initial state-variable combinations that enable viable outcomes (Krawczyk and Pharo, 2013; Oubraham and Zaccour, 2018). Computational algorithms that lead to kernel determination should be improved to define solutions to high-dimensional problems. Implementing viability theory poses some challenges: Since the approach is problem-oriented, specialized algorithms that are not easily adaptable to other contexts are needed. Yet, its versatile framework has numerous applications and could benefit from dedicated software addressing common viability issues. Viability theory stands to gain from the established optimal control solvers and forest decision-making frameworks. At the same time, these systems could benefit from resilience, necessity, and chance concepts offered by viability theory. Despite the scarcity of expertise in viability theory, especially within forestry, the growing number of applications in the literature indicates a readiness to embrace it. Current efforts in forestry decision-making are aimed at effectively capturing system complexity and uncertainty and may very well lay the groundwork for the adoption of viability theory in forestry decision-making processes as a complementary method.

5. Conclusion on pros and cons of resorting to viability theory in forest management science

Forests play a crucial role in supporting and generating a cascade of values through their provision, regulation, and cultural services. Thus, managing forests as complex adaptive systems requires considering the perspectives and behaviors of stakeholders, operators, and passive users as well as including biodiversity and ecological considerations. Viability theory has been formalized and developed for studying the evolutions of uncertain systems confronted with viability constraints arising in socioeconomic and biological sciences, as well as in control theory (Aubin et al., 2011).

This study provided a historical overview of the evolution of optimization techniques and viability theory, and examines how they can be integrated to make forest management decisions under conditions of uncertainty. Despite an apparent division between operational and viability methods in the 1990s, optimization and viability theory share common goals in addressing uncertainty, understanding complexity, and assessing the importance of information.

To effectively manage forest ecosystems, defining the boundaries of management capabilities is critical since ecosystems are facing growing and complex changes. Highlighting clearly the boundaries raises awareness of the irreversibility of unsustainable forest practices and the importance of anticipatory actions. Recent studies suggest the potential for reversing adverse effects and avoiding irreversibility in forest management (Andrés-Domenech et al., 2011, 2015; Keenan, 2015), but there is a concern that stakeholders may perceive the situation as not being urgent enough to justify bold actions and innovation. For example, the risks associated with investing in long-term equipment or new road networks, as well as the reaction of intertwined industries along the supply-chain, must be considered when evaluating potential innovation in management practices (Rönnqvist et al., 2015). In fact, this review is primarily forest-oriented, ensuring the functionality of such ecosystems

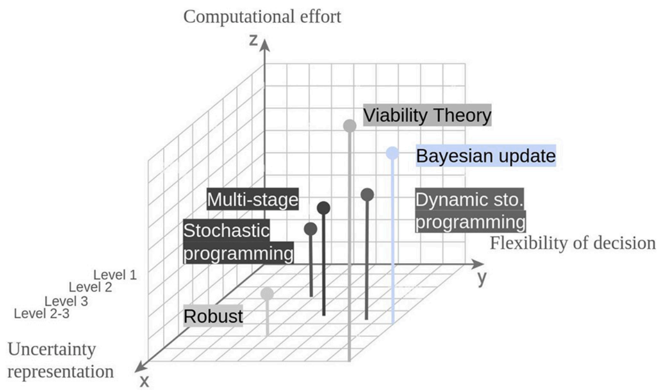


Fig. 7. Performance levels of existing decision-making tools for forestry. This figure evaluates the performance of decision-making tools in forestry along three dimensions: the level of knowledge utilized to describe phenomena (uncertainty representation), the computational effort required to solve decision problems, and the adaptability of decision strategies during the decision-making process (flexibility of decision). Stochastic and robust programming methods provide flexibility by considering future scenarios and uncertainty spaces to adjust decisions accordingly. Most robust applications found in this review are static, meaning the decision-making process remains unchanged throughout the optimization. Multi-stage stochastic programming enhances flexibility further by allowing decisions to be deferred pending additional information. In contrast, dynamic stochastic programming optimizes decisions across all possible scenarios and for any possible forest state. Spatial programming offers greater decision-making flexibility compared to stochastic programming by showcasing not only temporal but also spatial adaptability in the decision space. However, due to the consideration of spatial constraints like habitat connectivity, the computational demands of spatial programming are notably higher. Addressing realistic spatial forest-management problems with stochastic dynamic programming remains an ongoing scientific pursuit. Bayesian updates (process-based methods) offer a dynamic evaluation of the decision-making process by adjusting decisions based on evolving beliefs over time. Viability theory adds another layer of complexity and flexibility to decision-making under uncertainty. It can model evolutions based on stochastic processes and incorporate intervals to consider extreme events. The flexibility of decision-making is enhanced by seeking any potential winning combination of natural evolution and management control to avoid system failure such as forest dieback. However, the computational effort for viability theory is significant, as most applications are still theoretical, and integrating dynamic equations substantially impacts solvability. Reflecting on the performance of the decision-making methods used to balance uncertainty representation, computational complexity, and decision flexibility highlights viability theory as a comprehensive approach, albeit with increased computational demands.

to maintain provision in the face of global change, but similar conclusions and considerations could be extended to the entire sector.

Adapting optimization methods to enhance ecosystem resilience is crucial, especially in the context of more frequent unpredictable environmental changes and disturbances. The recent work of Knoke et al. (2023) highlights an approach to ecosystem resilience by focusing on minimizing recovery time, which is one of the key resilience metrics. By minimizing the time it takes for an ecosystem to return to a stable state after a disturbance, the study provides insights into how management strategies can be optimized for both resilience and recovery. Similarly, *viability theory* is also a significant tool in this context. Based on the degree of control we can technically achieve in a forest system, the viability theory emphasizes consistency between dynamics and constraints to reveal whether or not the situation we model can be sustainably managed with greater or less flexibility. Including viability considerations in forest management could enrich traditional optimization models. Viability theory allows for versatile use of mathematical tools and could be instrumental in improving the integration of process-based descriptive models or their meta-models. It provides valuable insights into how much decision-makers can influence the system under a potentially wide array of uncertain changes that are driven by non-deterministic and stochastic effects. This theory is particularly useful in refining forest management problems, as it identifies where critical decisions must be made. The boundaries of the viability kernels highlight where management controls are limited to sustaining key system properties. Moreover, it can be employed to assess whether current management alternatives align with pre-defined sustainability goals. However, while viability theory outlines the boundaries of what can be achieved, it does not define the optimal strategies for sustaining forest provisions at the highest guaranteed level. Therefore, it should be seen as a complementary method, working alongside other decision-making frameworks.

One additional approach to combine viability theory with current decision-making methods is to assess if management solutions derived from stochastic, robust, or agent-based programming are viable with respect to long-term forest functioning. Determining the best strategy to adapt to climate change and mitigate its impacts requires considering factors such as wind hazard, genetic perspectives, and functional traits. For example, while shorter rotation periods might seem more appealing to address wind hazards which occur every five years that affect mature stands, promoting young forests could be more robust in preventing the forest from capitalizing disturbance and changing selection rules. Viability theory can serve as a stress-tester, as demonstrated by the multi-scenario multi-objective robust optimization approach proposed by Shavazipour et al. (2021), which combines all single-scenario multi-objective optimization problems into a meta-optimization problem to explore the trade-off between optimality and feasibility of stochastic analysis and robustness across a broader range of scenarios.

In conclusion, viability theory offers valuable insights into understanding the behaviors of forest ecosystems under various controls and physical drivers. By identifying decision rules and assessing the degree of freedom in management, viability theory contributes to the preservation, permanence, and sustainability of forest conditions essential for survival, safety, and effectiveness. While its application necessitates additional efforts, viability theory concepts hold significant promise for complementing forest decision-making processes. As forest management increasingly emphasizes resilience, stability, and adaptability, viability theory provides a theoretical framework that aligns with these objectives. Despite the challenges of implementing the theory, the concepts raised by viability theory could be integrated into forest management practices to support sustainable forest ecosystems (see Document S1).

As a perspective note, forest managers must make decisions without certainty on how the future will unfold, and may not know with confidence the potential role that some specific forest management decisions can play in mitigating global warming while fostering opportunities (Bagaram and Tóth, 2020). Currently, forest policies aiming to promote sustainability lack clear target definitions and are overly broad and complex. It is thus crucial to understand how research on forest management examines silvicultural alternatives (Hoganson and Meyer, 2015) to propose and evaluate strategies for adaptation to global change and potential disturbances.

CRediT authorship contribution statement

Clémence Labarre: Writing – review & editing, Writing – original draft, Validation, Methodology, Investigation, Formal analysis, Conceptualization. **Jean-Christophe Domec:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Pablo Andrés-Domenech:** Writing – review & editing, Methodology, Investigation, Conceptualization. **Kai Bödeker:** Writing – review & editing, Conceptualization. **Logan Bingham:** Writing – review & editing, Conceptualization. **Denis Loustau:** Supervision, Methodology, Conceptualization.

Declaration of competing interest

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

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Appendix A. Supplementary data

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Data availability

Data will be made available on request.

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