Universitat de Lleida

A decision support framework for holistic forest management: bridging policy and practice

Irina Cristal

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TESI DOCTORAL

A DECISION SUPPORT FRAMEWORK FOR HOLISTIC FOREST MANAGEMENT:
BRIDGING POLICY AND PRACTICE

Irina Cristal

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Programa de Doctorat en Gestió Forestal i Medi Natural

Director
Jordi Garcia-Gonzalo
José Ramón González Olabarria

Tutora
Cristina Vega-Garcia

Abstract

The challenge of managing forests amidst global changes requires holistic approaches rooted in Sustainable Forest Management (SFM) principles. Yet, this concept is poorly translated into operational criteria for Decision Support Systems (DSS) development. This doctoral thesis aims to translate sustainability principles into practical methods, providing a tangible framework to address forest management decision complexities.

Three aspects of SFM were explored and operationalized through three case studies. The first aspect, the geographically oriented management, was approached in the first case study through a spatiotemporal analysis of forest Ecosystem Services (ESs) based on the Spanish National Forest Inventory (NFI). Local spatial statistics methods were employed to study ESs dynamics, considering geography as a continuum and accounting for the ESs cross-scale interactions. The second aspect, the adaptive management, was addressed in the second case study through a simulation experiment conducted employing two forest dynamics models. This experiment used regional forest management guidelines and different climate change scenarios to project their combined impact on *Pinus sylvestris* stands along an aridity gradient in north-east Spain. In addition, to assess simulation robustness, variation partitioning was performed to quantify the influences of the simulator, climate change, management, and the site factors on the variations in the simulation outputs. The third aspect, the stakeholder engagement, was addressed in the third case study by developing a Virtual Reality (VR) application to visualize these simulations and by conducting an online opinion survey to estimate the efficacy of 3D modelling and VR in aiding decision-making. The insights from these three case studies framed the DSS architecture, providing technological solutions for different stages of forest management decision-making. Specifically, the first case study, by revealing heterogeneity in spatiotemporal changes in forest ESs and showing localized effects in their cross-scale interactions, stressed the necessity of applying NFI timeseries and local spatial statistics to guide geographically oriented management. The second case study showed that forest simulation models accounted for 70% of the output variations, advocating for multi-model analyses to address both modelling and climate change uncertainties. The third case study proved the usefulness of VR and 3D visualizations in interpretating forest simulations, emphasizing the necessity of these tools in engaging stakeholders and the public in decision-making. Finally, these combined insights and the usability assessments, conducted at different development stages, defined the DSS components and their interactions in the fourth case study.

An integrated forest management approach is crucial in prioritizing actions and tackling climate change implications, thereby improving decision-making aligned with sustainability principles. This work operationalized SFM principles into decision-making processes at different stages, stressing the importance of considering varying scales and spatiotemporal heterogeneity in ESs dynamics, employing adaptive multi-modelling approaches in forest projections and use immersive visualizations to engage stakeholders and the public in decision-making. These operational criteria were integrated into a holistic DSS that helps to address the complexities of a sustainable forest management planning. Overall, the outcomes of this thesis offer a practical framework for decision-making in line with policy and societal demands.

Resum

La gestió forestal en temps de canvi global requereix un enfoc holístic basat en els principis de la Gestió Forestal Sostenible (GFS). No obstant, aquests principis rarament es consideren en criteris operatius per al desenvolupament de Sistemes de Suport a la Presa de Decisions (SSPD). La present tesi doctoral té com a objectiu traduir els principis de sostenibilitat en mètodes pràctics, proporcionant un marc tangible per treballar les complexitats de la presa de decisions en la gestió forestal.

En el marc d'aquesta tesi, es van explorar tres aspectes de la GFS y es van operacionalitzar a través de tres casos d'estudi. El primer aspecte, la gestió geoespacial, es va abordar en el primer cas d'estudi mitjançant un anàlisi espaciotemporal dels Serveis Ecosistèmics (SE) forestals basat en l'Inventari Forestal Nacional d'Espanya. A través de l'ús d'anàlisis geoespacials locals es van estudiar els canvis en els SE forestals, considerant el terreny com a un continu i tenint en compte com interacciona a diferents escales. El segon aspecte, la gestió adaptativa, es va abordar en el segon cas d'estudi a través d'un experiment de simulació amb dos models de dinàmica forestal. Per les simulacions, es van utilitzar directrius de gestió forestal regional i diferents escenaris de canvi climàtic amb la finalitat de predir el seu impacte combinat en rodals de *Pinus sylvestris* al llarg d'un gradient d'aridesa al nord-est d'Espanya. A més, per avaluar la robustesa de la simulació, es va dur a terme un anàlisi de partició de variacions per quantificar la influència del simulador, de l'escenari de canvi climàtic i de gestió utilitzats, així com de les característiques del lloc sobre la variació en els resultats de les simulacions. El tercer aspecte, la participació de les parts interessades, es va abordar en el tercer cas d'estudi a través de la visualització dels resultats de les simulacions del segon cas d'estudi en aplicacions de Realitat Virtual (RV) y la realització d'una enquesta d'opinió online per estimar l'eficàcia de la modelització en 3D i de la RV en la presa de decisions.

Els resultats d'aquests tres casos d'estudi van ajudar a configurar l'arquitectura del SSPD en el marc del quart cas d'estudi, proporcionant solucions tecnològiques per diferents etapes de la presa de decisions en la gestió forestal. Específicament, el primer cas d'estudi va revelar la heterogeneïtat dels canvis espaciotemporals en els SE forestals i va mostrar els efectes localitzats de les seves interaccions a diferents escales, posant èmfasi en la necessitat de combinar l'anàlisi de sèries temporals de l'Inventari Forestal Nacional amb anàlisis geoespacials locals. El segon cas d'estudi va mostrar que el 70% de la variació en els resultats prové del model de simulació forestal utilitzat, demostrant la importància d'utilitzar anàlisis multi-model per abordar les incerteses tan en la modelització com les relacionades amb el canvi climàtic. El tercer cas d'estudi va demostrar la utilitat de la RV i de les visualitzacions en 3D per interpretar les simulacions forestals, emfatitzant els beneficis de l'ús d'aquestes eines per involucrar a les parts interessades i al públic en general a la presa de decisions. Finalment, combinant aquests resultats amb les avaluacions d'usabilitat en diferents etapes del desenvolupament, es van definir els components del SSPD i les seves interaccions, configurant així l'arquitectura del SSPD.

Un enfoc integrat de gestió forestal és crucial per prioritzar accions i abordar les implicacions del canvi climàtic, millorant així la presa de decisions en línia amb els principis de sostenibilitat. Aquest treball va operacionalitzar els principis de GFS en processos de presa de decisions en diferents etapes, destacant la importància de considerar diferents escales i l'heterogeneïtat espaciotemporal en la dinàmica dels SE, utilitzant anàlisis multi-model adaptatius per predir la dinàmica forestal i utilitzant visualitzacions immersives per involucrar a les parts interessades i al públic en general en la presa de decisions. Aquests criteris operatius es van integrar en un disseny holístic de SSPD que ajuda a abordar les complexitats relacionades amb la sostenibilitat en la planificació de la gestió forestal. En general, els resultats d'aquesta tesi ofereixen un marc pràctic per la presa de decisions en línia amb les demandes polítiques i socials.

Resumen

La gestión forestal en tiempos de cambio global requiere un enfoque holístico basado en los principios de Gestión Forestal Sostenible (GFS). Sin embargo, estos principios raramente se consideran en los criterios operativos para el desarrollo de Sistemas de Apoyo a la Toma de Decisiones (SATD). La presente tesis doctoral tiene como objetivo traducir los principios de sostenibilidad en métodos prácticos, proporcionando un marco tangible para abordar las complejidades de la toma de decisiones en la gestión forestal.

En el marco de esta tesis, se exploraron tres aspectos de la GFS y se operacionalizaron a través de tres casos de estudio. El primer aspecto, la gestión geoespacial, se abordó en el primer caso de estudio mediante un análisis espaciotemporal de los Servicios Ecosistémicos (SE) forestales basado en el Inventario Forestal Nacional de España. A través del uso de análisis geoespaciales locales se estudiaron los cambios en los SE forestales, considerando el terreno como un continuo y teniendo en cuenta sus interacciones a diferentes escalas. El segundo aspecto, la gestión adaptativa, se abordó en el segundo caso de estudio mediante un experimento de simulación con dos modelos de dinámica forestal. Para las simulaciones, se utilizaron directrices de gestión forestal regional y diferentes escenarios de cambio climático con el fin de predecir su impacto combinado en los rodales de *Pinus sylvestris* a lo largo de un gradiente de aridez en el noreste de España. Además, para evaluar la robustez de la simulación, se realizó un análisis de partición de variaciones para cuantificar la influencia del simulador, del escenario de cambio climático y de gestión utilizados, así como de las características del sitio sobre la variación en los resultados de las simulaciones. El tercer aspecto, la participación de las partes interesadas, se abordó en el tercer caso de estudio mediante la visualización de los resultados de las simulaciones del segundo estudio de caso en aplicaciones de Realidad Virtual (RV) y la realización de una encuesta de opinión online para estimar la eficacia de la modelización en 3D y de la RV en la toma de decisiones.

Los resultados de estos tres casos de estudios ayudaron a configurar la arquitectura del SATD en el marco del cuarto caso de estudio, proporcionando soluciones tecnológicas para diferentes etapas de la toma de decisiones en la gestión forestal. Específicamente, el primer estudio de caso reveló la heterogeneidad de los cambios espaciotemporales en los SE forestales y mostró efectos localizados de sus interacciones a diferentes escalas, enfatizando así la necesidad de combinar el análisis de series temporales del Inventario Forestal Nacional con análisis geoespaciales locales. El segundo estudio de caso mostró que el 70% de la variación en los resultados proviene del modelo de simulación forestal utilizado, abogando por análisis multi-modelo para abordar las incertidumbres tanto en la modelización como las relacionadas con el cambio climático. El tercer estudio de caso demostró la utilidad de la RV y las visualizaciones en 3D para interpretar las simulaciones forestales, enfatizando los beneficios del uso de estas herramientas para involucrar a las partes interesadas y al público en general en la toma de decisiones. Finalmente, combinando estos resultados con las evaluaciones de usabilidad en diferentes etapas de desarrollo, se definieron los componentes del SATD y sus interacciones, configurando así la arquitectura del SATD.

Un enfoque integrado de gestión forestal es crucial para priorizar acciones y abordar las implicaciones del cambio climático, mejorando así la toma de decisiones alineada con los principios de sostenibilidad. Este trabajo operacionalizó los principios de GFS en procesos de toma de decisiones en diferentes etapas, destacando la importancia de considerar diferentes escalas y la heterogeneidad espaciotemporal en la dinámica de los SE, utilizando análisis multi-modelo adaptativos para predecir la dinámica forestal y empleando visualizaciones inmersivas para involucrar a las partes interesadas y al público en general en la toma de decisiones. Estos criterios operativos se integraron en un diseño holístico de SATD que ayuda a abordar las complejidades relacionadas con la sostenibilidad en la planificación de la gestión forestal. En general, los resultados de esta tesis ofrecen un marco práctico para la toma de decisiones en línea con las demandas políticas y sociales.

Table of Contents

Table of figures

Declaration of Originality

I, Irina Cristal, declare that this thesis, entitled “A decision support framework for holistic forest management: bridging policy and practice” submitted in fulfilment of the requirements for the degree of Doctor of Philosophy at University of Lleida, represents my own work. All ideas, concepts, and findings presented herein are the result of my original research and intellectual endeavours, unless otherwise attributed.

I confirm that:

- Any sources of information or assistance used in this thesis are acknowledged and properly referenced in accordance with the accepted academic conventions and guidelines of the University of Lleida.
- All quotations, paraphrases, or borrowed ideas from other works are duly cited and referenced.
- The content of this thesis has not been submitted in whole or in part for any other academic qualification or degree at any other university or institution.
- Any contributions made by others to this work are duly acknowledged and credited in the acknowledgments section of this thesis.

I understand that any act of academic dishonesty, including plagiarism or misrepresentation of sources, is a breach of academic integrity.

Irina Cristal

Solsona, 19/01/2023

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List of Abbreviations

General

etc.	et cetera
i.e.	id est
e.g.	exempli gratia
cf.	confer

Specific

SFM	Sustainable Forest Management
AFM	Adaptive Forest Management
BA	Basal Area
DBH	Diameter at Breast Height
DSS	Decision Support System
DST	Decision Support Tool
EM	Empirical Modelling
ESs	Ecosystem Services
NFI	National Forest Inventory
PM	Process Modelling
VR	Virtual Reality

1. Introduction

1.1. Background and motivation

The growing evidence of global changes impacts on forests has prompted both policymakers and the scientific community to develop tools to mitigate these effects. The evolution of policy instruments for sustainable management began with the World Commission on Environment and Development (WCED) Bundland Report in 1987, defining sustainability by addressing current needs without compromising future generations. Subsequently, the United Nations Conference on Environment and Development (UNCED, 1992) outlined the principles of Sustainable Forest Management (SFM), emphasizing the balance among social, economic, and environmental needs (cf. Agenda 21). The Ministerial Conference on the Protection of Forests in Europe (MCPFE, now referred to as FOREST EUROPE) developed 6 criteria and 36 indicators for monitoring, evaluating, and reporting progress towards SFM (cf. EFI, 2013). While the Millennium Ecosystem Assessment (MEA) promoted the adoption of Ecosystem Services (ESs) concept as an umbrella framework to address the triptych of SFM (cf. M.E.A., 2005). More recently, the European Commission published the New EU Forest Strategy for 2030 recognizing the need for forests to contribute to the European Green Deal and global targets (i.e., Agenda 2030). This new strategy acknowledges the changing priorities and evolution of the SFM concept and paves the way to develop a revised, more ambitious framework for sustainable forest management, including geographically oriented management, adaptive management, training and education, stakeholder involvement and determine “boundaries” of sustainability (Lier et al., 2022).

On the other hand, the scientific community continuously creates tools and methods to support sustainable decision-making in forest management. These include predictive forest modelling techniques addressing climate change impacts on forest dynamics and associated ecosystem services, and decision algorithms for optimal resource management and facilitating participatory planning among others. Nevertheless, a notable discrepancy arises in the combined effort to implement environmental sustainability actions (Terribile et al., 2023). Policymakers often find Decision Support Tools (DSTs) developed within research environments difficult to use, while developers of DSTs struggle to keep pace with rapidly evolving policy demands (Linkevičius et al., 2019). A proposed solution to overcome these challenges is to involve end-users and stakeholders throughout the entire design and development process (McIntosh et al., 2011). Another solution, from a DST development perspective, is to mask the underlying complexity of these tools by determining appropriate system restrictiveness (Walling and Vaneeckhaute, 2020), or by narrowing the scope of these tools (e.g. Gordon, 2006). However, challenges posed by the increasing environmental, social, and economic changes extend beyond traditional forest management issues, encompassing broader social and environmental crises, necessitating a holistic approach. This concern has found expression in the universal acceptance of the sustainability principles (Wang, 2002). Achieving sustainability is referred to as a “wicked” problem (Rittel and Webber, 1973) i.e., a problem that has no straightforward solution, and is interconnected with social, economic, and ecological uncertainties. While there has been an effort to establish measurable criteria and indicators for assessing Sustainable Forest Management (SFM) (i.e., MCPFE, 2013), these indicators are poorly translated into practical forest management DSTs. Translation of SFM principles into operational criteria are key for developing effective and functional tools to support management decisions.

1.2. Problem statement

Forest management is typically facilitated by a top-down hierarchical structure, where strategic planning focuses on long-term forest strategies at regional or national scales; tactical planning generates management plans at a landscape/stand-level scale for mid-term planning periods; and operational planning implements tactical management plans on the ground (Pukkala, 2002). Each level is expected to transition linearly to the next, with strategic goals translating into mid-term objectives, which then provide instructions for the operational level management (Figure 1a).

Given the growing scientific evidence of global changes affecting forests, that include climatic, economic, and land use changes, adaptive management approach emerged as pivotal principle (Vacik and Lexer, 2014). Adaptive forest management requires the flexibility of adjusting management plans in response to new conditions or knowledge. In this regard, the hierarchical top-down approach presents some limitations, as the outputs of one level may be inconsistent with the outputs of the other level (Weintraub and Davis, 1996). These inconsistencies are stemming from both spatial and temporal scales, as well as from the methods applied to address each level (Ulvdal et al., 2023). Thus, an integrative approach is needed (Figure 1b). Several studies have proposed to solve this issue by harmonizing scales and addressing both strategical and tactical management objectives at a stand-level unit (Andersson, 2005).

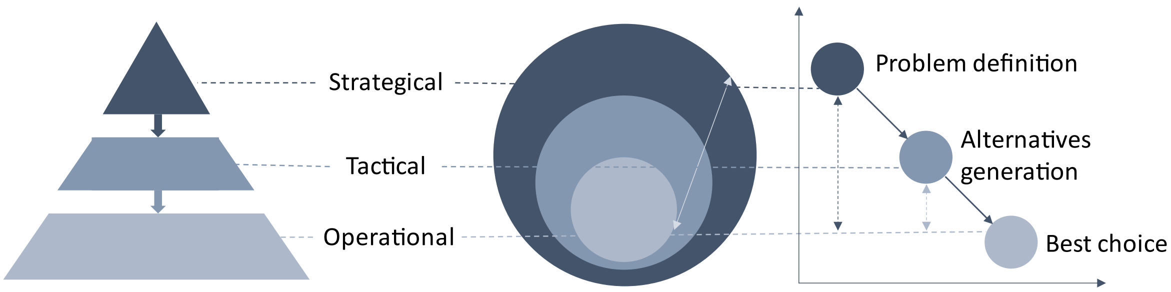


Figure 1. Forest planning concepts and decision-making: (a) top-down forest management planning; (b) integrated forest management; (c) adaptive decision-making model linked with the 3-level forest planning.

The central idea of Sustainable Forest Management (SFM) is to integrate economic, ecological, and social dimensions of forest ecosystems (UNCED, 1992). To facilitate this integrations, Ecosystem Services (ESs) concept is key, as it translates forest functions into benefits for the society that can be valued in monetary terms, thus acting as an umbrella term for societal, economical and forest dimensions. ESs pertain to different spatial and temporal scale (Rodríguez et al., 2006; Willemen, 2020). For instance, climate change regulation operates at large geographical and temporal scales, while mushroom production at a local scale and shorter time windows. Scaling issues have been addressed in forest modelling literature by aggregation (cf. Seidl et al., 2013). Aggregation presumes a bottom-up approach, where e.g., tree-level information is aggregated to stand and landscape level. ESs, however, often require to be assessed simultaneously, i.e., when evaluating their trade-offs and synergies. Thus, ESs assessments require cross-scale approaches.

Another aspect of SFM is encouraging participatory planning and emphasizing the role of stakeholders and the public in decision-making. The literature has addressed methods to integrate public and stakeholder opinion through multicriteria decision analysis (e.g., Acosta and Corral, 2017). The challenge however persists in effectively communicating scientific findings to non-experts. Additionally, considering the uncertainty inherent in forest management planning, a crucial question arises regarding how to assess and communicate various sources of uncertainty to stakeholders in order to enhance transparency in decision-making processes. This multifaceted nature of sustainability necessitates decision support tools that allow decision-makers to harmonize forest management objectives with policy requirements, while adapting to the dynamic changes in environmental and socio-economic conditions.

The aim of this thesis is to translate the sustainability concept into explicitly defined, operationally practical tools for forest management decision-making. Emphasis is placed on addressing four key dimensions of SFM: 1) acknowledging the multi-scale nature of ecosystem services, 2) implementing adaptive management concepts, 3) addressing uncertainty in future projections, and 4) enhancing stakeholder engagement in decision-making. The ultimate goal is to explore these aspects for their incorporation into a comprehensive Decision Support System (DSS), able to address an integrated approach in decision-making (Figure 1c).

Specific aims:

- Identify gaps and limitations concerning the application of SFM principles within each stage of decision-making.
- Demonstrate how these gaps can be addressed to enhance decision-making.
- Develop a robust DSS incorporating the solutions derived from addressing these limitations, improving the efficacy of forest management decision-support.

1.3. Main concepts and definitions

Forest management is the process of planning and implementing practices for the stewardship and use of forests to meet specific objectives (FAO, 2020).

Management alternatives are the courses of action (prescriptions) and their implications regarding the desired state of the forest.

Sustainable Forest Management (SFM) integrates economic, ecological, and social dimensions of forests (UNCED, 1992).

Adaptive Forest Management (AFM) acknowledges that the ongoing changes driven by climate change, disturbances, and human interventions, require flexibility and continuous learning (Bolte et al., 2009), that would allow managers to modify strategies in response to the new conditions (Yousefpour et al., 2017).

Multi-objective forest management leverages the capacity of forest ecosystems to provide multiple services concurrently, enabling the identification of solutions that optimize multiple objectives (Pukkala, 2002), while addressing trade-offs and synergies among them (Manning, 2018; Deal 2012).

Ecosystem Services (ESs) are the diverse benefits that forests provide to people and the environment (Duraiappah et al., 2005). They include provisioning services such as timber and non-timber forest products, regulating services such as climate regulation, cultural services, such as recreation, and supporting services (Haines-Young and Potschin, 2011). By assessing ESs, forest management can adjust management strategies, ensuring the continued provision of these services to society (Thorsen et al., 2014).

Forest modelling is the development of a simplified representation of a forest system using mathematical formulations. Computer-based implementations of a forest model that generates future scenarios based on the system's behaviour are referred to as **simulations** (Botkin, 1993).

Process Modelling (PM) involves formulating mathematical relationships of processes that govern forest dynamics, relying on established scientific knowledge and understanding (IPBES, 2016).

Empirical Modelling (EM) constructs mathematical functions that fit the pattern of the observed data.

Forest simulator or simulation tool is a software tool that calculates the results for a model using a sample of representative scenarios. Simulators for decision support may preferentially focus on model simplification, automation and visualization (Muys et al., 2010).

Decision-making is the process of arriving to a conclusion following a series of steps, including defining the problem, generating, and choosing alternatives (Simon, 1960).

Decision Support Tools (DST) refer to software, models, and methods, aimed at facilitating different aspects or stages of decision-making.

Decision Support Systems (DSSs) in forest management are computer-based systems that integrate data and databases, models, interfaces and effective visualizations to assist forest managers and stakeholders in decisions related to ill-structured management problems (Reynolds et al., 2008; Sprague, 1980; Vacik et al., 2015).

1.4. Historical evolution of forest management decision support

Throughout history, the understanding of forest ecosystems and the approaches to their management have evolved, reflecting changes in societal values and ecological knowledge. In the pre-industrial era, forests served as sources of timber, fuel, and hunting grounds (Soler-Sala, 2019), with early forest management practices involving controlled burning, selective cutting, and restrictions on tree felling (Paletto et al., 2008). During the Middle Ages, forest laws were established by monarchies to manage and protect timber resources, introducing the concepts of forest reserves and logging restrictions (Fernow, 1911; Valbuena-Carabaña et al., 2010). With the Industrial Revolution, timber demand surged, leading to more intensive exploitation, deforestation, and degradation of forests. During this period, forest science emerged as a discipline, introducing the concept of sustained forest yield (Shugart, 2008; Walker, 1990), encouraging professionals to apply scientific principles to forest management (Johann, 2007; Linares, 2007). The yield tables, based on systematic yield observations, emerged as decision support tools to assist in decisions regarding harvest regulation, rotation length, growth estimates, and forest production assessments (Assmann, 1970; Fontes et al., 2011; Pretzsch, 2009; Sterba, 1998).

In the mid-20th century, the multiple-use forestry paradigm recognized forest management objectives beyond timber (Clawson, 1978), exemplified by the Multiple Use Sustained Yield Act (MUSY) of 1960 in the United States. In 1962, the release of Rachel Carson's book "Silent Spring", contributed to a broader shift in environmental consciousness and indirectly influenced various aspects of environmental management thinking. At the same time, technological advancements allowed the development of the first forest simulation tools marking a change from empirical yield tables (cf., the individual tree growth model developed by Newnham, 1964).

In the same period, forest management theories started adopting Simon's decision-making model (Simon, 1947) composed by a three-stage process: (i) intelligence stage or problem definition, (ii) designing stage or alternative generation, and (iii) decision stage, or selection of best alternative.

Figure 2. Historical evolution of concepts and approaches in forestry and forest management

In the late 20th century, the management paradigm shifted towards an ecological perspective, recognizing the role of maintaining the integrity of forest ecosystems, that would support sustained forest yields (Franklin et al., 2018). The 1970s saw the adoption of forest policies, such as the U.S. Endangered Species Act of 1973 and the U.S. Forest Management Act of 1976, mandating sustainable forest management of national forests. In Europe, the European Conservation Year campaign (1970) laid the foundation for European environmental policies, stressing the importance of adopting scientifically informed, and ecologically sound approaches in environmental management (FAO, 1988; Leprince-Ringuet et al., 1970).

The combined policy demands, and technological advancements promoted innovative numerical methods in forestry (Figure 3). Ecological modelling emerged, with one of the most notable examples: the development of JABOWA forest succession model, introduced by Botkin in 1972. This model, later named *gap model* by Shugart and West, (1980), played a fundamental role in the evolution of the gap modelling family (Bugmann and Seidl, 2022; Larocque, 2015). Operational Research (OR) and mathematical optimization techniques started to find their place in the fields of timber harvesting and resource allocation, by the means of linear programming (cf. FORPLAN; Kumazaki and Mashiba, 1970). At the same time, Management Information Systems (MIS) concept was introduced in forest management at strategic, tactical, and operational levels (cf. Grevatt, 1970) and paved the way for the development of Decision Support Systems (DSSs) in forest management. The 1980s witnessed the rise of DSS in forestry, with most of the systems focusing on well-defined problems, such as harvesting regimes, or pest management (Reynolds, 2005; Reynolds and Hessburg, 2014). Davis and Clark (1989) reviewed over 200 DSSs and reported about 100 systems related to environmental management (Davis and Clark, 1989; Reynolds and Hessburg, 2014).

Growing environmental concerns at a global level and the acknowledgment of the role of forests in maintaining ecological balance and human well-being led to the emergence of Sustainable Forest Management (SFM) paradigm. In 1987, United Nations Brundtland Commission defined sustainability as *"fulfilling current needs without jeopardizing the capacity of future generations to fulfil their own"*.

Later, the United Nations Conference on Environment and Development (UNCEF, 1992), recognized the importance of balancing ecological, economic, and social objectives of forests in a climate change era (cf. Agenda 21), and established a framework for climate change mitigation through the creation of the United Nations Framework Convention on Climate Change (UNFCCC). This laid the foundation for subsequent international agreements for reducing greenhouse gas emissions, including the Kyoto

Protoco l and the Paris Agreement. With the increased evidence of climate change impacts on forests, adaptive management emerged as a conceptual strategic framework (Vacik and Lexer, 2014). This framework implies continuously monitoring the effects of management practices to make necessary adjustments and strengthen forest resilience against the impacts of climate change (Bolte et al., 2009). SFM was further defined and operationalized through the Ministerial Conference on the Protection of Forests in Europe (MCPFE), and the Montreal process in North America. These initiatives established criteria and indicators for biodiversity, carbon sequestration, and socio-economic benefits from forests (Rametsteiner and Mayer, 2004). To support the integration of social, economic, and environmental dimensions of sustainability (Martynova et al., 2021), the concept of Ecosystem Services (ESs) emerged as a metaphor stressing society's reliance on natural ecosystems (Costanza et al., 1997). In the beginning of the 21st century ESs evolved into a comprehensive framework consolidated by the Millennium Ecosystem Assessment (M.E.A., 2005). The ES paradigm was soon adopted in forest management and policy making, due to its utilitarianism and ease of integration into decision making (Muradian, 2017).

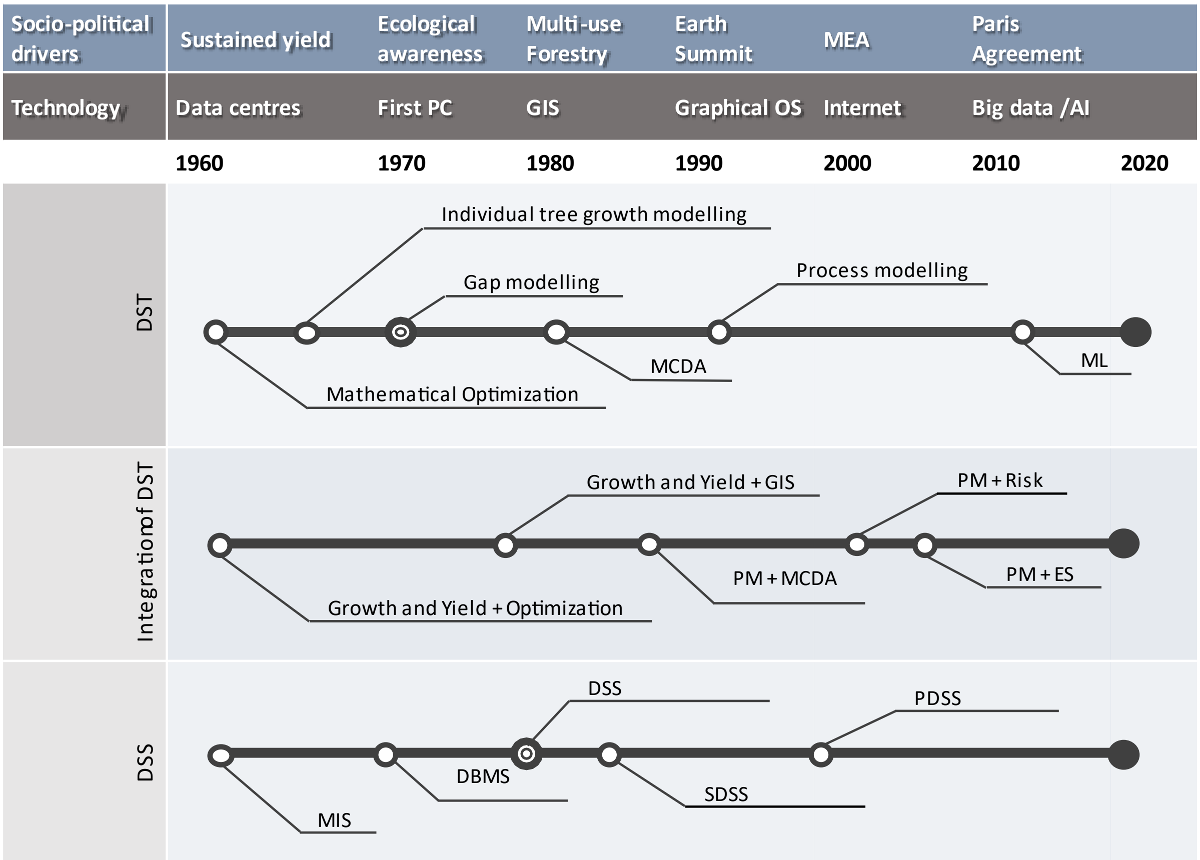


Figure 3. Historical evolution of decision support tools in forest management decision-making

Recent policy developments brought significant changes to global climate change mitigation and sustainability definition. In 2015, the adoption of the Paris Agreement established a worldwide commitment to limit temperature increases, encouraging concrete actions from nations (UNFCCC, 2015). In the same year, the United Nations Sustainable Development Summit introduced 17 Sustainable Development Goals (SDGs), covering economic, social, and environmental dimensions of sustainability. The recent policy instruments, such as the EU Green Deal (European Commission, 2019) and the subsequent New Forest Strategy for 2030 (European Commission, 2021) anchored on the EU Biodiversity Strategy for 2030 (European Commission, 2020), enhanced forest sustainability concept to promote “forest-based bioeconomy for a climate neutral future” (European Commission, 2021, p. 1). These developments direct forest policy objectives towards conservation of biodiversity, adaptive forest management, and the delineation of sustainability boundaries (Gordeeva et al., 2022).

The transitions in forest management paradigms - from multi-use forestry to timber production and subsequently toward biodiversity conservation and climate change mitigation - unfolded over time in response to diverse societal concerns and demands (Rauscher et al., 2005; Vacik and Lexer, 2014; Pretzsch et al., 2007). These transitions progressively introduced layers of complexity into forest management decision-making (Reinolds, 2005), necessitating the development of computer-based decision support tools to address these challenges (cf. Figure 3).

1.5. State-of-the-art in forest managment decision support

Effective forest policy implementation necessitates precise definitions for management objectives and decision-making processes. Forest management decision-making is facilitated by clear steps, starting with assessing the current state of the forest and defining management goals (problem definition stage), providing management alternatives, and assessing their potential outcomes (alternative generation stage), and aiding decision-makers in choosing the best course of action (decision stage) (Pukkala, 2002; Muys, 2010; Raucher, 2005). To assess how forest policy requirements are addressed in the decision support methods and tools, a comprehensive literature review was conducted spanning from 2010 to 2023 using the Elsevier SCOPUS database. The keywords encompassed terms related to each stage of forest management decision-making in combination with the selected sustainability dimensions (cf. Problem statement section). Specifically, the problem definition stage, involving evaluating the current state of the forest, SFM requires assessment of multiple ecosystem services that operate across various spatiotemporal scales. Therefore, the bibliographical search focused on studies assessing multiple ecosystem services on large spatial scales using periodic forest inventories, that encompass both temporal and spatial dimensions. The second stage involves generating management alternatives. SFM requirements include climate change mitigation measures, adaptive management support, natural risk assessment, and the assessment of multiple ES supply. Hence, the literature search focused on predictive modelling approaches able to simulate climate change effects on forests, integrate risks, uncertainties, and assess impacts on multiple ESs. The third decision stage involves selecting the most viable management alternatives. At this stage, SFM advocates for participatory decision-making and transparent communication regarding the impacts of these alternatives. Consequently, the literature review focused on studies aiming to engage stakeholders and the public in decision-making processes through immersive visualizations of forest management alternatives. Lastly, a literature review was conducted on forest management DSSs, aiming to understand how they address challenges related to SFM.

Following the identification of core articles through keywords, further reviews were conducted using either a snowball or systematic approach (Table 1).

Table 1. State-of-the-art review: scope and objectives

Decision support stage	Scope	SoA review objective	Method
Problem statement	Multiple ES assessment	Identify gaps and limitations in assessing the current provision of forest ecosystem services, with specific focus on spatiotemporal analyses.	Systematic review
Alternatives generation	Forest growth modelling, integration of risk and multiple ESs	Outline forest growth modelling techniques; understand how recent studies integrated forest disturbances and ESs in forest simulations.	Mixed snowball method
Decision stage	Uncertainty consideration	Understand how recent studies address future uncertainties in forest simulations.	
	Forest visualization	Review recent trends in forest visualization techniques.	
Decision Support	Decision Support Systems	Define the scope of DSS in forest management and review recent developments. Identify limitations regarding integration methods.	

1.5.1. Forest Ecosystem Services assessments

Ecosystem Services (ESs) assessment can promote sustainable and equitable forest management (Seppelt et al., 2011), by revealing areas of conflict or co-production (Sing et al., 2018). ESs assessment typically involves static mapping, that provides a snapshot of service provision at a specific time (Snäll et al., 2021). Nevertheless, ESs may change at fine temporal scales (Willemen, 2020), that can be also intensified by changing climatic patterns (cf. Albrich et al., 2018; Ma et al., 2017). As a result, static maps become quickly outdated (Snäll et al., 2021). In addressing the dynamics of ecosystem services, National Forest Inventories (NFIs) provide a robust foundation, as they rely on extended systematic periodic surveys that capture the spatiotemporal variability in forests. Hence, this literature review focused on scientific publications in the recent years related to forest ESs assessment based on NFI data. The objective here was to examine how recent studies addressed changes in spatiotemporal patterns at large spatial scales.

The search query in the SCOPUS database included the terms: *"National Forest Inventory" OR NFI AND "ecosystem services" OR "ES" OR "forest ecosystem services" OR "FES" AND "assess" OR "evaluate"* and yielded a total of 203 articles. After an initial screening based on titles, 140 articles that focused on topics related to remote sensing or urban green spaces were excluded, as they did not align with the scope of the literature review. The remaining 63 research articles underwent a more detailed evaluation, resulting in the exclusion of 41 articles that focused on qualitative methods or didn't specifically address the assessment of ESs. As a result, a total of 24 articles were ultimately chosen for inclusion in this review (the full list is presented in the Appendix i).

Table 2. Classification of the reviewed studies according to their main scope

Main scope:	Future ES assessment	ES drivers	Trade-off analysis	ES mapping	ES modelling	ES valuation
Number of studies:	7	7	3	3	3	1

The selected studies were centred on six main areas (Table 2). Future ES assessment studies employed forest simulation models to investigate the effects of management on the provision of ESs. The studies examining ESs drivers, identified drivers in terms of land use change, forest characteristics and environmental factors, and used descriptive statistic modelling approaches to quantify the influence of these drivers on single or multiple ESs. The studies conducting trade-off analyses used correlation methods to identify co-production or conflicts in multiple ESs. ESs mapping studies used both statistical modelling and Geographical Information Systems (GIS) to map spatial distribution of single ES. Modelling studies used quantitative and qualitative methods to quantify multiple ESs. Lastly, the ESs valuation study assessed the flow of benefits and the net present value in sustainable and unsustainable management regimes.

In terms of multiple ESs consideration, six studies focused on single ES: either Carbon (C) stock or wood production, while the remaining sixteen studies assessed at least two ESs. Twelve studies considered ESs associated with biomass production, from which other ESs metrics, such as C stock, timber, and dead wood, can be derived. Another twelve included additional metrics related to non-timber products and water regulation.

Most of the studies assessed ESs as a snapshot in time. For instance, the approaches employed for mapping, modelling, and valuation, assessed the current state of ESs based on NFI data. Simulation studies reported estimated ESs at the end of the simulation, therefore did not explicitly study their temporal variations. However, two studies exploring ESs drivers, considered ESs changes between inventories, with both studies being conducted in Spain. The first study (i.e., Vilà-Cabrera et al., 2017) employed linear regression to model growth rates and C stock using data from Spanish NFI2 and NFI3 for the entire Spain. The second study (Roces-Díaz et al., 2021) employed mixed-effect modelling to examine drivers affecting temporal changes in multiple ESs using the Spanish NFI2 and NFI4, and assessed their spatial variations considering four bioclimatic regions in Catalonia, north-east Spain.

In summary, the studies based on NFI data revealed limitations in addressing multiple ESs and a bias toward biomass-related quantification of their indices. Furthermore, limited consideration has been given to spatiotemporal dynamics. Although the two identified publications (i.e., Roces-Díaz et al., 2021; Vilà-Cabrera et al., 2017) did assess ESs dynamics, there is a gap in addressing how these changes evolve over time, i.e., whether they remain constant, accelerate, or decelerate.

1.5.2. Forest ecosystem modelling

Assessing the impact of management alternatives on the future state of the forest involves using predictive modelling approaches. The multitude of models available today encompass various aspects, including spatial scales (ranging from tree-level to global vegetation models), temporal scales (from hours to centuries), species considerations (single or mixed species, with, or without understorey), and the specific processes they model. These processes range from individual processes such as growth (i.e., diameter, basal area, height, and volume increment), mortality (either stochastic or influenced by biotic or abiotic factors), ingrowth (number of new trees per time step), and regeneration (e.g., seed dispersal), to combinations of these processes such as growth and yield or forest dynamics. The choice of one approach over the other depends on the specific objective of the study.

From a methodological perspective, previous review studies have categorized models into empirical, based on processes, and hybrid models (cf. Weiskittel et al. 2011). However, it's worth noting that nearly all models fundamentally combine mechanistic and empirical thinking (Adams et al., 2013; Monserud, 2003; Robinson and Monserud, 2003). All process-based models include some empirical information, and the correlative relationships of empirical models assume connection to underlying processes (Korzukhin et al., 1996; Mäkelä et al., 2000). Depending on the scope of the model, modelers may choose to emphasize physiological detail or statistical efficiency, but the ultimate goal is to achieve both biological and statistical accuracy (Vanclay, 2012). Thus, this study considers empirical approaches as those that are predominantly based on data, and process-based approaches as those that are predominantly based on scientifically grounded theory of processes that drive forest dynamics.

The following subchapters explain the basic concepts behind empirical and process-based modelling in forestry and provide examples of models from the recent literature. Given the inherent uncertainties in future projections and the increasing need to account for disturbances and multiple ESs, this review examines how forest modelling incorporates these aspects.

Empirical modelling

A common approach in empirical modelling involves constructing a mathematical function that fits the pattern of the observed data. Empirical growth models usually build upon inventory data or tree ring records (Pretzsch, 2009), and typically describe the statistical relationship between forest dynamics and site conditions, stand characteristics, and the environment (Dale et al., 1985). These models can operate at different scales, including stand, or single-tree level (Pretzsch et al., 2007). Stand-level models, such as yield tables and growth curves, were among the earliest models employed in forestry and continue to be used today (Twery and Weiskittel, 2013). Empirical individual-tree models typically use regression analyses to fit observations (Dale et al., 1985; Shifley et al., 2017). Other types of empirical models may include interconnected systems of equations (Bravo et al., 2011), or Machine Learning (ML), that emerged recently as a result of the growing amount of data and increased computer power (Jevšenak and Skudnik, 2021). Hence, "empirical modelling" pertains to data-centric approaches, where mathematical models, based on algebra, statistics, logic, ML algorithms, etc., are constructed based on empirical observations and measurements of a forest system.

Reviews by Pretzsch et al. (2015) and Bravo et al. (2019) provided state-of-the-art mixed-species empirical models in Europe. Some examples of empirical models developed recently are: a species-specific pan European diameter increment model based on NFI data from 10 European countries (Schelhaas et al., 2018a); a self-learning growth model based on Finnish NFI (Pukkala et al., 2021); species specific climate-sensitive models for stand dynamics based on Spanish NFI (Trasobares et al., 2022); growth models based on tree rings, that used both statistical and ML-based approaches (Bosela et al., 2023); and, basal area and diameter increment models that used ML algorithms (Jevšenak and Skudnik, 2021; Lin et al., 2023; Ou et al., 2019).

One common characteristic of all empirical models is that they are often constrained by the data they were originally developed for, making it challenging to apply them in different environments or novel conditions (Shifley et al., 2017). Nonetheless, these models are easier to develop and implement at larger geographical scales (Trasobares et al., 2022).

Process modelling

Process models (PMs) use mathematical formulations of explicitly stated processes or mechanisms based on established scientific understanding, therefore have a clear ecological interpretation defined beforehand (IPBES, 2016). These processes can encompass biological, ecological, or physical processes (Liu and Ashton, 1995; Mäkelä et al., 2000). Forest management studies frequently consider two types of modelling approaches driven by processes: gap and eco-physiological models. Gap models focus on how forest canopy openings influence individual tree dynamics by modelling factors such as light, temperature, and moisture (Bugmann, 2001; Bugmann and Seidl, 2022; Shugart et al., 2018). Some authors have categorized gap models into hybrid approaches (cf. Fontes et al., 2011; Peng, 2000), as they combine physical processes with empirical data (e.g., Pacala et al., 1993), while other authors place them in their own group (e.g., Bugmann, 2001; Weiskittel et al., 2011). The second type of models relies on biological and eco-physiological processes, such as photosynthesis and C assimilation (Adams et al., 2013; Kramer et al., 2002; Mäkelä et al., 2000), and usually are more data intensive in terms parameter estimation and model calibration. Both approaches rely on different processes and assumptions and may operate at different temporal and spatial scales. One common advantage is that both approaches consider climatic variables in the processes of growth, mortality, and regeneration (Figure 4), and can be used in climate change studies.

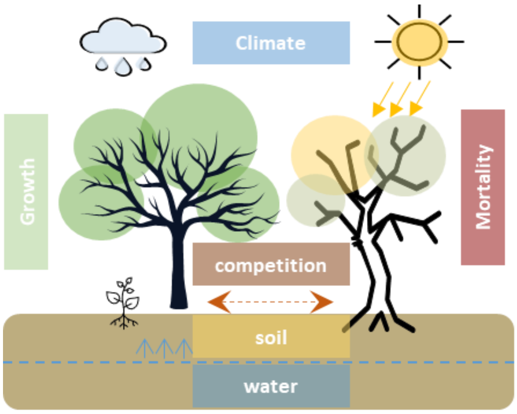


Figure 4. Schematic overview of process modelling

As the evidence of rapid environmental and societal changes increased, PMs gained popularity in forest management studies, particularly when models began incorporating harvesting regimes and user-friendly interfaces (Pretzsch et al., 2007). Additionally, with the mixed forests showing promise in adapting to climate change (Battles et al., 2007; Cotillas et al., 2009), the interest in developing PMs that account for mixed species stands grew substantially (cf. Bravo et al., 2019; Kolobov and Frisman, 2016; Porté and Bartelink, 2002). In their systematic literature review, Gonçalves et al. (2021) assessed 533 studies that employed PMs in forest research, finding that most of them focused on the impact of climate change on forests. Several recent studies that used PMs assessed: a) the response of forest productivity to climate extremes (e.g., Trotsiuk et al., 2020), b) the effects of adaptive management on C stock (e.g., Ledermann et al., 2022), c) the impact of management and climate on multiple ESs (e.g., Morán-Ordóñez et al., 2020; Simon and Ameztegui, 2023). While ecological studies and forest research often relies on PMs, practical forest management has been primarily using empirical models (Korzukhin et al., 1996). Despite the ability of PMs to depict forest dynamics under changing conditions, these models are seldom used in conventional forest management planning due to their complex structures, high computational cost, data-intensive parameterization, and species-specific calibration (Schuwirth et al., 2019).

Integration of risk

Integrating disturbances models into forest growth simulators was first discussed by Hanewinkel et al. (2010). Later, a systematic review by Yousefpour et al. (2012) analysed 112 studies integrating risk and uncertainty into forest management decision-making, revealing that 70% of the studies addressed economic risks, 20% addressed climate change risk, and the remaining 10% addressed fire risk, wind, and biotic factors. Similarly, Reyer et al. (2017) reviewed six case studies in Europe where climate-sensitive growth and yield models were combined with risk models to evaluate the joint impact of climate change and disturbances on forest production. Examples of integrated models included GOTILWA+ (Gracia et al., 1999; Nadal-Sala and Sabaté, 2013), adjusted to incorporate a fire risk model, MONSU (Pukkala, 2004) incorporating wind damage probability, and PICUS v1.5 (Lexer and Hönninger, 2001) integrating bark beetle models.

A recent review by Machado Nunes Romeiro et al. (2022), which examined studies focusing on natural disturbances and forest management, revealed a trend in projecting disturbance occurrences rather than assessing their impacts. However, several studies conducted impact assessments by integrating natural disturbances into forest management regimes. For instance, González-Olabarria and Pukkala (2011) examined the compound impact of fire risk and management regimes at both stand and landscape-scale simulations. Díaz-Yáñez (2018) presented a comprehensive framework for incorporating grazing and snow and wind damage risk into long-term forest management in Norway. This framework involved risk assessment (damage identification and modelling) and risk management (simulation and optimization). Selkimäki (2020) adopted a similar methodology, initially constructing an erosion risk model using Spanish NFI data, and subsequently assessing forest management impact on erosion risk in Catalonia, employing simulation experiments. In a more recent study, Barreiro et al. (2021) combined a forest simulator (i.e., StandsSIM.MD) with a landscape-level fire spread simulator to investigate the impact of forest management and fire occurrence on forest income and timber availability in Portugal.

Integration of ecosystem services

An increasing number of studies addresses the impact of management practices on forest ESs. A review by Başkent (2018) discusses simulation studies that assess management impacts on non-timber ESs supply. Some examples include bilberry and cowberry yields (Miina et al., 2010), mushroom production, (de-Miguel et al., 2014), cork production (Garcia-Gonzalo et al., 2015), and pine nuts yield (Calama et al., 2011). Hunault-Fontbonne and Eyvindson (2023) reviewed studies on forest planning that address biodiversity, noting that most of these studies primarily reported the outputs of forest simulators, overlooking the multi-scale aspects of biodiversity. In a similar manner, Seidl et al. (2013) addressed the scaling challenge across various management problems, including management for biodiversity and non-timber goods and services. Specific to Mediterranean regions, Morán-Ordoñez et al. (2019) reviewed 163 articles published between 1990 and 2016 that employed scenarios and models to project future ESs, reporting a lack of process modelling approaches in projecting ESs. Nocentini et al. (2022) reported 97 publications on forest management impacts on ESs conducted in the Mediterranean between 2010 and 2020. The authors found that wood production remained a predominant management objective, while C stock and biodiversity emerged as the most extensively investigated regulating services. Another review by Blanco et al. (2023) addressed several integration challenges in forest modelling, such as lack of precise biodiversity indicators, scaling issues in forest management, neglection of biodiversity in operational models, and omission of understorey vegetation in forest modelling. Nevertheless, to address scaling issues and the inclusion of multiple ESs in forest management, recent studies combined PMs with empirical ESs models (e.g., Morán-Ordóñez et al., 2020; Simon and Ameztegui, 2023).

In summary, while the number of studies in integrating ESs is increasing, there are still limitations in addressing multiple ESs, accounting for precise biodiversity indices, and assessing different spatiotemporal scales.

Uncertainty consideration

Forest modelling involves multiple sources of uncertainty that can affect the accuracy and reliability of model projections (Monserud, 2003). One source of uncertainty arises from the quality and availability of data used in the modelling process (Fortin et al., 2016). For example, tree characteristics, weather observations, and soil measurements, are among frequently used data in modelling and may have limitations in terms of accuracy, spatial coverage, or temporal resolution. Uncertainties related to parameter estimation, model calibration, and extrapolation can further affect the reliability of model outputs. Furthermore, climate projections, that are used to simulate future scenarios, are inherently uncertain due to the high variability of climate systems (Yip et al., 2011). Ultimately, the selection of the modelling algorithm can significantly impact outcomes due to biases stemming from its underlying assumptions and potential limitations (Petter et al., 2020; Thuiller et al., 2019). A common approach in uncertainty assessment, followed in the recent literature, is to evaluate simulation outputs against real data (cf. Bugmann et al., 2019). However, simulation studies have shown that future projections of forest dynamics become increasingly uncertain under the impact of climate change (cf. Thom et al., 2022). Thus, adjusting the performance of models based on empirical data does not guarantee accurate future projections. Climate change uncertainty is addressed in simulation studies by either presenting different contrasting climate change scenarios, based on Representative Concentration Pathways (RCP) (e.g., Morán-Ordóñez et al., 2021), or conveying the results of ensembles of climate projections (e.g., Thom et al., 2022). However, the contribution of forest modelling approaches to the overall uncertainty are less investigated. Two recent studies (Mahnken et al., 2022; Petter et al., 2020) assessed multi-model projections to understand how uncertainties are distributed among various factors. This method is widely used in climate projections (Yip et al., 2011), however, in forest management studies its application is still limited.

1.5.3. Immersive visualization in decision-making

Forest management and climate change impacts on forests often involve complex data, multidimensional relationships, and dynamic processes. Two-dimensional representations, such as graphs and tables, can sometimes be difficult to interpret, especially by non-experts. To address this issue, three-dimensional (3D) visualizations and Virtual Reality (VR) have been widely explored since the 1990s. In the recent years, advancements in 3D modelling and gaming technologies allowed for more realistic and intuitive representations, evolving from static images and fixed viewpoints to interactive formats that allow viewers to explore, manipulate data, and engage in “what-if” scenarios (Orland et al., 2001). Various types of data have been utilised to simulate virtual forest environments, such as 2D GIS data, remote sensing information, and forest inventory data (cf. Mingyao Qi et al., 2004). In a recent review, Murtiyoso et al. (2023) explored developments in 3D reconstruction techniques, where photogrammetry, remote sensing, and laser scanning were frequently used for landscape visualizations, often in combination with GIS technology. Additionally, synthetic 3D models have been employed for illustrating climate change and management impacts on forests (cf. Huang et al., 2020).

In the context of forest management decision-making, 3D representations have been usually employed to communicate the plans already prepared (Bell, 2001), either for informative purposes or to collect public opinion on different management scenarios. For instance, Huang et al. (2020) developed a VR application based on landscape-level forest simulations, which the authors shared with the indigenous community in Wisconsin, USA, to raise awareness about climate change impacts. However, communicating the simulated beforehand alternatives can create the perception of predetermined decisions, and hinder public participation (Orland et al., 2001). Recently, Fabrika et al. (2018) developed a VR application that allows creating management alternatives interactively and visualizing consequences of these alternatives.

In summary, 3D visualizations have been long explored in the context of forest management, mainly to present management plans to stakeholders and the public. However, there is a gap in exploring the efficacy of this form of visualisation in forest management decision-making.

1.5.4. Decision support systems

While previous sections addressed single facets of the decision problem, this review focuses on the integration of decision support tools under a common framework, known as Decision Support Systems (DSSs). Definitions of DSSs vary across cultures and disciplines, focusing either on system architecture, on the modelling approaches, or on the decision method (Olson, 2008). Gorry and Scott Morton (1971) suggested that the information systems supporting semi-structured and unstructured decisions should be termed “decision support systems”, thus coining this term in the literature. Definitions of DSSs often list the components of the system, i.e., data, models, and interfaces, such as the one attributed to Sprague (1980, p. 1), and widely adopted across disciplines:

DSSs are interactive computer-based systems, which help decision-makers utilize data and models to solve unstructured problems.

The component-driven definition is not always followed in the literature, with some authors using the term DSS more loosely to refer to any tool that would provide decision support (Reynolds and Hessburg, 2014; Sprague, 1980). Indeed, following Gorry and Scott Morton perspective, that categorized DSSs on the type of problem they solve (structured versus unstructured), every Decision support Tool (DST) is a type of DSS with different levels of detail, functionality, and complexity, which provide support for one or more stages of the decision-making process (Fatmah, 2008).

A less restrictive definition in terms of system components was adopted from Holsapple (2003, p. 551) and adapted to forest DSS by Reynolds (2005):

A DSS is a computer-based system composed of a language system, presentation system, knowledge system, and problem-processing system whose collective purpose is the support of decision-making activities.

Here, the authors shifted their focus away from specifying a particular technology and instead provided a more generic architectural approach. This definition integrates the database and model base into what is termed the *knowledge system*, while the user interfaces correspond to the *presentation system* and *the language system* (cf. Figure 5). Since it does not prescribe a particular technology, a spreadsheet could potentially replace the database.

Rauscher (1999) places decision-makers in the centre of the system, emphasising the importance of negotiation and group decision-making. The technological components outlined by the author encompass the knowledge base, the simulation model, the help component, and data visualisation management component. These components are designed to manipulate knowledge in the forms it is stored, represented, or coded.

Muys et al. (2010, p. 87) combining technical and functional descriptions, defined forest management DSS as a collection of tools that *provide support to ill-structured problems by integrating a user interface, simulation tools, expert rules, stakeholder preferences, database management and optimization algorithms.*

Similarly, Vacik and Lexer (2014, p. 3) defined the technical components while also addressed expert knowledge, stating that DSSs should be tailored to specific decision-making activities:

DSSs comprise computer-based tools which provide support to solve ill-structured decision problems by integrating database management systems (DBMS) with analytical and operational research models, graphic display, tabular reporting capabilities and the expert knowledge of scientists, managers and decision makers to assist in specific decision-making activities.

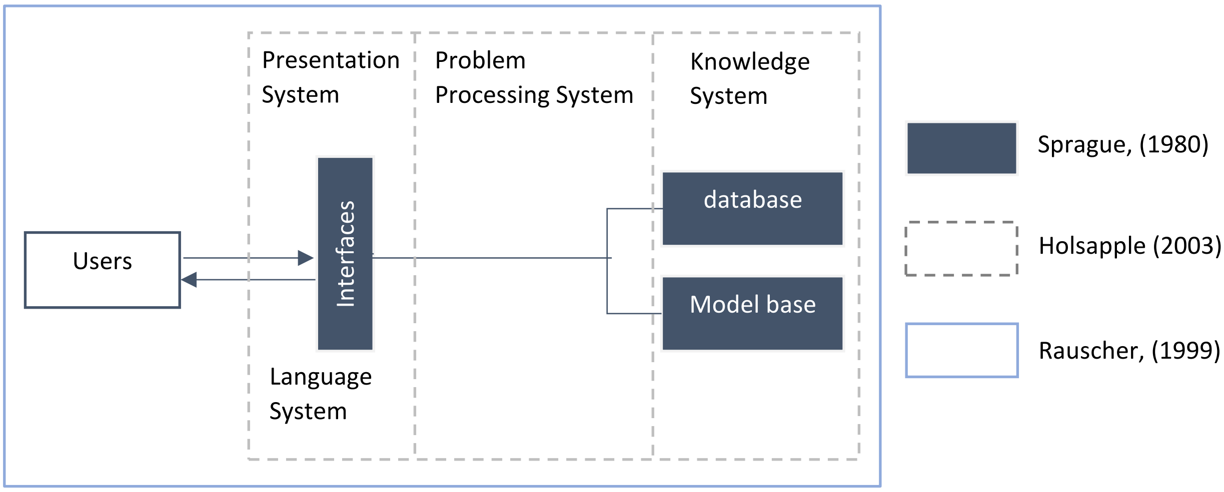


Figure 5. DSS architecture according to Sprague (1980), Holsapple (2003) and Rauscher (1999)

All the above definitions recognized that DSSs should be employed to ill-structured decision problems, by integrating different components and providing a unified user interface. In an ideal scenario, a DSS should cover all the steps in forest management decision-making in a user-friendly manner. However, Reynolds (2005) argued that integrating DSTs for forest management is a vast and complex task, making it too ambitious to complete in a single development cycle. Undeniably, Sustainable Forest Management (SFM) imposes assessments at various scales (Seidl et al., 2013), where operational, tactical, and strategical management planning require distinct decision processes (Vacik and Lexer, 2014). Moreover, involvement of stakeholders in the decision-making (Acosta and Corral, 2017; Kangas, 1994) adds another layer of complexity in the development of a "full stack" DSS. To address this complexity, Gordon et al. (2013) proposed narrowing the scope of the DSS to focus on specific management issues, whereas Reynolds (1999b) advocated for a generic DSS that relies on expert knowledge and can adapt to any management problem.

Another aspect of DSSs pertains to the way different components are combined, either through composition or integration. In the composition approach, DSS components function independently of each other. For instance, the SADfLOR DSS (Marto et al., 2016) follows a modular design, incorporating various process-based and empirical growth models, a trade-off analysis module (Garcia-Gonzalo et al., 2015) and a management-oriented interface (Barreiro et al., 2016). While in the integration approach, the components are interconnected and rely on each other. For instance, SILVA DSS (Pretzsch et al., 2002), integrates monetary values related to harvesting and biodiversity indices into a forest growth simulator (Nordström et al., 2019).

Several review studies conducted between 2014 and 2019, tackled different aspects in the development of DSSs. For example, Segura et al. (2014) discussed different aspects of DSSs in Europe, categorising them depending on their temporal scale (short-term, mid-term, long-term), spatial scale (stand, landscape, and regional level), the number of decision-makers they can involve, the number of considered objectives, and the number of the addressed ecosystem services. Vacik and Lexer (2014) focused on historical trends in DSSs, emphasising the growing complexity reflected in these systems, which the authors attributed to emerging challenges and an enhanced understanding of natural systems. In a more recent review, Nordström et al. (2019) examined how nine state-of-the-art forest DSSs in Europe address ecosystem services at the landscape level.

Despite the continuous development and improvement in various aspects of DSSs, their practical implementation remains limited. Linkevičius et al. (2019) conducted a qualitative analysis focusing on the use of DSSs in forest policy-making, indicating that users often lack confidence in employing these tools. The authors attributed this to the complexity of the systems, which are typically designed by and for scientists, and may not be well-suited for policy processes. Additionally, when consulting scientists, the authors noted that forest policy issues tend to emerge more rapidly than DSSs can be developed to address them. To enhance trust in DSS outcomes, Borges et al. (2014) stressed the importance of involving stakeholders in the development process. While Vacik and Lexer (2014) emphasized the need of simplicity and user-friendliness of these systems, especially given the increasing prominence of public involvement.

Walling and Vaneeckhaute (2020) reviewed 405 studies focusing on environmental DSSs and identified three major challenges that hinder their successful implementation. The first challenge is stakeholder-oriented and refers to the understanding the system's purpose and aligning it with user needs. The second challenge is model-oriented, that refers to the identification of problem types (structured, unstructured, semi-structured), the selection of models and algorithms, and the management of model complexity and uncertainties in the outputs. The third challenge is system-oriented and pertains to the visualization, communication of results, and the overall user-friendliness of the system.

In summary, forest management DSSs employ computer-based tools and models to aid decision-making (Rauscher et al., 2005) by integrating scientific knowledge and data with user-friendly interfaces (Vacik et al., 2015). They may encompass components such as data management, simulations, scenario analysis, risk assessment, visualization, and decision algorithms (Borges et al., 2014), aiming to evaluate management alternatives, assess trade-offs (Garcia-Gonzalo et al., 2015), and analyse potential climate change impacts (Yousefpour et al., 2017). Most of the DSSs do not encompass all the decision steps, and usually are restricted to the outputs of a forest simulator, which delineates the spatial context, spatial scale and the number of the ESs considered (Segura et al., 2014). Recent review studies have consistently reported the limited practical adoption of DSSs, primarily due to model and interface complexity and a failure to adequately identify stakeholder needs (cf. Linkevičius et al., 2019; Walling and Vaneeckhaute, 2020).

1.6. Gaps and opportunities

Forest management decisions have become increasingly complex, requiring decision-makers to balance multiple objectives amidst high levels of uncertainty stemming from various sources, including assumptions in forest modelling and climate change projections. As a result, a plethora of tools has emerged. This literature review tracked the evolution of the DSTs in response to policy requirements and technological advancements. The state-of-the-art (SoA) review focused on DSTs tailored for different stages and aspects of forest management decision-making.

To address the first decision-making stage, the SoA review focused on studies that use NFI data to assess forest ESs at large spatial scales. Most of the reviewed approaches adopted a static perspective, evaluating ESs as snapshots in time. Temporal changes were addressed in two studies, as the difference between two points in time. However, to guide strategic management goals, it is important to examine whether these changes remain consistent or if they are accelerating or decelerating, and what are the underlying factors driving these changes. Despite the acknowledgement of the importance of ESs temporal dynamics, there is a general lack of frameworks that could integrate them into ESs research (Rau et al., 2018). Similarly, regarding the spatial variation of the ESs dynamics, most of the studies considered global statistical approaches. To address spatial heterogeneity, these global approaches were applied to spatial subdivisions defined beforehand (cf. Roces-Díaz et al., 2021). However, ESs may exhibit variations across scales, that require methods that can capture ESs changes as a continuous spectrum rather than discrete subdivisions and should be able to adjust scales according to the specific ES under consideration.

To address the second stage in decision making, i.e., generation of management alternatives, the SoA review revealed a plethora of modelling approaches, spanning from pure empirical stand level models to models based on plant processes and their interaction with the environment. Studies assessing management and climate change impacts on forest dynamics, typically perform simulation experiments using process-based models, where management alternatives are defined beforehand. However, an adaptive management approach requires adjusting management prescriptions to new forest condition, e.g., the ones stemming from climate change impacts on forests. Therefore, these models should be adapted accordingly.

Forest management planning is inherently uncertain (Pukkala, 2002). Most of the simulation studies addressing forest management impacts, report results based on a single forest model and different climate change scenarios, where the uncertainties are attributed solely to the climate models. However, forest models differ greatly in their underlying assumptions, which can lead to divergence in results and uncertainties in the outputs (Monserud, 2003; Petter et al., 2020). Recent studies addressed this issue by multi-model assessment (e.g., Petter et al., 2020). While this concept is widely used in climate studies, in forestry it has received little attention.

The review of integration techniques revealed shortcomings related to consideration of multiple ESs in simulation studies and a lack of attention to risk impacts. A distinct bias toward ESs associated with biomass was observed, largely stemming from model simplifications that focused primarily on tree species, neglecting for example understorey vegetation (cf. Blanco and Lo, 2023; Morán-Ordóñez et al., 2019).

Regarding immersive visualization methods, the literature recognizes their role, primarily for effective stakeholder communication and participatory planning. However, VR technologies hold substantial potential for enhancing decision-making processes. Nonetheless, there is a lack of empirical evidence proving the actual effectiveness of this form of communication in forest management decision-making.

The review of DSSs in forest management revealed a range of definitions and approaches. While the common definition pertains to the integration of data, models, and interfaces (Sprague, 1980) that guide decision-makers through the decision-making process (cf. Simon, 1960), in practice, many DSSs tend to focus on specific facets of this process. This approach is not inherently problematic, when considering the perspective that any system facilitating a decision-maker in reaching conclusions can be classified as a DSS (cf. Burstein and W. Holsapple, 2008). However, considering new policy demands for adaptive management approaches, it is important that the DSSs integrate the different hierarchical levels of forest management planning and consider different spatial and temporal scales in data management and analysis. Moreover, the sustainable management criteria suggest assessing multiple ESs when delivering management alternatives and including stakeholders and the public when deciding what alternatives to implement. This leads to the need of a holistic approach in DSS design and development. Recent review studies have reported a limited practical adoption of DSSs, primarily due to model and interface complexity and a failure to adequately identify stakeholder needs. (cf. Linkevičius et al., 2019; Walling and Vaneeckhaute, 2020). While some studies have addressed some of these limitations, for instance by proposing a management-oriented design (e.g., Barreiro et al., 2016), there is a need for a more systematic approach in addressing DSSs usability.

In conclusion, the DST landscape in forest management spans various scales and complexities. This review addressed some limitations and revealed opportunities for new research. Key areas include a deeper exploration of spatiotemporal aspects in forest ESs assessments, addressing uncertainties stemming from modelling approaches, exploring effective visualizations and communication methods in conveying scientific outputs, and quantifying their usability in forest management. Overall, there is a need for integrating adaptive and sustainable forest management concepts into decision support systems.

1.7. Research objectives

This doctoral thesis aims to address sustainability challenges in forest management through a systematic decision support framework. Systematic decision-making involves 1) establishing strategic goals, 2) proposing management alternatives adhering to these goals, and 3) selecting the optimal course of action (cf. Simon, 1960; Pukkala, 2002). Sustainable forest management, as stated earlier, a) defines ESs as an umbrella framework to integrate its economic, social and environmental aspects, b) promotes the adaptive management concept and c) encourages participatory decision-making (cf. Problem statement section). At each decision-making stage, the SoA review revealed shortcomings in addressing the abovementioned SFM dimensions (cf. Gaps and opportunities section). At the first stage of establishing strategic management goals, ESs research based on NFI data revealed limitations in accounting for spatiotemporal changes and varying operational scales. At the stage of proposing management alternatives, studies assessing management prescriptions under climate change showed limitations in employing adaptive simulations and in quantifying uncertainties from process-based models (required for transparent communication of results). At the stage of alternative evaluation using participatory approaches, studies on immersive visualizations (required in involving stakeholders and the public in choosing alternatives) were limited in determining the practical value of Virtual Reality (VR) in decision-making.

The current thesis addresses these limitations by operationalizing SFM criteria in systematic forest management decision-making. This is accomplished through the implementation of case studies for each decision-making stage, where sustainability principles are translated into tangible methodologies. The final goal is to establish a comprehensive Decision Support System (DSS) framework that integrates sustainability principles into forest management. To reach this goal, specific objectives are outlined, corresponding to a particular decision-making aspect or module within the DSS framework. The defined objectives are implemented through the abovementioned case studies, gradually unfolding the technological requirements for the DSS implementation.

Objective 1. Facilitate the integration of geographically oriented strategic management planning into the DSS framework.

Establishing strategic goals requires prioritizing management zones, that can be achieved by assessing multiple forest ESs across large spatial scales. The state-of-the-art review revealed that forest ES assessments typically involve static approaches or consider consistent (linear) changes over time. Few studies that assessed spatial dynamics used global methods, where ESs across large spatial scales were assessed as a single entity. Yet**,** forest ESs exhibit heterogenous spatial and temporal dynamics, and the choice of both spatial unit and temporal window may lead to conflicting management objectives.

To understand the contribution of the ES spatiotemporal assessment for decision-making in strategic forest management, the first case study asked fundamental questions regarding temporal and spatial dynamics in forest ESs, their drivers, and interactions.

Research question 1. What spatial and temporal patterns characterize changes in forest Ecosystem Services (ESs) and how it may affect management decisions?

This question aims to explore the recent spatiotemporal changes in ESs observed between consecutive forest inventories. If these changes remain stable over time, conventional methods of assessing snapshots in time may effectively assist in shaping future management objectives. On the other hand, if these changes show acceleration or deceleration, alternative techniques considering the factors driving non-stationarity should be considered.

The hypothesis posits potential deceleration in in the overall ESs temporal dynamics, particularly in ESs derived from forest attributes, consistent with previous studies (Astigarraga et al., 2020). No specific hypothesis exists for periodic ESs such as mushroom production. ES dynamics are expected to exhibit spatial variability, potentially demonstrating accelerated changes (cf. Thom and Seidl, 2022).

Should ES changes show non-stationarity, investigating the drivers underpinning spatial heterogeneity alongside assessing their temporal variability becomes crucial for informing decision-making.

Research sub-question 1a. What are the main drivers of changes in forest ESs, and how they vary in space and time?

ESs emerge from the interplay of socio-ecological drivers which interact across scales (Hedwall et al., 2021; D. Li et al., 2022; Xia et al., 2023). Identifying these drivers and understanding their behaviour can aid in establishing sustainable management objectives aligned with ecosystem needs. Previous research based on NFI data showed limitations in accounting for temporal dynamics, while spatial analyses were typically focusing on regional averages, without considering the continuity of the geographical space. Yet, ESs may transcend arbitrary boundaries and exhibit interconnection across landscapes (Rodríguez et al., 2006). These limitations are addressed by employing a non-parametric geographically weighted algorithm, that treats the geographical space as a continuum and accounts for the non-linear relationships between ecosystem services and their drivers. To answer the research question, the relationship between each individual ES is examined against its direct and indirect drivers and for each time interval between inventories.

The hypothesis posits that forest attributes may be the primary drivers for multiple forest ESs, consistent with recent studies (Felipe-Lucia et al., 2018; Roces-Díaz et al., 2021), however they may change in time given that tree life circles are characterized by non-linear temporal patterns (Rau et al., 2018). Their spatial variability is expected to follow biogeographical regions (cf. Roces-Díaz et al., 2021), however, it might depend on the variability in the ESs operational scales, which leads to the following question:

Research sub-question 1b. Given the multiple scales at which Ecosystem Services (ESs) operate, how are their interactions manifested spatially, and how do these interactions change over time?

The differences in ESs operational scales are widely recognized in the literature, however, limited attention has been accorded to address their cross-scale interactions. Yet, these interactions generate behaviours that cannot be assessed based on observations at single or multiple independent scales (Peters et al., 2007). Here, a multi-scale geographically weighted regression (MGWR) is applied on pairs of ESs, and for each NFI interval, to identify the trade-offs and synergies in their temporal dynamics. MGWR allows the parameter-specific scale of the relationship between pairs of ESs to vary, enabling local (spatially non-stationary) and global (stationary) relationships between them (cf. Chang Chien et al., 2020).

The hypothesis, rooted in MGWR's ability to operate within spatially varying contexts, suggests that ESs functioning at similar scales might exhibit outcomes on a broader, more global scale. For instance, timber production and C storage could display a synergistic relationship across the entire study area.

Conversely, ESs operating at different scales might demonstrate varying degrees of localized effects. The temporal variability of these interactions is expected to diverge (cf. D. Li et al., 2022; Shen et al., 2020), since the ESs are acknowledged to change nonlinearly in time (i.e., periodically, episodically, or permanently) (Bastian et al., 2012). However, these temporal changes are anticipated in magnitude and location rather than in direction.

Objective 2. Facilitate adaptive management approach in the DSS development while considering modelling uncertainties.

The second phase in forest management decision-making refers to the development of management alternatives in compliance with the strategic goals. If spatial planning is considered, the landscape is divided into management zones, where management alternatives are proposed for each zone. A management alternative involves structured action plans (prescriptions) designed to change the forest over time, alongside with an impact assessment (Rauscher et al., 2000). The impact assessment is usually done using forest simulation models. Complying with SFM principles, these models should be able to assess how the management prescriptions and climate change may affect forest dynamics and associated ESs and consider the uncertainty in future projections.

Assessing pre-defined prescriptions remains the status quo for supporting silvicultural decision-making for future forest management (Knoke et al., 2020). Yet, these approaches may not comprehensively offer adaptive management solutions within the climate – management nexus. Moreover, they often overlook uncertainties arising from modelling assumptions (cf. Monserud, 2003). Addressing these limitations require simulation models able to modify management prescriptions based on forest responses to climate change scenarios. To account for modelling uncertainties, more than one forest simulation models should be considered. An important question arises at this point, on how well current management recommendations can fare under the future climate, and subsequently, how the choice of the simulation tool can affect the response to this question.

Research question 2. How current management recommendations perform under future scenarios of climate change in different sites?

This question is addressed by the means of a rule-based simulation experiment on *P. Sylvestris* stands along an aridity gradient, using two process-based forest dynamics simulators, namely, SORTIE-ND (Canham et al., 2005) and GOTILWA+ (Nadal-Sala and Sabaté, 2013) and three climate change scenarios. The management configurations are explicitly adapted to accommodate specific objectives outlined in the recent regional management guidelines.

The results are anticipated to show conformity of the management guidelines with the current climate, while climate change scenarios are expected to modify forest attributes as function of their severity and site conditions (Ameztegui et al., 2015; Thom et al., 2022). Based on the rule-based "adaptation" of management, the timing of the prescriptions will be adapted to the modified by climate change forest, which will depend on the underlying assumptions of the forest simulators. Based on the empirical evidence however, heavy thinnings are expected to shorten the rotation periods and alleviate climate change impacts due to competition reduction (Navarro-Cerrillo et al., 2019; Sohn et al., 2016).

Research sub-question 2a. What are the factors contributing to the variation of the simulation outputs and how the choice of the simulator can potentially affect management decisions?

The answer this research question builds upon the outputs of the simulation experiment and is addressed by quantifying the relative importance of the simulation tool, climate change scenarios, stand location, and management alternatives on the outputs of both simulators, using variation partitioning.

Due to the inherent differences in the underlying assumptions of the process models, it is anticipated that the simulation results will diverge. Similar approaches using landscape models showed that the simulation tool was the main factor contributing to the variation of the outputs (cf. Petter et al., 2020). However, considering that this study focuses on management across different site conditions, it is likely that both management and site will significantly contribute to these variations.

Objective* 3. *Develop immersive visualizations linked to the simulation outputs and assess how this type of communication convey management implications, particularly in facilitating participatory decision-making processes.

The third phase of decision-making entails choosing management alternatives, which may involve disseminating the results to stakeholders and the public, soliciting their feedback, and potentially refining management plans. Traditional tabular and 2D visualizations are effective decision-making tools, but they may not be familiar to stakeholders and the public, potentially impeding their engagement in the decision-making process. Immersive visualisations of forest simulations can improve decision-making, particularly in the context of participatory approaches, yet there is no evidence of their effectiveness.

Research question 3. Can 3D modelling and Virtual Reality (VR) improve decision making in forest management?

This question is addressed by conducting an online survey, aiming to collect feedback on the effectiveness of immersive visualizations in forest management decision-making. The survey results are likely to vary among respondents based on their familiarity and acceptance of immersive technology. Overall, it is expected that opinions will converge towards recognizing the usability of Virtual Reality (VR) in enhancing understanding of complex phenomena, which in turn is expected to aid decision-making processes in general.

***Objective 4.* Develop a holistic framework to support systematic decision-making in forest management.**

To aid adaptive and sustainable forest management in compliance with forest policy demands, a holistic approach in decision-making is needed. This may include integration of management planning levels, multi-scale assessments, consideration of multiple ESs and involving stakeholders in decision-making. The challenge to translate SFM principles into operational criteria of developing a forest management DSS was approached in the previous research questions by a) addressing multiple ESs across spatiotemporal scales, b) adapting management prescriptions to the climate change effects, c) increasing transparency in communicating the impact of management alternatives and d) facilitating the understanding of simulation outputs by providing immersive visualizations. Hence, to achieve the final objective, it is essential to integrate these criteria into a functional DSS architecture. The main concern is how to attain practical adoption of the system, particularly when addressing complexities associated with making sustainable management decisions at different levels.

Research question 4. What design principles and technical specifications should be prioritized in developing a Decision Support System (DSS) for sustainable forest management that improves its usability?

The answer to this question starts with identifying the system requirements. DSSs, by definition, require the integration of data, models, and intuitive visualizations. Previous research questions have laid the foundation for the technical specifications aligned with SFM criteria. Once the system requirements are established, the subsequent step involves defining the typology and design of the DSS, aligning them with users and system requirements. Therefore, it is important to define the minimum requirements for components integration and identify complementary tools for system composition. To address system usability, usability evaluation surveys and users feedback are needed at different stages of the system development.

Accommodating all decision support tools needed for each stage of decision making into one integral system could be a challenge, considering the different technological requirements, as suggested by Reinolds, (2005). In addition, end-users might be accustomed to broader-use software systems (e.g., spreadsheets), to support their decisions. Hypothetically, a system architecture that merges an integration of essential components through a single user-friendly interface, with additional auxiliary tools might improve the general acceptance and adoption of DSSs.

1.8. Thesis structure

The introductory chapter set the problem and traced the evolution of Decision Support Tools (DST) over time, considering technological advancements and policy developments. The subsequent state-of-the-art review highlighted specific gaps and opportunities in addressing key aspects of sustainable forest management, contributing to the formulation of the research objectives and the tailored research questions. Following, each research objective is approached by a case study addressing these research questions. The methodology section describes the study area and navigates progressively through the methods applied in each of the cases studies. Similarly, the results and discussion sections address each topic formulated in the case studies. Finally, the thesis summarises the general conclusions and future perspectives and concludes with the 10 theses (Figure 6).

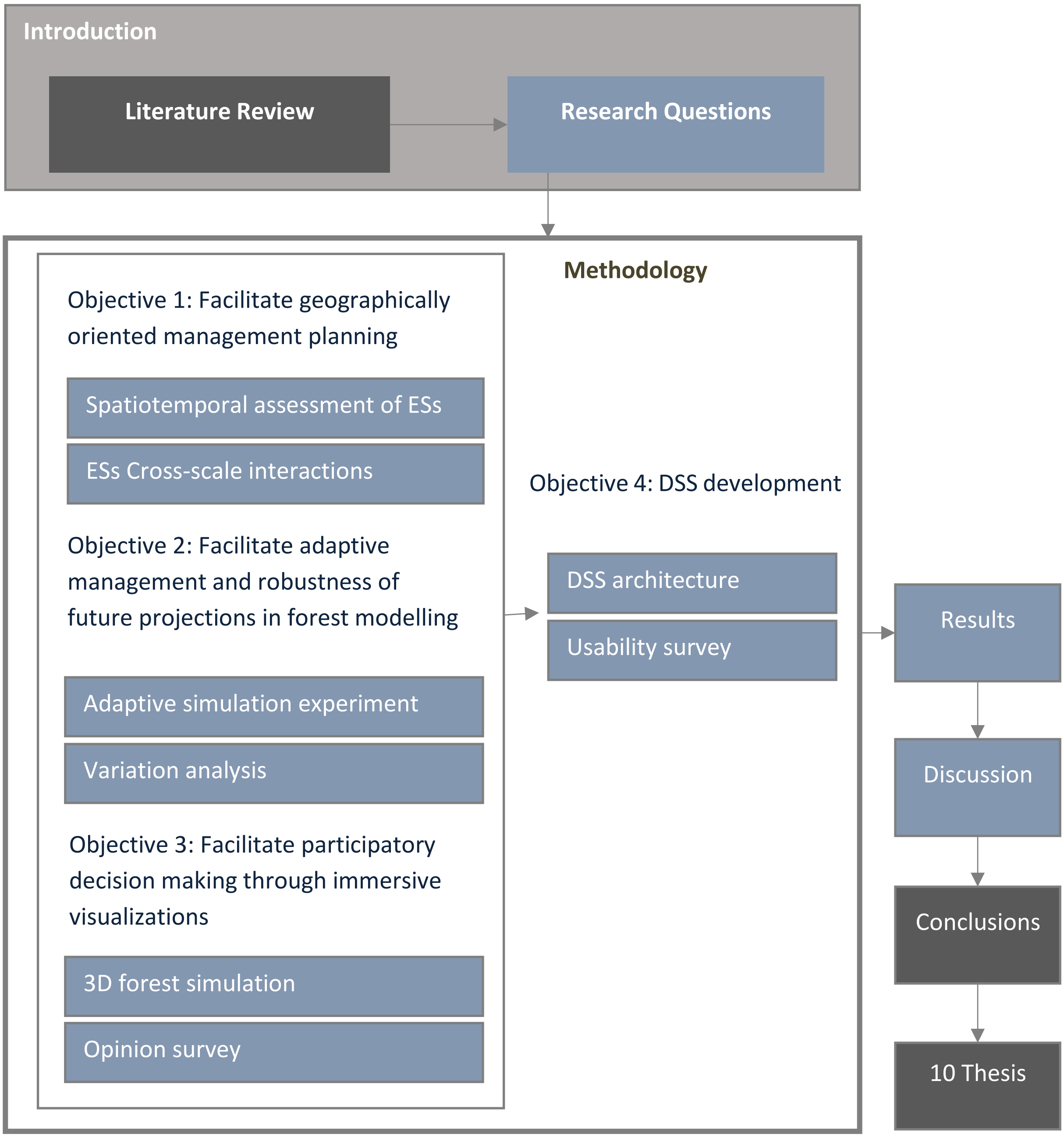


Figure 6. Thesis structure

2. Methodology

2.1. Research outline

To achieve the outlined objectives, the workflow initiated with data collection and pre-processing, encompassing forest and climate data (Figure 7). The first objective required quantifying Ecosystem Services (ES) and identifying their potential drivers, which are needed to explore specific research questions regarding spatiotemporal variations in multiple ESs dynamics, as well as their interactions over space and time (case study I). The second objective involved simulating virtual stands based on National Forest Inventory (NFI) locations, under climate change scenarios, and subject to management alternatives aligned with regional recommendations. These simulations followed an adaptive management approach utilizing two forest dynamics simulators, and their outputs were analyzed using variation partitioning (case study II). Addressing the third objective, the simulation outputs were translated into immersive 3D virtual stands. An online survey assessed the effectiveness of these immersive visualizations in facilitating forest management decision-making (case study III). Finally, insights from all three case studies were integrated to establish the foundation for the development of the Decision Support System (DSS) framework (case study IV).

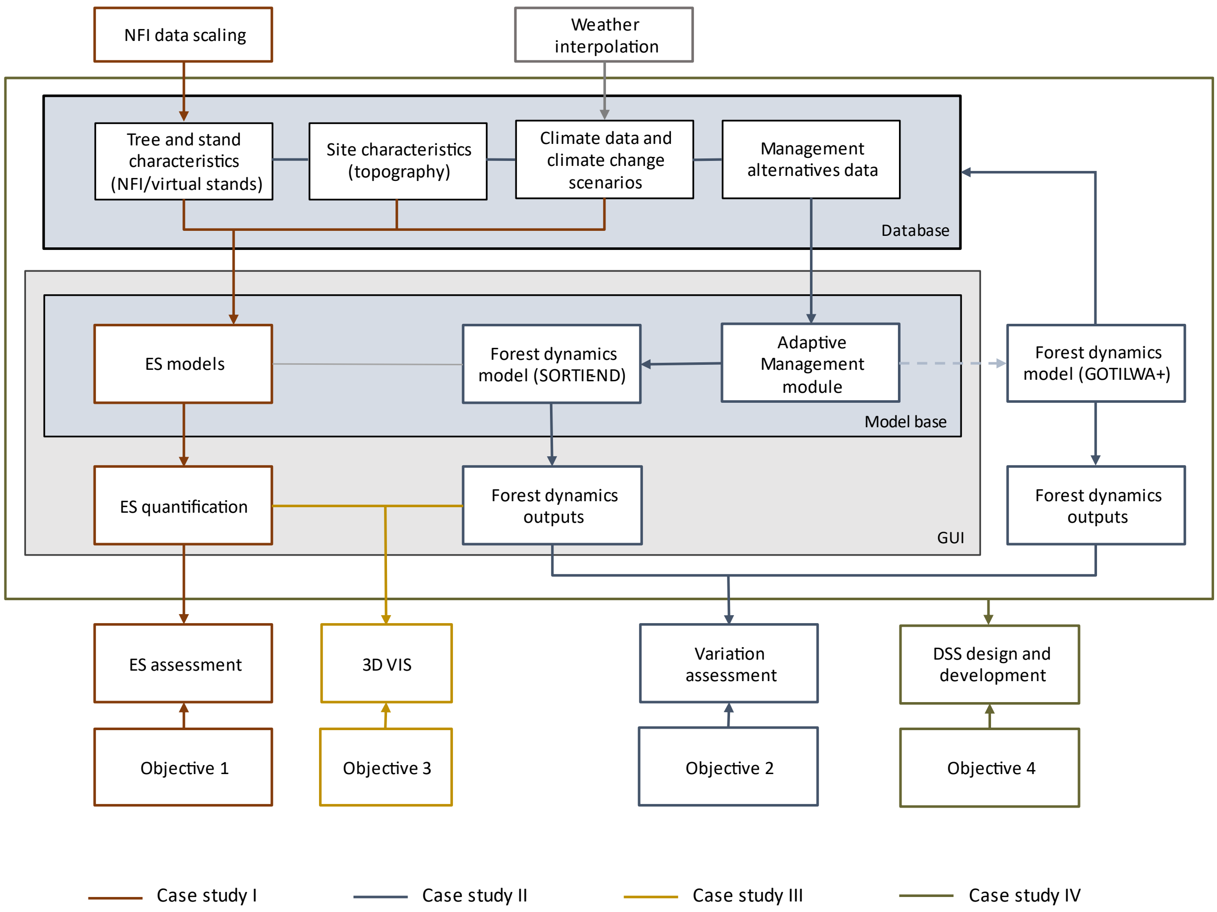


Figure 7. The workflow and connections with the thesis objectives, the case studies, and the DSS components

2.2. Study area and data

2.2.1. Forests and forest management in Catalonia

The study area covers the sub-Mediterranean and subalpine coniferous forests in Catalonia, northeastern Spain (Figure 8), focusing on *Pinus sylvestris L*. (Scots pine), *Pinus nigra Arn. spp. salzmannii (Dunal) Franco* (black pine), *Pinus uncinata Ram.* (mountain pine) and *A. alba* (European silver fir) tree species. These species collectively occupy a significant portion of the total forested area, comprising approximately 36% where they are dominant and approximately 23% where they form mixed forests. *Pinus sylvestris* holds particular importance in the region due to its high timber production and wide distribution: it grows at altitudes ranging from 800 to 1600 meters above sea level (m.a.s.l.). *Pinus nigra*, which is also used for timber, thrives at elevations between 500 and 1000 m.a.s.l. *Pinus uncinata*, the second most abundant species in the Pyrenees and pre-Pyrenees mountain ranges, flourishes at high altitudes between 1800 and 2400 m.a.s.l., although sometimes it can also be found at lower elevations. *A. alba* is a relatively rare species in the Catalan forests, occupying approximately 2% of the total forested area. It grows at altitudes ranging from 800 to 2200 m.a.s.l.

Mediterranean forests have long been recognized as biodiversity hotspots, offering a multitude of ESs that have sustained communities for centuries (Myers et al., 2000). Within the Mediterranean region, Spain, in particular, has a history of intensive management that have shaped forest development over time (Soler-Sala, 2019; Valbuena-Carabaña et al., 2010). However, past decades have witnessed a substantial rural exodus, resulting in the abandonment of agricultural land. This transition had facilitated the expansion of forests, that enhanced the provision of ESs in montane areas. While this expansion serves as a valuable carbon sink and protects soil from erosion (Varela et al., 2020), it also increases the risk of wildfires (Jordi Vayreda et al., 2012). Recent years have evidenced a notable forest decline, mainly attributed to droughts and the escalating frequency and intensity of wildfires, which are anticipated to worsen due to changing climatic patterns (Martinez-Vilalta et al., 2019; Pausas et al., 2012; Tague et al., 2021). Furthermore, disturbances such as pest outbreaks and diseases are deeply affecting forest dynamics, subsequently lessening the provision of ecosystem services (Lindner et al., 2010; Seidl et al., 2014).

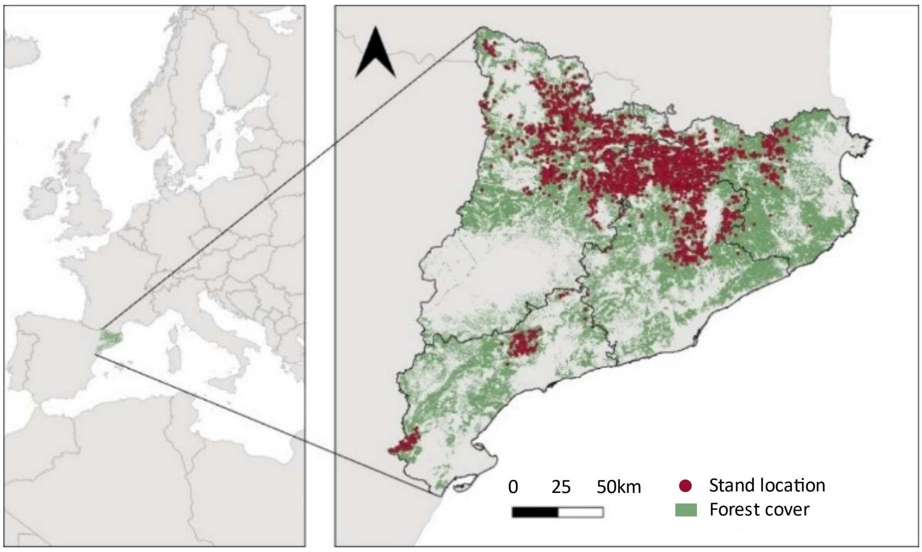


Figure 8. Study area and location of the stands

ORGEST: sustainable management of Catalan forests

Forest ownership in Catalonia is 22% public and 78% private, with family small-scale forestry being the most common. Approximately 95% of these owners possess less than 25 hectares, while the remaining 5% own more than 25 hectares. The Forest Ownership Centre (CPF), established in 1988, aims to promote sustainable forest management in private forests, primarily through the approval of forest management plans. These plans are voluntary; however, they are encouraged through tax reductions, insurance options, and priority access to subsidies. To aid management plans, CPF has published various guidelines and suggested management models for different forest types, known as ORGEST, which translates as Sustainable Forestry Management Guidelines (Piqué et al., 2017). Table 3 to 5 illustrate management models for *P. sylvestris* stands. Stand structure is described in terms of mean tree height, stand density, mean DBH, and age. Management is proposed by varying the frequency and intensity of thinnings, depending on site conditions, and the final harvest is proposed by implementing the shelterwood method. The shelterwood method involves a gradual removal of old trees while retaining healthy "seed trees" to encourage new tree ingrowth and create a structurally diverse forest ecosystem. The process comprises three stages: preparatory stage, establishment stage, and regeneration stage.

Table 3. ORGEST models specifications

Code	Thinning frequency (years)	Thinning intensity	Stand structure	Final DBH (cm)	Rotation period (years)
Ps08	17-29	light	regularized	40	115-140
Ps09	15-27	heavy	regularized	35	100-125

Table 4. ORGEST model Ps08: medium site quality and low fire risk on pure *P. sylvestris* stands

H (m)	N ($trees^{-ha}$)	DBH (cm)	BA ($m^{2\ -h}$)	Age	Harvest type	N to cut ($trees^{-ha}$)	BA to cut (%)
10.5	1500	15	27	36-44	thinning	450	11
14.5	1050	23	42	56-70	thinning	450	26
17.5	600	31	43	79-99	thinning	300	30
19.5	300	40	40	100-125	preparatory	135	43
20	165	40	23	107-133	establishment	90	52
20.5	45	40	11	114-142	regeneration	75	100

Table 5. ORGEST model Ps09: medium site quality and low fire risk on pure *P. sylvestris* stands

H (m)	N ($trees^{-ha}$)	DBH (cm)	BA ($m^{2\ -h}$)	Age	Harvest type	N to cut ($trees^{-ha}$)	BA to cut (%)
13	1100	21	35	48-59	thinning	500	29
17.5	600	35	43	79-99	preparatory	250	40
18.5	350	35	28	89-110	establishment	200	54
19.5	150	35	14	100-125	regeneration	150	100

2.2.2. Spanish National Forest Inventory

For monitoring the status and development of forests, European countries have implemented national sampling frames (Gschwantner et al., 2022). The Spanish National Forest Inventory (NFI) uses a stratified sampling design based on volume uniformity and forest type relevance for management (Alberdi et al., 2017). To define forest strata, dominant species, crown coverage, and development stage were considered based on aerial photographs and forest maps (Fortin et al., 2016). The systematic campaign, with the establishment of permanent plots, started in the second inventory (NFI2) in the 1980s. Subsequently, it has been conducted at approximately 10-year intervals with the third (NFI3) and fourth (NFI4) inventories. Plots' locations follow a regular grid of 1km^2, ensuring a systematic design and consistent sampling intensity. Each permanent plot consists of four concentric circular subplots, with radii 5, 10, 15 and 25m (Figure 9). Trees within the concentric circles are measured based on DBH thresholds, the inner circle having the lowest (7.5 cm) and the outer the highest DBH threshold (>42.5 cm) (Figure 9 left). Species identity, DBH, height, distance from the plot centre and azimuth are recorded for each tree. Dead and damaged trees, as well as recruits – trees that reach the minimum DBH within the inventory interval - are recorded during the revisit of plots. Land use changes led to the omission of some plots during revisits. Additionally, new permanent plots were established to cover new forested areas.

The sample plots are used to scale up trees to 1 ha stand level, which is considered the forest management unit. Scaling up entails calculating how many times the area of the circular plot is contained inside the area of a stand (Figure 9 right). To calculate the scaling factor *k,* the area of the stand (here, 1 ha or 10000m^2) is divided by the area of the plot:

$$k = \frac{10000\ (m^2)}{\pi r^2\ (m^2)}$$

Table 6 provides the scaling factor for each concentric circle and the corresponding DBH class. Multiplying each sampled tree by the scaling factor gives an estimate of the stand density.

Table 6. NFI plots: radii, DBH thresholds and scaling factor.

r (m)	5	10	15	25
DBH (cm)	7.5 - 12.5	12.5 - 22.5	22.5 - 42.5	> 42.5
k	127.39	31.85	14.15	5.09

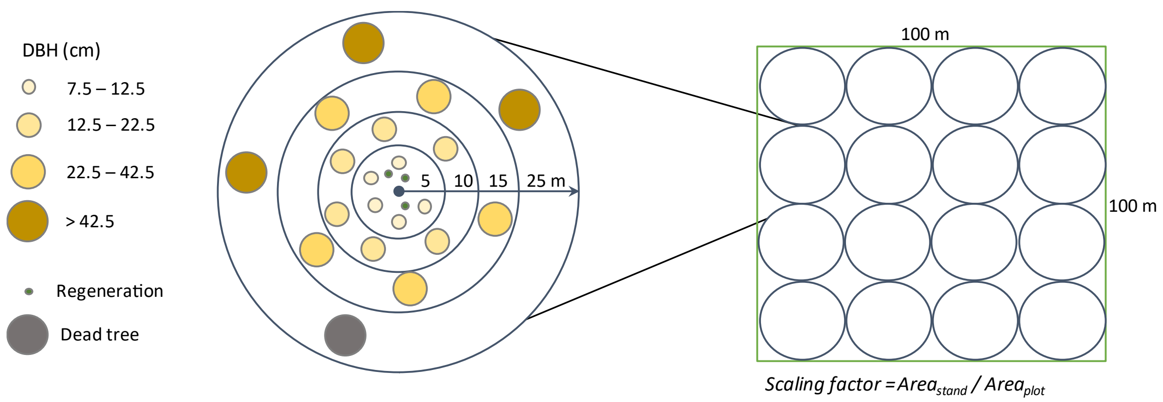


Figure 9. Spanish NFI nested plot sampling design (left), and scaling plot to stand (right)

Selection of plots

NFI data used in this thesis is a subset of the second (ICONA, 1995), third, and forth Spanish NFI (NFI2 NFI3 and NFI4) conducted in Catalonia during 1989-1990, 2000-2001, 2010-2015 respectively. NFI data were analysed in two case studies. The first case study examined pure and mixed plots of *P. sylvestris*, *P. uncinata*, *P. nigra* and *A. alba*, censused in all three forest inventories (n = 399). These plots are distributed at an elevation range between 169 and 2315 m.a.s.l. Plot level data were scaled to 1 ha stand level by multiplying each censused tree by its scaling factor (Table 6). Table 7 shows the stand characteristics, as mean DBH and stand Basal Area (BA), with their minimum and maximum values provided in parentheses. Mean annual temperature and total annual precipitation are based on 10-year averages preceding each inventory, following Ruiz-Benito et al. (2013).

The second case study examined three pure *P. sylvestris* stands, located on a representative gradient of precipitation and temperature (Table 8). Stand locations were chosen from the NFI database, while stand structure was adjusted to the ORGEST Ps08 and Ps09 models (Table 4 and 5). The initial density was assigned to 1450 trees with a DBH between 10 and 20 cm. 700 trees were allocated in the DBH class 10 – 15 cm, and 750 trees were allocated in the DBH class 15 – 20 cm. Within each DBH class, DBH values were randomly assigned. All stands were given identical structure (Table 9) to minimize variability in data input and facilitate comparison between outputs (cf. Robinson and Monserud, 2003).

Table 7. Stand characteristics: averages and ranges of values (in parenthesis)

	Mean DBH ha^{-1} (cm)	**Total BA ha^{-1} (cm)**	**Density (trees ha^{-1})**	**Precipitation (mm year^{-1})**	**Temperature (°C year^{-1})**
IFN2	18.45 (8.37; 45.62)	17.28 (0.40; 57.15)	650 (14; 3232)	887.62 (515.51; 1561.29)	10.59 (4.81;15.91)
IFN3	19.34 (9.49; 48.31)	23.58 (0.45; 64.03)	807 (26; 4311)	820.14 (452.50, 1281.50)	10.54 (4.43; 16.46)
IFN4	20.14(10.29; 47.69)	29.45 (0.92; 69.70)	903 (28; 3958)	785.09 (439.52; 1256.04)	11.52 (4.43; 16.53)

Table 8. Site characteristics and means of precipitation and temperature

	Latitude (degrees)	**Longitude (degrees)**	**Precipitation (mm year^{-1})**	**Temperature (°C year^{-1})**	**Elevation (m.a.s.l)**	**Slope (degrees)**
Humid	42.33	1.99	1096	6.3	1740	27.05
Mesic	42.10	1.91	857	11.4	724	30.82
Xeric	41.73	1.99	657	12.9	472	15.85

Table 9. Initial stand characteristics

Site	**Density (trees ha^{-1})**	**BA (m^2)**	**Mean DBH (cm)**
Humid/Mesic/Xeric	1450	22	15.17

2.2.3. Climate data and climate change scenarios

Case study I used historical weather records to assess the drivers of Ecosystem Services (ESs) spatiotemporal changes. This involved calculating the mean monthly precipitation and the total monthly temperature from the decade preceding each NFI census, for which ESs were assessed, thus accounting for climate variability (Ruiz-Benito et al., 2013). Variations in temperature and precipitation from the established climatic baseline (1961-1990) were considered as indicators of climate change.

For the case study II, climate scenarios were developed based on the 30-year climatic baseline 1981 - 2010, that more accurately represents the current climate conditions (Liersch et al., 2020; Thom et al., 2022). To establish the current climate scenario (RCP 0.0), the 30-year daily weather data obtained from meteorological stations were interpolated onto the 10m Digital Terrain Model (DTM) of Catalonia. Subsequently, the 30-year climatic time series were concatenated to form a 100-year time series. The weather data were downloaded from surface stations of the Catalan Meteorology Service (SMC) and the Spanish National Meteorology Agency (AEMET), and the interpolation was performed using the *meteoland* R package v.1.0.3 (De Caceres et al., 2018). To construct climate change scenarios, the climatic baseline was combined with two Representative Concentration Pathways (RCP) projections, namely RCP 4.5 and RCP 8.5, using the GOTILWA+ software (Nadal-Sala and Sabaté, 2013). Timeseries medians of the projected climatic variables are provided in Table 10.

Table 10. Current climate and climate change scenarios: medians and median absolute deviations (in parentheses) of total annual precipitation and average annual temperature for the years 80–100 of the simulations in humid, mesic and xeric sites.

	RCP 0.0		**RCP 4.5**		**RCP 8.5**	
	Precipitation (mm year^{-1})	**Temperature (°C)**	**Precipitation (mm year^{-1})**	**Temperature (°C)**	**Precipitation (mm year^{-1})**	**Temperature (°C)**
Humid	928 (221)	8.5 (0.9)	829 (208)	10.0 (1.3)	757 (213)	11.5 (2.2)
Mesic	808 (161)	13.7 (0.4)	713 (175)	15.1 (1.2)	651 (193)	16.5 (2.1)
Xeric	590 (89)	15.0 (0.5)	518 (99)	16.5 (1.1)	475 (101)	17.9(2.0)

To ensure compatibility with simulation models, climate scenarios were stored in two temporal resolutions: daily climate timeseries and monthly temperature and precipitation timeseries.

2.3. Case study I. Current forest assessment: Patterns and drivers of ES dynamics

To effectively support sustainable forest management, it is crucial to understand the spatiotemporal patterns and trade-offs of multiple Ecosystem Services (ESs) at large spatial scales. These assessments can help evaluate and prioritize potential management activities across ownerships. Addressing the first research objective, this case study explores the need and the contributions of geospatial tools to strategic management planning through multiple ESs assessments. The methodological approach involved five steps:

1. Quantifying ESs indicators based on National Forest Inventory (NFI) data.
2. Identifying the primary drivers of these changes based on literature.
3. Assessing the temporal changes in ESs and examining their spatial variability.
4. Identifying the primary drivers using Geographic Random Forest (GRF) algorithm and examining how these drivers vary in space and change over time.
5. Assessing cross-scale interactions in multiple ES dynamics applying Multi-scale Geographically Weighted Regression (MGWR).

2.3.1. Quantifying forest ecosystem services

Following established international classification from the Common International Classification of Ecosystem Services (CICES) (Haines-Young and Potschin, 2018), ESs were grouped into provisioning, regulating, and cultural services. ESs indicators (Table 11) were quantified using empirical models from the literature (Equations 1 - 8), based either on data from Spanish NFI (e.g., fire risk, and biomass production), or field data (e.g., mushroom production). Further details regarding the construction of these models can be consulted in the references provided in the table below.

Table 11. Ecosystem services indicators and their metrics

ES	ES indicator	Metrics	Main reference
Provisioning	Timber production	Volume of standing timber and Volume of harvested timber (wood density at 12% humidity) (m^3ha^{-1})	(Borràs and Gené, 2012) (Ruiz-Peinado et al., 2011)
	Mushroom production	Total, edible, and marketed mushroom yield (kg $ha^{-1}year^{-1}$)	(de-Miguel et al., 2014)
Regulating	Carbon storage	Carbon stored in tree biomass (including roots, stem, branches and needles) (Mg t^{-ha})	(Ruiz-Peinado et al., 2011)
	Potential fire risk	Probability of fire occurance (%)	(González et al., 2005)
Cultural	Scenic beauty	Degree of aesthetic attractiveness of a stand (0 to 1)	(Blasco et al., 2009)

Timber production was calculated in two steps. First, stem biomass was calculated based on the empirical tree-level biomass models provided by Ruiz-Peinado et al. (2011). As an example, equation 1 represents the fitted stem biomass equation for *P. sylvestris*:

$$w_{Ps} = 0.0154 \times DBH^2 \times h \qquad \textit{(Equation 1)}$$

Where, W_{Ps} is the stem biomass for P. Silvestris, DBH is the diameter at breast height of the tree and h the hight of the tree

Subsequently, timber volume was calculated by multiplying the 80% stem biomass by wood density at 12% humidity, provided by Borràs and Gené (2012) (Table 12).

Table 12. Wood density at 12% humidity

Species	*A. alba*	*P. sylvestris*	*P. nigra*	*P. uncinata*
Wood density at 12% humidity	470,99 kg m^{-3}	527,46 kg m^{-3}	563,80 kg m^{-3}	504,74 kg m^{-3}

Mushroom production was based on the empirical models provided by de-Miguel et al. (2014), where first, the probability of mushroom production is calculated based on the following equation:

$$p(y_{ijk}) = 1) = \frac{1}{1 + e^{-\left(\beta_0 + b_{0j} + b_{0k} + \beta_1 \ln(G_{ijk}) + \beta_2 \sqrt{G_{ijk}} + \beta_7 + \beta_3 \cos(Asp_{ij}) ln(Slo_{ij}+1)\right)}} \qquad \textit{(Equation 2)}$$

Subsequently, total, marketed, and edible mushroom production models take the following forms:

$$\ln(tot_{ijk}) = \beta_4 + b_{4j} + b_{4k} + \beta_5 \ln(G_{ijk}) + (\beta_6 + b_{6j})\sqrt{G_{ijk}} + (\beta_7 + b_{7j} + b_{7k})\sqrt{Alt_{ij}} + \beta_8 Alt_{ij} + \beta_9 \cos(Asp_{ij})\, ln(Slo_{ij} + 1) + \varepsilon_{ijk} \qquad \textit{(Equation 3)}$$

$$\ln(mk_{ijk}) = \beta_4 + b_{4j} + b_{4k} + \beta_5 \ln(G_{ijk}) + (\beta_6 + b_{6j})\sqrt{G_{ijk}} + \beta_7\sqrt{Alt_{ij}} + (\beta_8 + b_{8j} + b_{8k})Alt_{ij} + \varepsilon_{ijk} \qquad \textit{(Equation 4)}$$

$$\ln(ed_{ijk}) = \beta_4 + b_{4j} + b_{4k} + \beta_5 \ln(G_{ijk}) + (\beta_6 + b_{6j})\sqrt{G_{ijk}} + \beta_7 \ln(Alt_{ij}) + \beta_9 \cos(Asp_{ij})\, ln(Slo_{ij} + 1) + \varepsilon_{ijk} \qquad \textit{(Equation 5)}$$

Where tot is the total mushroom production, mk is marketed mushroom production, ed is edible mushroom production, G is stand basal area, Alt (altitude) is the stand elevation in m.a.s.l., Asp is the stand aspect, Slo is the stand slope β and b model parameters (cf. Appendix ii), and ε, the residuals.

Carbon stored in trees was calculated based on tree-level empirical biomass models provided by Ruiz-Peinado et al. (2011), considering stem, branches, needles, and roots. The biomass value was multiplied by the conversion coefficient *0.507* to calculate the amount of C stored in trees, following Montero et al. (2006).

Fire risk index was given by González et al. (2005):

$$F_{risk} = \left(1 + exp\left\{\left(-1.925 - 2.256\, ln(max\{Ele - 7.1\}) - 0.015Dg + 0.012G - 1.763P_{hard} + 2.081\left(\frac{SD}{Dg + 0.01}\right)\right)\right\}\right)^{-1} \quad \textit{(Equation 6)}$$

where F_{risk} is the fire risk index, referring to the 12-year probability of the occurrence of fire in the stand. Dg the basal area-weighted mean diameter (cm), G is the total basal area (m^2ha^{-1}), Phard is the proportion of hardwood of the number of trees, and SD is the standard deviation of diameters at breast height (cm). The last predictor (SD/(Dg + 0.01)) expresses the variability of diameters in relation to the basal-area-weighted mean diameter. Ele is based on the following equation:

$$Ele = ln(max\{Elevation - 7.1\}) \quad \textit{(Equation 7)}$$

Where Elevation is the stand elevation (in hundreds of meters) above sea level.

Scenic beauty indicator was based on the empirical model provided by Blasco et al. (2009):

$$\ln(v) = \beta_1 NB + \beta_2 NT + \beta_3 Dg + \beta_4 NP > 5 + \beta_5 DV + b_6 NT < 5 \quad \textit{(Equation 8)}$$

Where, v is the priority of stand with respect to scenic beauty, βi (i= 1, 2, 3…, p) the regression coefficient, NB the number of bushes per hectare; NT the number of trees per ha; NP>5 the number of pines per hectare with diameter at breast height more than 5 cm; DV a dummy variable that indicates whether the stand is represented by virtual reality image (0) or by photograph (1).

Metrics for the five indicators of ecosystem services were computed for each of the 399 selected NFI plot locations, as well as for every NFI census.

2.3.2. Identifying potential drivers of changes in ecosystem services

Millennium Ecosystem Assessment (M.E.A., 2005) categorize ESs drivers into direct and indirect. Indirect drivers, such as population growth and infrastructure development, through demand for resources and land conversion, affect the direct drivers (e.g. management practices), responsible for forest changes. These changes in turn affect ecosystem services provision, ultimately impacting human well-being. These interactions can occur at multiple spatial scales and over various timeframes. For instance, global timber demand may result in regional deforestation, leading to increased flooding in a local river segment (M.E.A., 2005).

Specific to forest ESs, the literature identifies drivers such as forest attributes, site conditions, disturbances, and climate change (e.g., Brockerhoff et al., 2017; Felipe-Lucia et al., 2018; Helseth et al., 2022; Mina et al., 2017; Morán-Ordóñez et al., 2021). Forest attributes encompass stand structure, stand diversity, and dead wood. Stand structure is the horizontal and vertical distribution of trees (Vayreda et al., 2012; Zeller et al., 2018), expressed by the stand mean DBH and the standard deviation in DBH (horizontal heterogeneity), dominant height and the height standard deviation (vertical heterogeneity), and the stand basal area. Stand diversity can be expressed by species richness (number of species per stand). The amount of dead wood can be approximated by the total basal area of dead trees in the stand. Site attributes determine the site quality, which refers to the ability of a forest to produce biomass (Avery and Burkhart, 2001). This, in turn, directly affect biomass related ESs indices (e.g., C stock, timber production). Site attributes include a variety of physical attributes of a forested area, including its soil, topography, and climate. Forest management is considered a direct driver, although it is essential to acknowledge its role in shaping forest attributes. Soil water availability is an important driver of tree growth (Nadal-Sala et al., 2017; Reich et al., 2014), especially in water limited Mediterranean forests (Bolle, 2003; Resco de Dios et al., 2007). To address soil water availability, Leaf Area Index (LAI) (Equation 9) can be used as a proxy.

LAI represents the total one-sided (in the context of this study) leaf area per square meter. Therefore, it measures the surface involved in radiation absorption and transfers between vegetation and the atmosphere, which makes LAI a key variable to model evapotranspiration (Kergoat, 1998). Evapotranspiration is the amount of water absorbed from the soil and released to the atmosphere. In Mediterranean forests, where high temperatures lead to elevated evaporative demand, a higher LAI can suggest greater water availability. Furthermore, global patterns of LAI sensitivity to soil moisture were demonstrated by Li et al. (2022). Considering the above, LAI can be considered an indicator of water availability in the Mediterranean context.

LAI (m^2m^{-2}) of a given stand is calculated from its foliar biomass (in $kg\ m^{-2}$) by using a species-specific *Specific Leaf Area* coefficient (*SLA*, in m^2kg^{-1}):

$$LAI = FB \times SLA \qquad \textit{(Equation 9)}$$

Where, the foliar biomass of a single tree (FB_{tree}) is given by:

$$FB_{tree} = a_{fbt} \times DBH^{b_{fbt}} \times e^{c_{fbt} \times BAL} \times e^{-0.0001 \times N} \qquad \textit{(Equation 10)}$$

Where DBH is the tree diameter at breast height, BAL is the cumulative basal area of larger trees, N is the number of trees, $a_{fbt}, b_{fbt}, and\ c_{fbt}$ are species specific coeficients, the factor $e^{-0.0001 \times N_i}$ reduces the foliar biomass of very dense stands.

The stand foliar biomass is given by:

$$FB_{stand} = FB_{tree} \times \frac{N}{10000} \qquad \textit{(Equation 11)}$$

Where, FB_{stand} is the stand foliar biomass, FB_{tree} is the tree foliar biomass, and N is the number of trees.

The coefficients for the species considered in the study are given in the table below:

Table 13. Coefficients used in the LAI calculation; source: *meteoland* (de Caceres et al., 2018)

Species	***SLA***	a_{fbt}	b_{fbt}	c_{fbt}
Abies alba	7.768174	0.12311379	1.452404	0
Pinus nigra	4.569508	0.0488278	1.620804	-0.02836286
Pinus sylvestris	4.897943	0.07679426	1.410637	-0.03876777
Pinus uncinata	3.80439	0.17386849	1.236472	-0.01663784

Considering all the above, and relying on data availability, the following site characteristics were considered: soil characteristics (soil texture and “rockiness”), topography (slope, aspect, and elevation), climate (averages of precipitation and temperature), climate change (deviations of precipitation and temperature from the baseline climatic normal, (cf. Climate and climate change data section), management (managed/unmanaged stands and management type), and LAI.

Table 14. Direct drivers of ecosystem services changes

Direct divers	Variable	Description	Source
Forest attributes	mean DBH (cm)	Average tree diameter at breast height. Potential indicator of stand maturity	NFI
	SD DBH (cm)	Standard deviation of DBH, indicator of horizontal heterogeneity	
	Dominant height (m)	Mean height of the tallest trees of the stand	
	SD height (m)	Standard deviation of height, indicator of vertical heterogeneity	
	Stand basal area (m^2)	Cumulative tree basal area of all the trees of the stand.	
	Basal area of the dead trees in the stand (m^2)	Cumulative basal area of all the dead trees in the stand.	
	Species richness (number of species)	Total number of tree species in a stand, expressing species richness.	
Management	Managed (boolean)	Variable classifying the stands in managed and unmanaged	NFI
	Type of management (category)	NFI management categories, including soil improvement, structure and composition improvement, or combination of them (6 categories).	
Site attributes	Elevation (m.a.s.l.)	The variation in height of the Earth surface measured in metres above sea level	DTM (10m resolution)
	Slope (degrees)	The steepness of a surface, described as the ratio of elevation difference and eucledian distance between two points (or pixels).	
	Aspect (degrees)	The direction a slope is facing relative to north.	
	Soil texture (category)	Categorical variable extracted from the NFI database	NFI
	LAI (m^2/m^2)	One sided area of the tree leaves in a square meter (Equation 9). Potential indicator for soil water availability	de Caceres et al. (2018)
	Precipitation (mm)	10 year averages of total monthly precipitation	R Package *meteoland* (De Caceres et al., 2018)
	Temperature (degrees Celsius)	10 year averages of mean monthly temperature	
Climate change	Precipitation anomaly (mm)	Difference of the actual means from the baseline climatic normal	
	Temperature anomaly (degrees Celsius)		

Following the characterisation of the indirect drivers in M.E.A. (2005), population and infrastructure development were considered. In terms of population, total population, population density and population change at municipality level were calculated. Population change was calculated as the difference between the years when NFI censuses were conducted. In terms of infrastructure development, forest roads and nearby settlements were considered. The total length of forest roads was calculated at municipality level. While distance to nearest settlements was calculated as the minimum Euclidian distance from each NFI plot. Settlement data were acquired from the Cartographic and Geologic Institute of Catalonia (www.icgc.cat), which, when combined with population density, can serve as a proxy for human-infrastructure pressure.

Table 15. Indirect drivers of Ecosystem Services change

Indirect drivers	Variable	Unit	Description	Source
Demographic	Population density	inhabitants per km^2	The dataset is a shapefile representing municipal boundaries, where each polygon contains population density values for each municipality.	Statistical Institute of Catalonia (www.idescat.cat)
Infrastructure development	Forest roads	km	Total length of forest roads within each municipality boundaries	Cartographic and Geologic Institute of Catalunya (www.icgc.cat)
	Nearest settlement	km	Euclidian distance from nearest settlement of each NFI plot, calculated in GIS software.	

2.3.3. Assessing spatiotemporal ecosystem services dynamics

Assessing temporal stability

To answer the first research question, the initial step was to define ESs changes as the relative changes of five ESs indicators (i.e., timber production, mushroom production, carbon storage, potential fire risk and scenic beauty) between National Forest Inventories (NFIs). Specifically, the changes were calculated between second and third inventories (NFI3 – NFI2), and third and fourth inventories (NFI4 – NFI3), applying the equation 1 on 399 plot locations (see plots selection section). These changes reflect the gain or loss of each individual ecosystem service compared to its historic state, providing an overview of their temporal dynamics.

$$ES_{RC} = \frac{ES_i - ES_{i-1}}{ES_{i-1}} \quad \text{(Equation 12)}$$

Where, ES_{RC} is the ecosystem service relative change, ES_i is the current value of the ES and ES_{i-1} is the historical value of the ES.

For each stand and ES indicator, relative change of the first period (NFI3 – NFI2) was subtracted from the relative change of the second period (NFI4 – NFI3), revealing the temporal patterns. Positive values indicate acceleration, negative values indicate deceleration, and values close to zero indicate temporal stability.

To visually assess the outputs, a boxplot diagram was plotted to show snapshots of the ESs for the whole study area and three NFIs. To examine the changes in space and time, the relative changes, as well as the direction of these changes were mapped using the QGIS software (QGIS, 2022).

Assessing spatiotemporal drivers

To address the second research question regarding the underlying mechanisms that promote or impede changes in multiple ESs, Geographical Random Forest (Georganos et al., 2021; Georganos and Kalogirou, 2022) was employed. GRF is a non-parametric, geographically weighed method, based on the Random Forest (RF) algorithm (Breiman, 2001). Non-parametric implies that no strict assumptions about the shape of the relationship between ESs changes and their potential drivers are made, instead the pattern in data allows to reveal the form of this relationship. Geographically weighted implies that, at any given location, data from nearby locations are considered and given weights based on their proximity. The difference from the typically used global methods, is that instead of producing average estimates over large spatial scales, where a single coefficient account for the relationship between each explanatory variable and the dependent variable, geographically weighted methods allow the coefficients to vary over the space. This enables identification of the spatial variation in the primary drivers responsible for changes in the ESs in the geographical space as a continuum.

GRF uses the RF algorithm to build ensembles of decision trees for each specific location, given a predefined number of neighbours, called bandwidth (Figure 10).

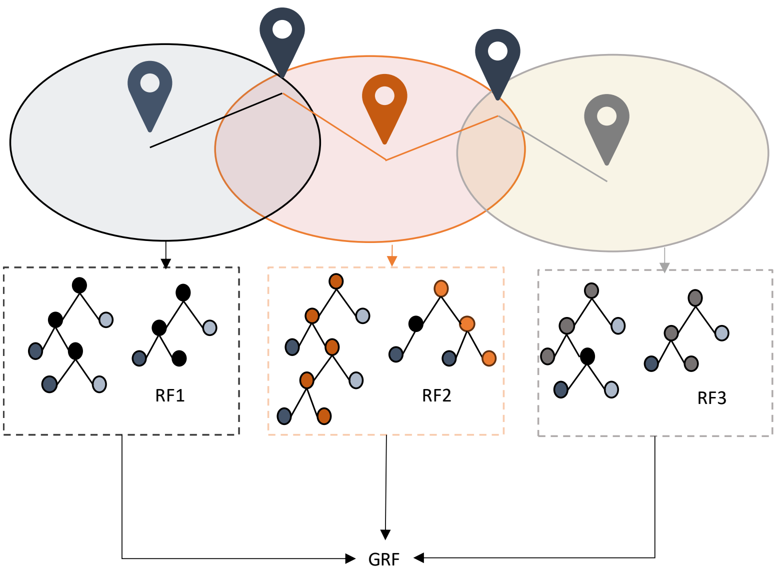


Figure 10. Schematic structure of the GRF algorithm

In these ensembles, each tree is trained on a randomly sampled subset of the data, and a random feature selection. The construction of each decision tree involves recursively partitioning the data based on the maximum number of predictors that optimize the information gain. By selecting random features, each tree is trained on a distinct subset, reducing correlations among the trees. Final prediction is determined through majority voting (classification) or averaging (regression). This ensemble approach mitigates overfitting and enhances generalization. To determine the optimal value for random predictors, 10-fold cross-validation was employed. This technique divides the data into 10 subsets, recursively training the model on 9 subsets, and evaluating performance on the remaining subset. To determine the main ESs drivers, permutation importance algorithm was employed to measure the drop in accuracy when predictors were shuffled to estimate their influence on the model's accuracy.

GRF models were created separately for each ES indicator and NFI census interval, and trained using the entire datasets, focusing on identifying primary drivers rather than creating a general predictive model. The datasets used to train the models were the ones described in the “Identifying potential drivers of changes in ecosystem services” section.

Assessing cross-scale interactions in multiple ESs

Trade-off analyses within ESs are common practices to uncover areas of co-production or conflict, and thus inform management policies, or refine management strategies. Typically, these analyses use global methods (e.g., Pearson’s r, or linear regression), that estimate averages across large regions and assume same operational scales. To address spatial heterogeneity in data, geographically weighted linear regression, assumes that elements that are closer together are more related to each other (Tobler’s I law of geography). Similar to GRF, Geographically Weighted Regression (GWR) creates a relationship for the response and explanatory variables based on the given number of neighbours (bandwidth). The distance between each given point and its neighbours is weighted, such as closer points get bigger weights. However, ESs are known to operate at various scales. For example, climate regulation is assessed a regional scale, while biodiversity indices may require finer spatiotemporal scales. To address the varying geographic scale over which different processes operate, Multi-scaled Geographically Weighted Regression (MGWR) relaxes the bandwidth restriction by allowing the neighbourhoods around each location to vary (cf. Fotheringham et al., 2017 for the implementation details).

For each observation $i \in \{1, 2, \dots, n\}$ at location $u_i v_i$, the linear MGWR takes the following form:

$$y_i = \sum_{j=0}^{m} \beta_{bwj}(u_i v_i) x_{ij} + \varepsilon_i \qquad \textit{(Equation 13)}$$

Where y_i is the response variable, x_{ij} is the jth explanatory variable, β is the jth coefficient, bwj the bandwidth, and ε is the error term.

To assess the interaction between ESs dynamics, MGWR was applied for every pair of ESs changes for the NFI intervals NFI2 – NFI3 and NFI3 – NFI4. To ensure adherence to the assumptions of the linear model, the variables were first transformed to achieve normal distribution, and then standardized by subtracting the mean and dividing by the standard deviation. When variables are standardized, the resulting regression line has an intercept of 0 and a slope equal to the correlation coefficient, which simplifies the interpretation of ESs associations.

2.4. Case study II. Future forest assessment: Adaptive simulation experiment

Changes in climatic patterns affect the way forests respond to management, necessitating the adaptation of management strategies to new environmental conditions. Timber and wood production remain key forest ecosystem services, and their demand is expected to rise further, particularly with the emergence of new bioenergy objectives (FAO, 2020). It is important to develop a thorough understanding of how current management guidelines will fare under future climate scenarios and determine whether adjustments are necessary to align with the changing conditions. Given the future uncertainties, it is important to communicate the robustness of the future projections when presenting management alternatives, to establish trust between scientists and decision-makers. To address these issues, in the second case study an adaptive simulation experiment was conducted. To assess how current management guidelines respond to the future climate, ORGEST management models were combined with three climate change scenarios and used to simulate virtual *P. sylvestris* stands in three representative locations of varying precipitation and temperature patterns. One control (i.e., without management) simulation was applied for each stand location and climate change scenario.

To identify factors influencing simulation output variation, two forest simulation models were employed. One model is driven by neighbourhood competition (i.e., SORTIE-ND, Canham et al. 2005), while the other is based on tree physiological processes (i.e., GOTILWA+, Nadal-Sala et al. 2013). The choice of the models was based on the fact that a) both models are extensively used in forest research which indicates their reliability, b) both consider climate change and management, and c) both are freely available and have a user interface that could potentially facilitate their use by forestry practitioners. The simulation outputs of both simulators were used separately and in combination, to conduct variation partitioning analysis.

The methodology comprised the following steps:

1. Selecting representative *P. sylvestris* stands and creating climate change scenarios for the specific locations of the stands (cf. “Selection of plots” and “Climate change scenarios” in the “Methodology” section)
2. Conducting simulation experiments of management alternatives based on ORGEST models Ps08 and Ps09 (cf., “ORGEST: sustainable management of Catalan forests”) employing two forest simulation models.
3. Performing variance partitioning on the simulation outputs.

2.4.1. Forest simulation models

GOTILWA+

GOTILWA+ (Growth of Trees is Limited by Water) Version 74.2 (http://www.creaf.uab.es/gotilwa) (Gracia et al., 1999; Nadal-Sala and Sabaté, 2013) is a deterministic stand-level forest model that

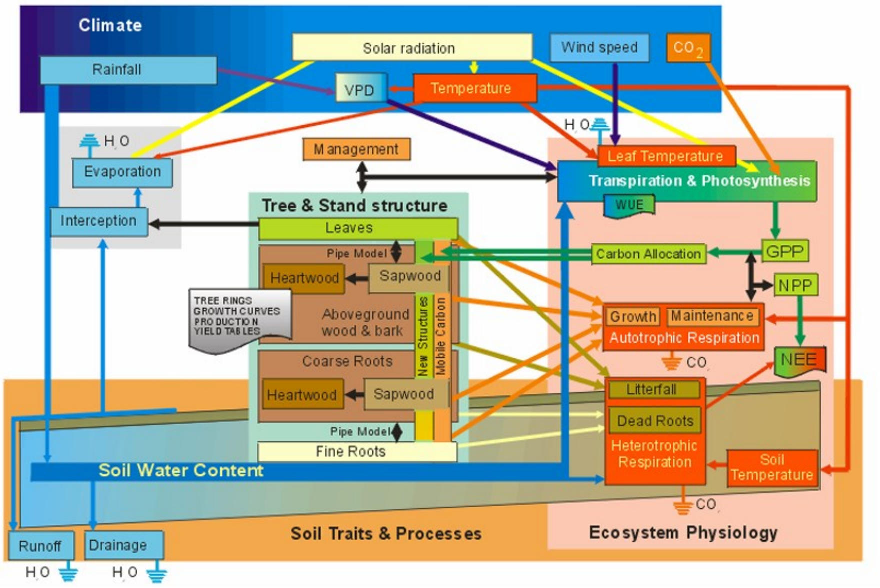


Figure 11. GOTILWA+ model. Source: http://www.creaf.uab.es/gotilwa

simulates how forest growth processes are influenced by climate, tree and stand structure, management, soil properties, and climate change (Figure 11). It analyses daily climatic data, estimating water interception and its impact on soil water storage. Water availability is the main factor influencing the proportion of sapwood to heartwood, the leaf area of each tree, and consequently, the Leaf Area Index (LAI) of the forest in the model. Hydraulic limitations due to cavitation are also considered. Mortality in GOTILWA+ is driven by the balance of available carbohydrates for a given tree.

The model operates with a 1-hour time step for physiological processes (i.e., photosynthesis, stomatal conductance, respiration, etc.) and 1-day timestep for estimating structural values (tree ring formation, biomass, etc.). 1-day temporal resolution is required for the weather data input, i.e., daily values of the incoming radiation, maximum and minimum air temperature, rainfall, wind speed, vapor pressure deficit, and atmospheric CO2 concentration. The initial tree population structure is defined using total tree density (trees ha^{-1}) and the distribution of trees in DBH classes. The results are computed for each DBH class which are aggregated at the stand level. The outputs are generated at daily, monthly, and yearly intervals.

GOTILWA+ comes with parameter files for seven common tree species in Catalonia. These files contain species-specific parameters for photosynthesis and stomata conductance, and site-specific soil parameters, such as mean soil depth, hydraulic gradient, soil hydraulic conductivity, soil Carbon (C) flux parameters etc.

Some limitations in the model include that it simulates only single species stands, it does not consider the nutrient cycle, does not include regeneration processes and does not consider tree height.

SORTIE-ND

SORTIE-ND, (Canham et al., 2005) is an individual-based forest dynamics model, that was initially developed to simulate gap dynamics in transitional oak-northern hardwood forests in the north-eastern U.S. (Pacala et al., 1993). Its further development incorporated a management module (Coates et al., 1990). The current version, SORTIE-ND Version 7.05.07 (http://www.sortie-nd.org) encompasses local neighbourhood dynamics based on species-specific empirical and mechanistic processes and competitive interactions for resources between individuals (Ameztegui et al., 2015; Bose, A.K., Harvey, B.D., Coates, K.D., Brais, S., Bergeron, 2015). This allows simulating the dynamics of mixed stands with complex, uneven-aged diameter distributions.

SORTIE-ND simulates the life cycle of every individual tree based on demographic and biological processes, for each species and life-stage (seedlings, saplings, and adults). For each tree, available light is determined by finding all neighbouring trees that shade that point. The model encompasses various modules, or “behaviours”, including: 1) allometric equations for each species, 2) light transmission functions that describe the movement of the sun throughout the growing season, 3) juveniles’ growth as a function of light availability, 4) adults’ growth, as a function of potential growth limited by competition, tree size and climate, 5) mortality for juveniles as a function of the radial growth of recent years, 6) mortality for adults as a function of tree size. For example, adult growth (DBH >7.5 cm) is calculated as a function of the maximum potential diameter growth (PDG), limited by factors such as tree size, climate, and the amount of competition exerted by their neighbours (Canham et al. 2005):

$$Dg = PDG \times Size\ effect \times Crowding\ effect \times Temp.Effect \times Prec.Effect \qquad \textit{(Equation 14)}$$

where Dg is the diameter growth and PDG is the average maximum potential diameter growth (in mm yr^{-1}).

The limiting growth factors are formulated as follows:

$$Size\ effect = e^{-0.5\left[\frac{ln\left(DBH/X_a\right)}{X_b}\right]^2} \qquad \textit{(Equation 15)}$$

where DBH is diameter at breast height and X_a and X_b are the tree parameters

$$Temperature\ effect = e^{-0.5\left(\frac{abs(T-T_a)}{T_b}\right)^{T_c}} \qquad \textit{(Equation 16)}$$

where T_a, T_b and T_c are estimated parameters, and T is annual precipitation in degrees Celsius.

$$Precipitation\ effect = e^{-0.5\left(\frac{abs(P-P_a)}{P_b}\right)^{P_c}} \qquad \textit{(Equation 17)}$$

where Pa, Pb and Pc are estimated parameters and P is annual precipitation, in mm

$$Crowding\ effect = e^{-C \cdot DBH^{\theta} NCI^{D}} \qquad \textit{(Equation 18)}$$

where C, ϑ and D are estimated parameters, and NCI is the Neighbourhood Competition Index, calculated as:

$$NCI = \sum_{i=1}^{n} \lambda \frac{DBH_i^{\alpha}}{distance_i^{\beta}} \qquad \textit{(Equation 19)}$$

Where α, β and λ are the estimated parameters and DBH is the diameter at breast height.

SORTIE-ND model was parameterized for four forest species in Catalonia, namely, *P. Sylvestris, P. Uncinata, P. Nigra and A. Alba.* Parameters for *P. Sylvestris* stands used in this simulation experiment were obtained from Ameztegui et al. (2015) and based on data from the Spanish NFI (Table 16).

Table 16. Parameter estimates for *P. sylvestris* (Ameztegui et al., 2015)

Potential Growth	PDG	0.960
Crowding effect	*C*	0.03506
	Θ	-1.11
	D	1.0
	A	1.82
	B	1.65
	Λ	0.63
Size effect	*Xa*	19.92
	Xb	1.11
Temperature effect	*Ta*	1.09
	Tb	11.75
	Tc	2.0
Precipitation effect	*Pa*	2386.82
	Pb	2660.83
	Pc	2.0

The model has certain limitations, as for example, it lacks a water balance module, and its current parameterization in Catalonia does not consider natural regeneration and disturbances.

2.4.2. The experiment

The simulation experiment was conducted in SORTIE-ND and GOTILWA+ simulation models, which require defining management configurations beforehand (i.e., defining the simulation horizon, thinning years, and the amount of Basal Area (BA) to remove). However, to answer how current management recommendations fare under future scenarios of climate change, this experiment was based on rules defined in the ORGEST management models (Table 4). Instead of defining the thinning timings, each thinning was triggered whenever the BA and the mean Diameter at Breast Height (DBH) reached the predefined thresholds outlined in the models Ps08 and Ps09. Final harvest was applied based on the shelterwood principles, with 10 years interval between the harvests (refer to ORGEST section for details). Additionally, a no-management alternative was implemented to compare the outputs.

The simulation routine involved running simulations until stand BA and mean DBH thresholds were reached; recording thinning years, and applying designated harvests as depicted in Figure 12. The simulations were iterated with updated configurations for each thinning. The final harvest, following a shelterwood method, was executed 30 years after the last thinning. In the no-management alternative, the simulation horizon was set to 100 years.

The three management alternatives were combined with three climate change scenarios, applied to three *P. sylvestris* stands (humid, mesic, and xeric), and executed in two simulators, resulting in a total of 54 simulation cases. To account for the stochasticity of the models, each simulation case was replicated 10 times, resulting in 540 simulations.

No management Ps00

i	-
BA (m2)	-
DBH (cm)	-
Harvest (% BA)	-

Management configuration Ps08

i	1	2	3	4	5	6
BA (m2)	27	42	43	40	23	11
DBH (cm)	15	23	31	40	40	40
Harvest (% BA)	11	26	30	43	25	100

Management configuration Ps09

i	1	2	3	4
BA (m2)	35	43	28	14
DBH (cm)	21	35	35	35
Harvest (% BA)	30	40	54	100

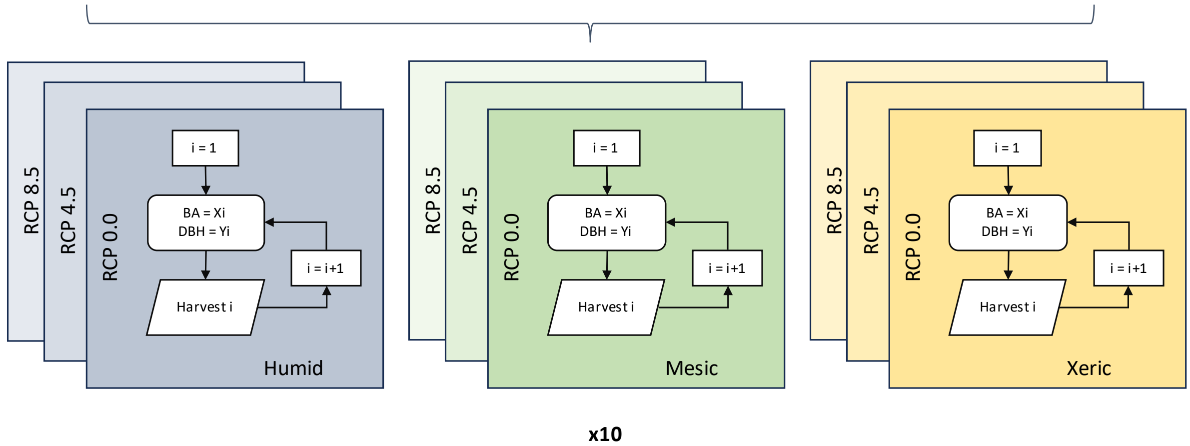


Figure 12. Schematic representation of the simulation experiment

2.4.3. Analysing the effects of management and climate change on timber production

The understand how current management recommendations affect future timber production, two indicators were examined: *total timber yield* and *mean annualized timber*. Total timber yield refers to the actual amount of harvested timber, calculated as the sum of timber harvested during the thinnings and final harvests. While the mean annualized timber refers to timber “productivity” and is calculated in terms of the average of both standing and harvested timber at the end of the simulation period. “Productivity” in this sense measures how efficiently forest resources can be used to generate harvest outputs (not to be confused with net or gross primary productivity). For example, tree growth rates are influenced by site conditions: in better-quality sites trees grow faster, leading to shorter thinning intervals and, consequently, shorter rotation periods. As a result, the productivity of these sites is higher.

While GOTILWA+ simulated stand-level values of standing and harvested timber volume per each year of the simulation, SORTIE-ND provided tree-level data in terms of DBH and height. Consequently, these outputs were used in the equation 1 to estimate standing and harvested stem biomass. Next, the timber volume was calculated by applying the coefficients of wood density at 12% humidity (Table 12).

The simulation outputs were visually analysed through graphs that were created to illustrate both timber production indicators across sites, management alternatives, and climate change scenarios.

2.4.4. Analysing factors influencing timber production simulations

To understand and quantify the relative contributions of different factors to the variation observed in the simulation outputs, Variation Partitioning (VP) method was employed. VP was introduced by Borcard et al. (1992) and has been widely used in ecological studies. The method divides the total explained variation of the response variable in distinct components attributed to the explanatory power of different sets of factors (Figure 13). These components comprise variance explained by 1) one group of factors (unique contribution), 2) variance resulting from the overlap or interaction between two or more groups of factors (shared contribution), and 3) any unexplained variance. The aim of VP is to quantify the relative significance of these components, allowing to assess the extent to which each group of factors contributes to the observed variation while also identifying the proportion of variance that remains unexplained.

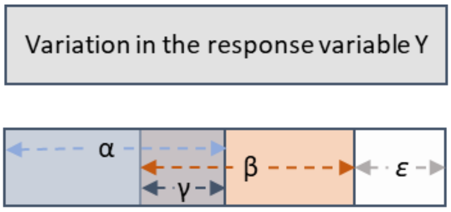


Figure 13. Variation partitioning concept: The variation in the response variable Y is partitioned into *α, β, γ,* and *ε* components, where *α* and *β* represent unique contribution of A and B explanatory variables, *γ* is their shared contribution and *ε* corresponds to the unexplained variance.

To assess the impact of site, management, and climate change scenarios on timber production, VP was conducted separately for the outputs of each simulator. In this analysis, the response variable was defined as the mean annualized timber, with site, management, and climate change scenarios considered as the factorial attributes. To assess the relative contribution of the simulation tool, a similar approach was applied to the combined outputs from both simulators, adding simulator identity to the factorial attributes. The steps involved in VP analysis are 1) calculating the fractions of variation, 2) testing their significance, and 3) mapping the fitted values to aid interpretation. All the analyses were performed using R Statistical Software (R Core Team 2021). In particular, *dplyr* package (Wickham et al. 2023) was used for data organization, *vegan* (Oksanen et al. 2022) and *VCA* (Schuetzenmeister and Dufey 2022) packages for variance partitioning, and *ggplot2* package (Wickham 2016) was used for data visualizations.

2.5. Case study III. Decision-making and VR

Forest ecosystem dynamics and their response to climate and management intervention can be challenging to communicate to non-experts. To enhance comprehension, 3D modelling and Virtual Reality (VR) can be employed to create immersive experiences that facilitate a better understanding of these concepts. In recent years, advancements in 3D modelling and VR technology offer opportunities for creating realistic visualizations. Both web-based and desktop-based technologies now enable the development and rendering of 3D objects with varying levels of detail. The objective of this case study was to develop a VR application that renders virtual forests in real time, based on forest simulation outputs, and to investigate whether immersive forest visualization can enhance decision-making in forest management and planning. The methodology encompassed:

1. Developing an image-based 3D virtual forest based on management alternatives and integrating the 3D virtual environment with a forest simulator, enabling real-time rendering.
2. Conducting a pilot survey to collect expert opinion on the utility of VR in forest management decision-making.

2.5.1. Developing interactive 3D virtual forest stands

An image-based model reconstruction approach was used to build the three-dimensional scenes. A Q3D (quasi three-dimensional) method was chosen over the detailed 3D reconstruction model for reducing the computational time and allowing real-time rendering. Using an extensible three-dimensional graphics framework (X3D), Q3D was achieved via the "billboard" node (Figure 14). Billboard is a grouping node that allows all the children elements to rotate in a specified axis towards the current viewpoint. Children nodes in this case are pictures of trees in the stand. The images were taken in the field and processed by removing the background and correcting the geometry and colour. The image collection contains representative pictures for each tree species and DBH class. Multiple pictures can be added to create one Q3D model, where each picture will correspond to the relative position and orientation of the model and observer. However, to reduce the computational time, only one picture per node was added.

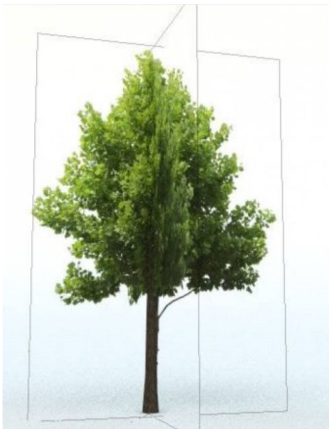


Figure 14. Quasi-3D illustration. Source: https://www.giantbomb.com/

Initially, SORTIE-ND simulation outputs were chosen to develop the virtual 3D forest, as the simulator provides tree-level information. Therefore, relative coordinates of each tree were extracted to position the image elements in the 3D space, while DBH and height of each tree was used to scale the images. The terrain was generated from 10m resolution Digital Elevation Model (DEM) and processed in a GIS software (QGIS, 2022) to extract an array of elevation values, for a rectangular 100m x 100m stand based on the IFN plot coordinates. The 3D content, in the form of X3D files was imported into X3DOM, an open-source framework that displays the 3D scenes in a standard web browser without the need of plugins. The developed *3D_scene* module takes as input tabular data providing information for each tree, such as location (relative coordinates expressed in a grid 100m x 100m), DBH and tree height. Additionally, for the situations where specific tree locations are not available, the *NFI_scene* module was created, that takes as input tabular data of species identity and number of trees per DBH class. The position of each tree is then generated randomly. The automatization of 3D scenes generation and the integration with the forest simulator was implemented in Python Version 3.7. Specifically, the *Pillow* library was used to process the images, *lxml* library was used to generate the X3D content, and the *pandas* library was used to handle tabular data.

2.5.2. Designing the opinion survey

To assess the potential utility of VR in the context of forest management decision-making, a pilot survey using non-random haphazard sampling method was adopted. Haphazard or convenience sampling is typically applied in pilot studies, or when the target population is hard to be identified (Stratton, 2021). The study was announced in March 2022 to a list of 20 experts in forestry-related fields.

The questionnaire was structured into sections gathering demographic and background information, as well as exploring participants' perspectives on the utility of VR in decision-making. Furthermore, open-ended questions were included to provide participants with the opportunity to communicate their ideas and suggestions.

Technical specifications of the questionnaire

Title:	Users' opinion about the use of Virtual Reality in forest management decision-making
Study population:	20 experts in forestry-related fields
Sampling method:	Non-probabilistic haphazard sampling
Objective:	Assess the potential utility of a VR system in forest management decision-making.
Questionnaire administration:	Online platform
Languages:	Catalan and English

The Questionnaire

1. Before starting, and for technical reasons, please provide the unique code assigned the invitation email.
2. Name (optional)
3. Age
4. Gender M/F/O
5. Relation to forestry science (select one choice)
- Not related
- Undergraduate student in forestry or related field
- Postgraduate student (MSc, PhD) in forestry or related field
- Faculty member or researcher
- Forestry professional
6. how much do you enjoy technology? (rate 1 to 5, where 1 = not at all, 5 = very much)
7. How much do you enjoy playing video games?

8. How familiar are you with the virtual reality? (rate 1 to 5, where 1 = not at all, 5 = very much)

9. Forest modelling and simulation aim to project the future of the forest ecosystems given different hypothetical scenarios (e.g climate change, forest management). How would be most comfortable for you to interpret these simulations? (rate each statement 1 to 5, where 1 = not comfortable, 5 = extremely comfortable)

a. In form of tables e.g., changes in the amount of biomass per year.
b. In form of graphs and charts (eg. Graph representing the growth of the trees in a stand)
c. In form of maps/GIS
d. In form of 3D representation of the trees
e. In form of VR (immersive and interactive visualizations where the user can literally walk in the virtual forest of the future)

10. From 1 to 5 (where 1 = not at all and 5 = very much), What do you think VR applications are most useful for:

a. Education
b. Public engagement
c. Forest management

11. VR applications of forest stands are useful for (rate 1 to 5, where 1 = not al all, 5= very much):

a. Understanding how climate change and management can affects forest ecosystems
b. Understanding how forest management can mitigate the current and potential impacts of climate related hazards
c. Distinguish between different management alternatives and make informed decisions
d. Integrate and prioritize new information
e. Better retain knowledge through immersive participation
f. Increasing awareness in climate change related threats

12. How would you envision a VR application for forest management and decision making?
13. What other potential applications of VR would you find useful and impactful?

Responses for the online survey were collected over a 14-day period following the initial invitation. To facilitate a comprehensive understanding of the results, visually representative graphs were used, enhancing the interpretative aspects of the data analysis.

2.6. Case study IV. DSS framework

The insights gained from prior case studies formed the basis for outlining the purpose, the intended users, and the architecture of a forest management Decision Support System (DSS). Adhering to the standard DSS definition, the system architecture combined data, models, and user interfaces. The iterative development process allowed for adjustments based on user feedback and usability evaluations, resulting in a flexible design, that followed both integration and composition approaches.

2.6.1. System requirements

The purpose of the DSS is to provide decision makers with technological aid in adaptive forest management, in line with the sustainability principles. Adaptability in decision-making refers to the capacity to flexibly navigate through decision stages and adjust plans in response to new goals or changing conditions. On the other hand, adaptive management is the concept of adjusting management prescriptions based on how anticipated future climate change impacts forest attributes. It involves a proactive approach that considers and incorporates evolving conditions to ensure effective and sustainable management practices in the face of environmental uncertainties.

To operationalize the first concept of adaptability, from the thesis outline was predetermined integrating the three decision-making levels (problem definition, alternative generation, alternative selection). This integration was facilitated by ensuring compatibility of data scales, and consequently, data from the National Forest Inventory (NFI) were chosen as the basis for all the analyses. The second aspect of adaptability was addressed in the second case study through the development of a module for adaptive simulations. This involved the creation of computational algorithms to facilitate simulations that dynamically adjust management prescriptions in response to evolving forest conditions. The principles of Sustainable Forest Management (SFM) were addressed in the context of geographically oriented management (case study I), consideration of multiple Ecosystem Services (ESs) (case study I), and the facilitation of participatory decision-making by conveying complex scientific information in an accessible manner (case study III). The intended users of the DSS are forest managers and stakeholders with potentially diverse backgrounds.

According to the DSS definition (cf. state-of-the-art review), the core components of the system are the database, the model base, and the user interface (cf. Burstein and W. Holsapple, 2008; Rauscher et al., 2005). The specifications for each component of the system were derived from the preceding case studies. Table 17 provides a summary of the data, methods, and tools employed in each case study, aligning with a particular decision-making phase.

Table 17. Needs assessment based on the case studies I, II, and III.

Decision phase /study addressed	Data	Methods	Tools
Problem definition/ Case study I	▪ NFI timeseries ▪ Weather observations ▪ GIS data (administrative units, population, roads, topography)	Precipitation and temperature interpolation	meteoland (R package)
		ES quantification	Empirical models (implemented in Python)
		Quantification of ES drivers	GIS | R | empirical models
		Identification of primary drivers of ESs	GRF (R package)
		Trade-off analyses	GWMR (GIS module)
Alternatives generation/ Case study II	▪ NFI data ▪ Climate change scenarios ▪ Management configurations	Forest simulation	GOTILWA+, SORTIE-ND
		Variance partitioning	R packages
Alternative selection/ Case study III	▪ NFI data ▪ Simulation outputs	3D image reconstruction	X3DOM/ web browser

The first case study assessed changes in multiple ESs at regional scale, relying on NFI and climatic data, and used geo-statistic methods (i.e., GRF and MGWR). The second case study generated future management alternatives at a stand-level scale. This analysis relied on stand-level data derived from NFI locations and incorporated daily and monthly weather data representing different climate change scenarios. The tools employed in this study encompassed two forest simulators, both including species-specific parameters. Additionally, to convey the uncertainty in the projections, a variance partitioning method was implemented using the *vegan* R package (Oksanen et al., 2022). The third study focused on the generation of virtual forest stands through a quasi-3D image reconstruction. The data employed in this study included tree-level simulation outputs and DBH-class-level NFI data. The tools required to operate the VR environment are a standard web browser and a web server.

2.6.2. System architecture

The building blocks that ensure the basic functionality of a forest management DSS are the database, a forest dynamics model, ecosystem services models, visualization tools, and the user interface. Their *integration* is necessary to provide a unified and user-friendly interface for system use. SORTIE-ND was selected for integration for several reasons. First, it enables mixed species simulations, aligning well with the forest characteristics in the study area. Second, it operates on an individual tree basis, facilitating the creation of 3D stand visualizations. Third, its open-source design facilitates the integration into the DSS architecture.

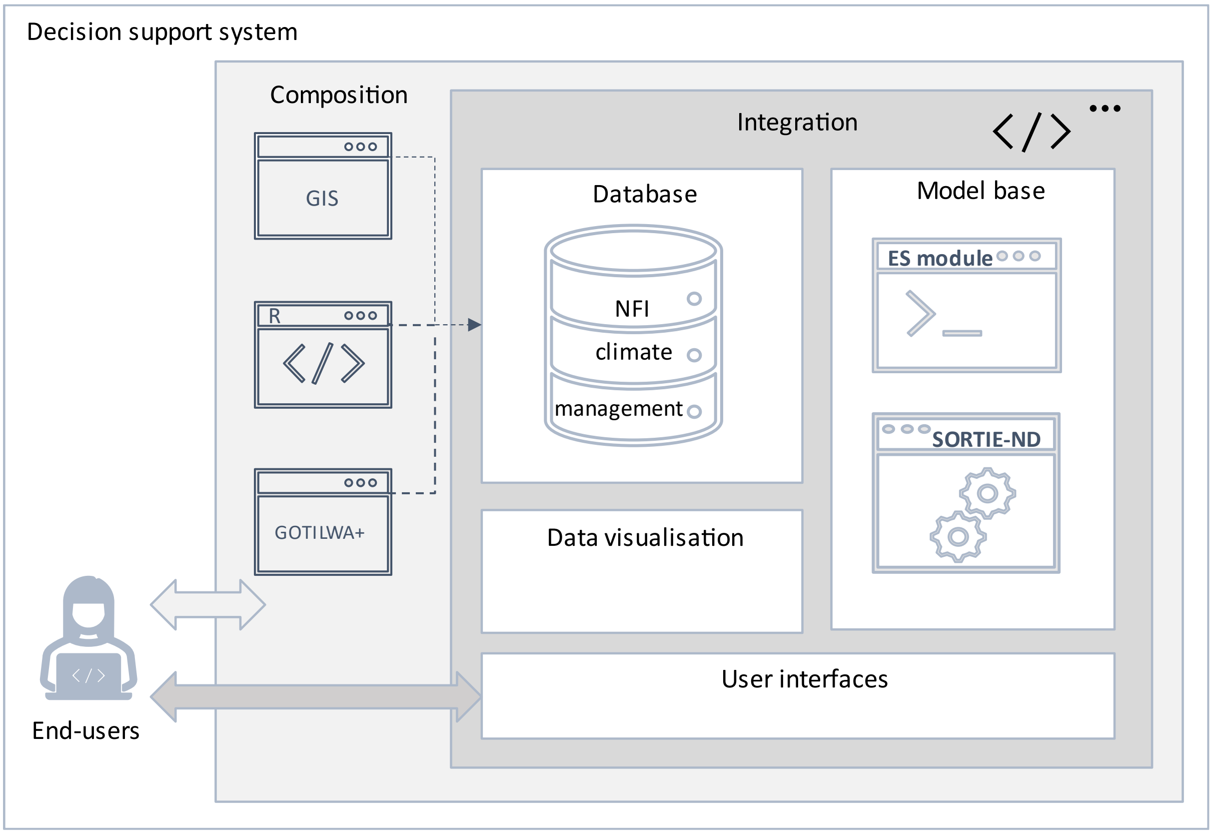


Figure 15. DSS architecture

In addition to basic functionalities, the three prior case studies emphasized the role of specific technological approaches to align forest management planning with sustainability principles. Case study I proposed the use of spatial statistics to assess multiple ESs aiming to define geographically oriented management objectives. Case study II considered multiple forest modelling approaches to address robustness in forest projections. Case study III used internet technology to render real-time 3D forest stands. While these aspects are not essential for the basic functionality of the DSS, their consideration is crucial in the context of SFM. The technologies used in the mentioned case studies are standalone applications, making complete integration into the DSS impractical. Developing these functionalities within the system without pre-existing frameworks would demand substantial time and effort. Therefore, their inclusion is conceptualized within the composition architecture (Burstein and W. Holsapple, 2008) and is achieved by ensuring compatibility of data formats for effective data interchange. It is important to note that their utilization remains optional and depends on the user's expertise.

2.6.3. Database design

Data acquisition and processing

The data requirements (Table 17) identified four main sources and types of data: NFI data, climate data, GIS data, and ORGEST management configurations. The integration of NFI data into the DSS is imperative, given its demonstrated suitability for both large-scale ESs assessments and stand-level simulations. To utilize the NFI data, it was necessary to convert the plot-level measurements into stand-level characteristics. The methodology employed in this process involved data cleansing and data scaling (cf. *Plot selection*). Climate data, similarly, played a key role in all the analyses conducted. To obtain climate data, weather observations from meteorological stations in Catalonia were interpolated across the entire region. Subsequently, a time series of weather data was extracted for each plot location (cf. *Climate data and climate change scenarios*). GIS data, such as administrative boundaries, road networks, topography, etc., played an intermediate role, such as, for instance, in the analyses of ES drivers (cf. *Identifying potential drivers*). Management configurations were based on the ORGEST management models cf. *Forests and forest management in Catalonia*), that represent the latest recommendations for timber and fire risk reduction objectives in Catalonia. This information is crucial for integration into the system, alongside any other relevant guidelines.

Database development

In the context of database development, the data model was established by delineating stand characteristics, tree characteristics, management configurations, historical climate timeseries, and climate change scenarios. To enhance visualization, a relational schema (Figure 16) illustrates the interrelationships among these datasets.

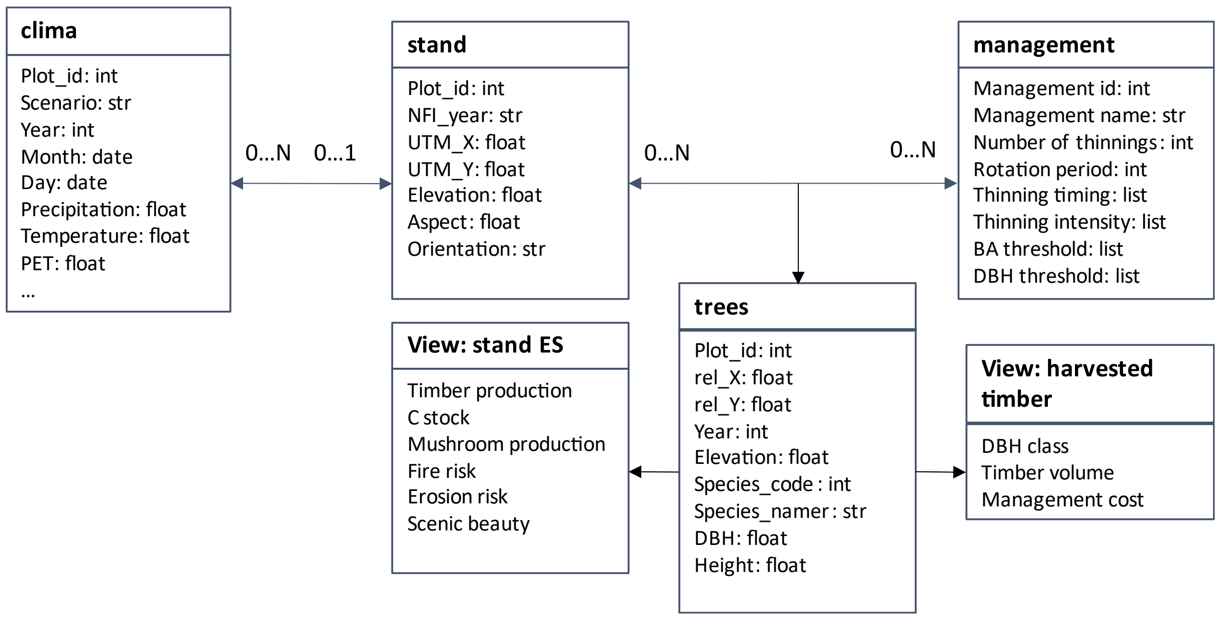


Figure 16. Database schema

It is important to note that relational databases have limitations in managing some types of data identified in this study. These include unstructured data, and timeseries at varying temporal scales and levels of detail. To clarify this point, a relational database is a structured data storage system where data are organized into tables with rows and columns, and relationships between tables are established through primary and foreign keys. To handle a relational database, SQL (Structural Query Language) is used. The structured nature of relational databases, with predefined schemas, can hinder flexibility when adapting to changing data requirements, such as adding new models with different input criteria. Moreover, relational databases are not well-suited for handling unstructured or semi-structured data, such as, when considering storing management guidelines in PDF files (e.g. ORGEST) or 3D forest scenes in X3D file format. In the recent years, various types of databases have been developed to accommodate timeseries, big data, graphs, spatial data, etc. A NoSQL (Not Only SQL) database is designed for unstructured and semi-structured data, enabling nested structures, and typically utilizing key-value pairs for data retrieval, often with JSON (JavaScript Object Notation) formatting. Therefore, the data model was implemented into a JSON structure that is compatible with both structured and unstructured database management systems (DBMS). A nested structure was selected, with the stand representing the highest level of hierarchy (cf. Appendix iii). The NoSQL database was implemented using the MongoDB infrastructure.

2.6.4. Model base design

The second essential component of a DSS is the model base. In the system requirements outlined in Table 17, two distinct categories of models were identified: empirical ESs models and forest dynamics Process Models (PM). While integration is commonly advocated in DSS literature for system implementation, practical limitations such as closed-source code or incompatible technologies may impede the integration of diverse components. In such cases, the composition method becomes a more viable approach. Model composition entails merging independent models to enable the utilization of their outputs by other models (cf. Burstein and W. Holsapple, 2008). Consequently, the model base embodied a combination of both integration (ESs models) and composition (forest dynamics models) approaches.

Regarding the ESs models (cf. equations 1 - 8), they were based on statistical approaches, resulting in a simple structure that allows for easy integration. These models were implemented using Python Version 3.7 and organized as a distinct module, adopting an object-oriented approach. The ES module is constructed within a class structure that necessitates seven parameters associated with stand and tree attributes. These parameters include slope, aspect, elevation, Diameter at Breast Height (DBH), species identity, and tree height. The class structure is designed to receive input values for these specific attributes, facilitating the calculation of ESs indicators and intermediate variables. The outputs of the ES module include stand basal area, tree and stand biomass, carbon storage in trees, CO2, standing timber volume, harvested timber volume, roadside prices in euros, mushroom production (wild, edible, and total), scenic beauty indicator, and potential fire risk. The calculation of each ES indicator is formulated as a function within this class (see Appendix iv), which allows easy integration of additional ESs.

In the case of the forest dynamics models, they consist of stand-alone software tools comprising a complex system of sub-models, parameters, and behaviours, making their integration into the DSS difficult. The identified technological requirements imposed the inclusion of two forest predictive models to address uncertainties stemming from modelling assumptions. However, for ensuring the basic functionality of the DSS, one model suffices. SORTIE-ND was selected for this purpose due to its ability to simulate mixed stands and its open-source structure, facilitating its integration into the system. Since SORTIE-ND is written in JAVA and the DSS in Python, direct intervention into the SORTIE-ND code was not undertaken. Consequently, the DSS loosely integrated SORTIE-ND through an XML "instruction" file, generated via the graphical user interface. In essence, the DSS communicates with

SORTIE-ND by providing simulation instructions and interpreting its outputs. These outputs are subsequently utilized for the calculation of ESs indicators and for organizing the results in a management-oriented manner (e.g., providing harvesting information per DBH class). In contrast, GOTILWA+ operates as a closed system, where communication occurs solely by reading its outputs. Simulations within GOTILWA+ must be exclusively conducted through its proper user interface.

2.6.5. User interface design

In the DSS development, both data visualization and the user interfaces facilitate the human-computer interaction (HCI) and are referred to as *the language system* (Holsapple, 2003). The 3D stands visualizations, described in the third case study, aimed at conveying simulation outputs to stakeholders and the public. Besides this form of communication, an equally important consideration is the Graphical User Interface (GUI). Several studies have addressed usability issues in forest DSSs (e.g., Linkevičius et al., 2019; Walling and Vaneeckhaute, 2020), advocating for user-centred GUI design. In this study, forest managers were identified as the primary users of the DSS, and the user requirements were assessed in collaboration with forestry experts and re-adjusted after the usability evaluation tests (cf. next section). Responding to user requirements, the management-oriented GUI encompassed five modules: data entry, climate definition, management definition, simulation, and visualization (Table 18). To ensure system's usability, the principles of efficiency, effectiveness, and user satisfaction outlined in ISO 9241-11:2018 were applied.

Table 18. user interface conceptual design

Data entry	
Manually define stand characteristics	Upload file or query database
Climate definition	
Select climate change scenario	Upload climate timeseries file
Management definition	
Manually define management configurations	Upload management
Simulation	
Current forest ecosystem services	Future forest dynamics and associated ESs
Visualization and communication	
2D graphs, tables, maps	3D virtual forest scenes

The five conceptual modules were translated into a tab-based interface design, with each module corresponding to a tab. The code was implemented in Python Version 3.7, using the *pyQt* library.

2.6.6. System usability test

To ensure a user-centred design, usability evaluation was conducted using the System Usability Scale (SUS) method (Brooke, 1996) in two stages. The initial usability test involved forestry experts with a scientific background (n = 10). The participants interacted with the GUI through a use-case scenario and were subsequently asked to complete a usability questionnaire (Table 19). The late-stage usability test was conducted after incorporating the users feedback from the initial evaluation. Due to COVID-19 restrictions, this evaluation was conducted online, were the functionality of the DSS was presented following the same use-case scenario. The participants were potential stakeholders (n = 14) with or without forestry background.

The usability questionnaire included general and background questions, and the usability assessment based on the SUS method. The SUS method employs 10 predefined statements related to the learnability, efficiency, and satisfaction of using a system (Table 19). To mitigate response biases, positive and negative statements were alternated. Respondents rated the statements on a five-point Likert scale, ranging from “strongly disagree” to “strongly agree”.

Table 19. Usability evaluation based on the System Usability Scale (SUS)

Question	SUS statements
Q1	I think that I would like to use this system frequently.
Q2	I found the system unnecessarily complex.
Q3	I thought the system was easy to use.
Q4	I think that I would need the support of a technical person to be able to use this system.
Q5	I found the various functions in this system were well integrated.
Q6	I thought there was too much inconsistency in this system.
Q7	I would imagine that most people would learn to use this system very quickly.
Q8	I found the system very cumbersome to use.
Q9	I felt very confident using the system.
Q10	I needed to learn a lot of things before I could get going with this system.

The formula for calculating the SUS score is as follows:

$$SUS\ score = [(Q1 - 1) + (5 - Q2) + (Q3 - 1) + (5 - Q4) + (Q5 - 1) + (5 - Q6) + (Q7 - 1) + (5 - Q8) + (Q9 - 1) + (5 - Q10)] \times 2.5 \qquad \textit{(Equation 20)}$$

The SUS score ranges from 0 to 100, with higher scores indicating better usability. A score above 68 is generally considered above average, while below 68 suggests room for improvement. SUS score is non-diagnostic, and its interpretation can vary based on the context and the specific system under evaluation. To supplement the non-diagnostic SUS results, additional questions were included to identify usability issues and gather user feedback. In addition, an overall satisfaction questionnaire (Lewis, 2018, 1995) was included.

The open-ended questions included:

1. Are you satisfied with the presented functionalities?
2. Observing the functionalities of the system, what would you improve/add/remove and why?
3. List the most negative aspects of the system.
4. List the most positive aspects of the system.
5. Do you have any thoughts on how to improve the system?

The overall satisfaction questionnaire, according to Lewis (1995), comprise two Likert scale questions:

1. Overall, I am satisfied with the ease of completing the task(s)
2. Overall, I am satisfied with the amount of time it took to complete the task(s)

3. Results

3.1. Case study I. Current forest assessment: Patterns and drivers of ES dynamics

3.1.1. Temporal patterns of ecosystem services

The goal of the temporal analysis was to assess the changes in ESs based on three consecutive forest inventories and examine their stationarity. Overall, the ESs directly associated with biomass production, such as timber production and carbon storage, as well as those linked to tree attributes such as scenic beauty, saw an increase from 1990 to 2010 (corresponding the NFI2 – NFI4), while the fire risk index saw a decrease, and mushroom production exhibited almost no change (cf. Figure 17, Appendix v).

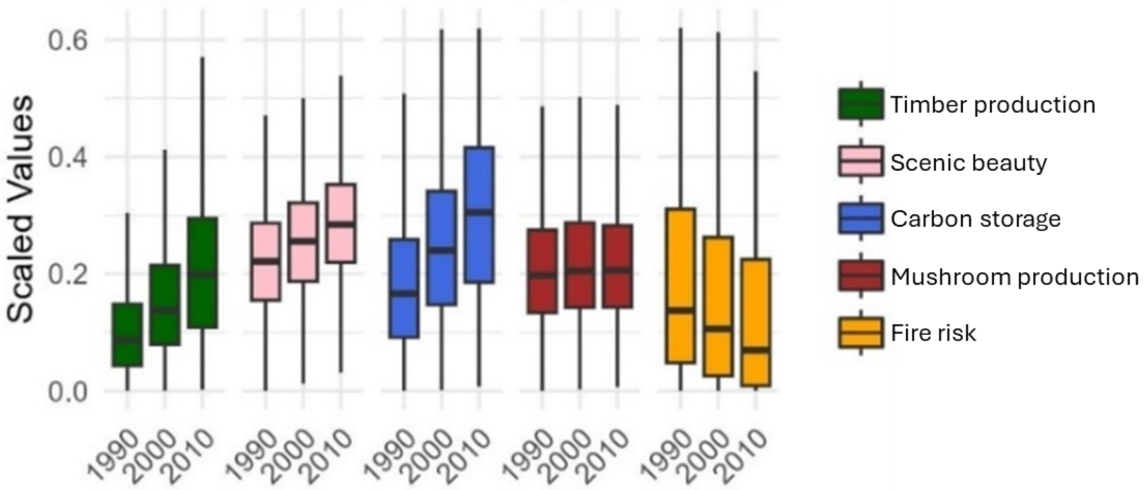
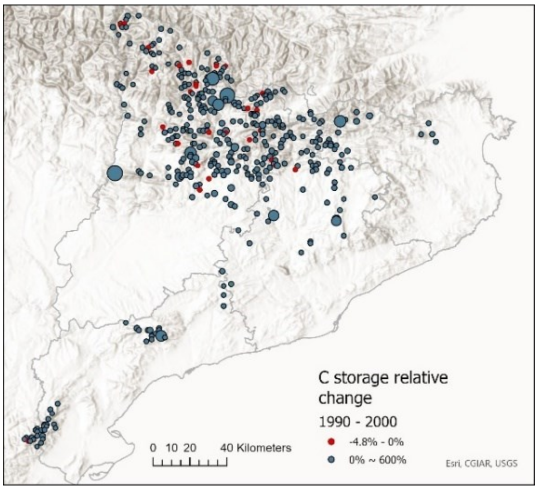
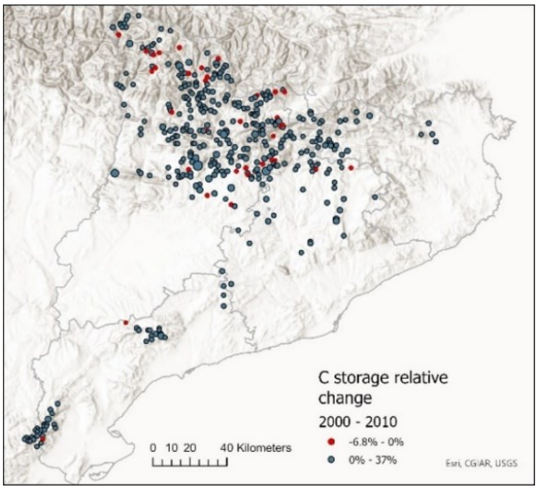


Figure 17. Total changes in ESs values across inventories. The values were scaled to compare the direction and magnitude of change.

Particularly, carbon storage, increased 71.5% from 1990 to 2010. However, the first decade saw a 34.2% average increase (Figure 18A), followed by a 27.8% average increase in the second decade (Figure 18B). Carbon losses in both study periods reached approximately -5% per hectare, affecting around 7% of the plots in the first period and around 9% of the plots in the second period, exhibiting a heterogeneous spatial distribution.



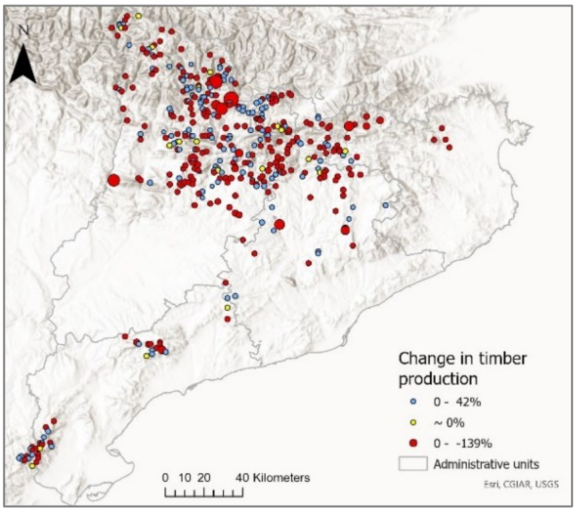


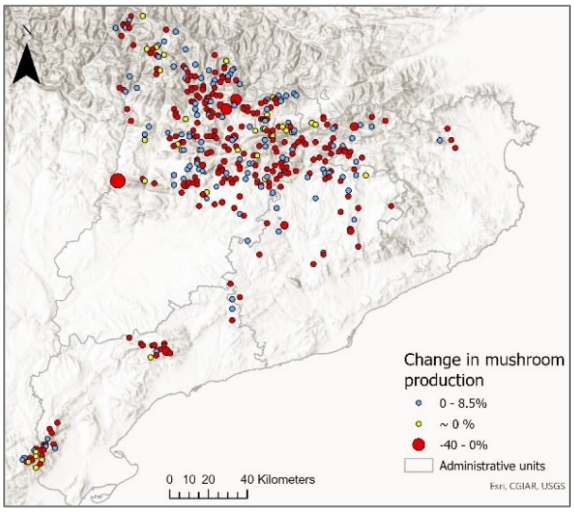
(A) (B)

Figure 18. Relative changes in C storage: (A) from 1990 to 2000 and (B) from 2000 to 2010. Red colour represents negative change (loss), blue colour represents positive change (gain). Symbols size represents the magnitude of change.

The changes between the NFI periods differed both spatially and in magnitude. From 1990 to 2000 (corresponding to the NFI2 – NFI3) C storage increased in average 45%, with 4% of the stands showing a 6-fold increase (Figure 18A). In contrast, the period 2000 – 2010 (NFI3 – NFI4) showed a more uniform increase across the spatial extent, with an average relative rate of 40% (Figure 18B).

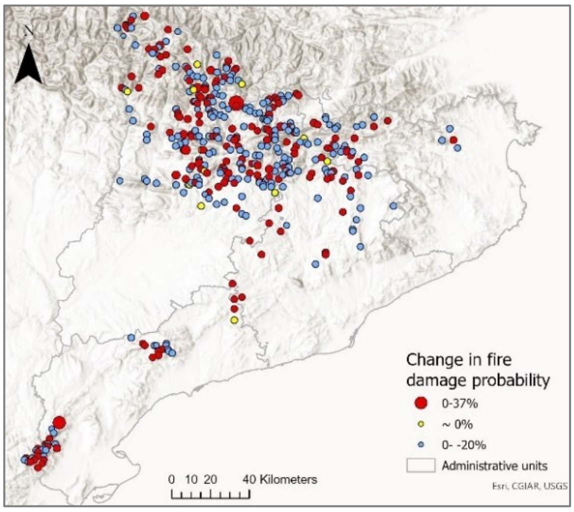
All the ESs exhibited both acceleration and deceleration, with the deceleration showing a bigger magnitude. For instance, changes in timber production showed a maximum of 42% of acceleration rate, while its deceleration rate in some cases exceeded 100% (Figure 19A). Acceleration rate in mushroom production reached 8.5%, while deceleration reached 40%. Scenic beauty values exhibited more stationarity in time (Figure 20B), while fire risk showed a decrease in most of the stands (Figure 20A). In all the cases the deceleration magnitude was bigger than acceleration. However, there was no obvious spatial pattern observed in the acceleration/deceleration distribution.

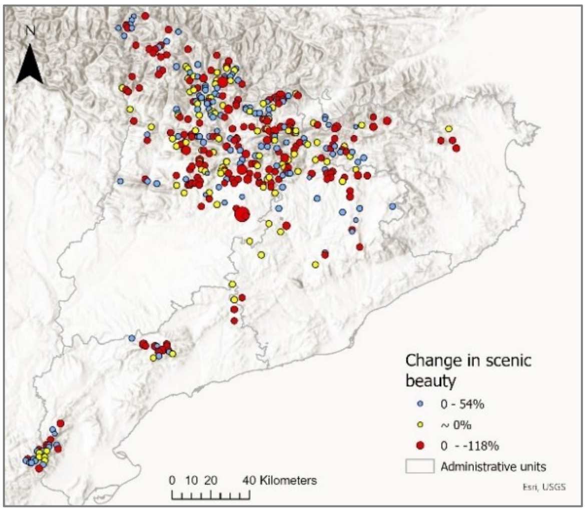




(A) (B)

Figure 19. Change rate in timber production (A) and mushroom production (B): blue represents acceleration, red represents deceleration, and yellow indicates a consistent change rate over time.





(A) (B)

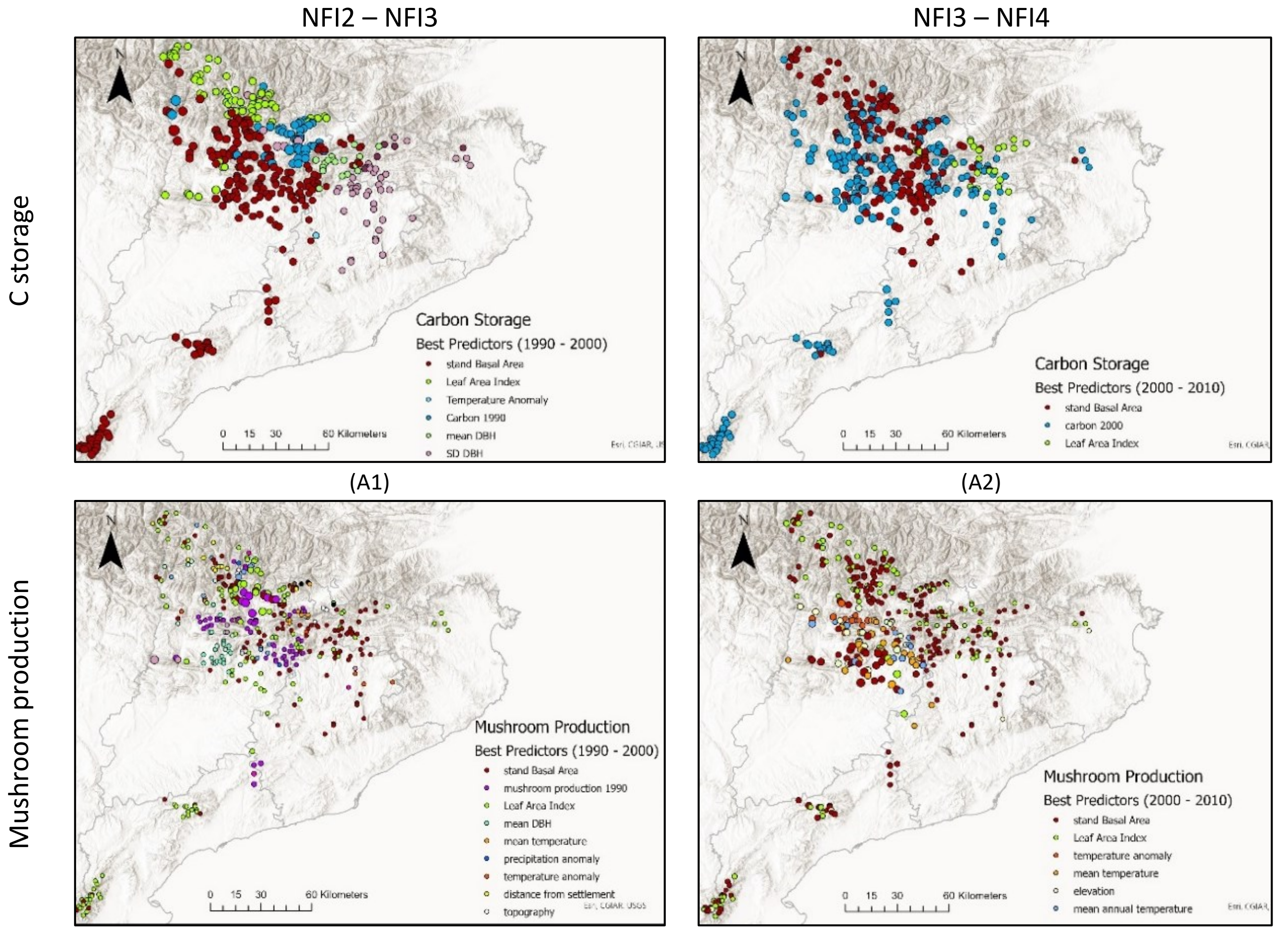
Figure 20. Change rate in fire risk (A) and scenic beauty (B): blue represents acceleration, red represents deceleration, and yellow indicates a consistent change rate over time. Note: Fire risk is visualized as blue for deceleration and red for acceleration, consistent with the visualization of negative changes.

3.1.2. Spatiotemporal drivers of ecosystem services changes

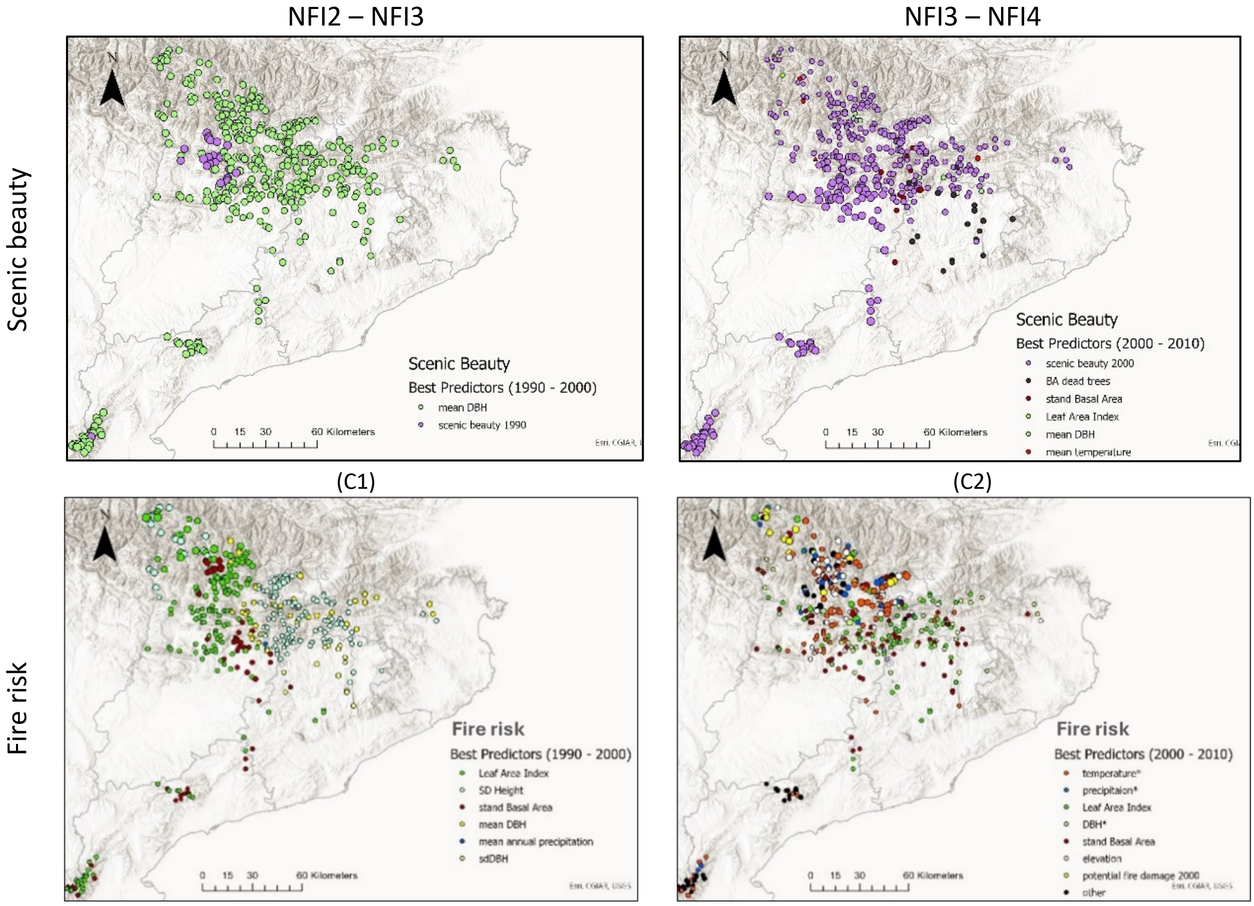
Geographic Random Forest (GRF) identified main ESs drivers and their spatial distribution. By applying GRF for each period between NFI measurements helped in examining how these drivers changed over time. The main drivers influencing changes in the selected ESs were stand attributes and climatic variables, in both periods. R-squared (R2) values ranged from 0.02 to 0.38, with the highest values observed in in modelling timber and C storage. The predictors exhibited substantial spatial and temporal variations in most of the cases. For instance, in the first period, stand basal area was most frequently explaining C storage (Figure 21A1), whereas in the second period (Figure 21A2), historical values of carbon were most frequent best predictors. The second period also exhibited a smaller number of main predictors.

Changes in mushroom production showed varying spatiotemporal distribution of drivers (Figure 21B1 and 21B2), which were more localized comparing with C storage. The main drivers encompassed a wide range of variables, including climate and stand structural attributes.

Predictors associated with scenic beauty showed a global uniform spatial distribution pattern. During the first period, mean DBH was the most frequent main driver (Figure 21C1), while during the second period, previous values of scenic beauty played a more prominent role (Figure 21C2).



(B1) (B2)



(C1) (C2)

(D1) (D2)

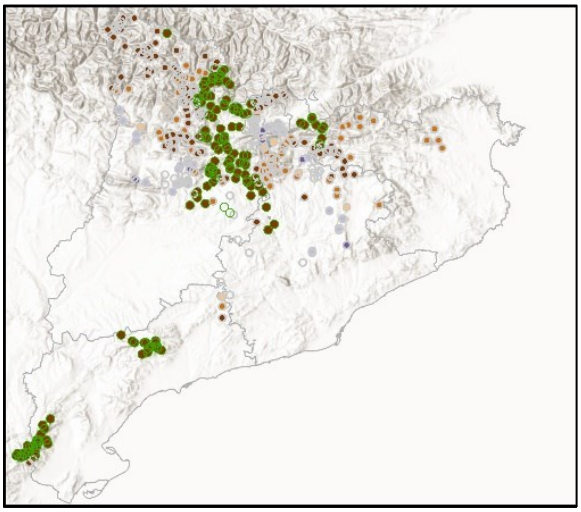
Figure 21.Temporal changes of ESs drivers: Left panel shows the spatial distribution of the main predictors in the first period (1990 – 2000) and the right panel depicts the main predictors in the second period (2000 – 2010).

In terms of potential fire risk, in the first period, the drivers exhibited spatial clustering, with the most frequent predictors being leaf area index (LAI), standard deviation of tree height, and stand basal area (Figure 21D1). However, in the second period, the drivers did not show a clear spatial clustering (Figure 21D2).

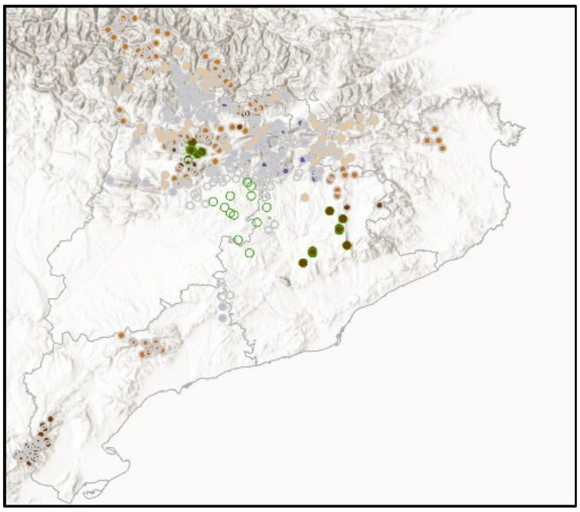
3.1.3. Spatiotemporal interaction between ecosystem services

The Multi-scale Geographically Weighted Regression (MGWR) revealed the spatial distribution of trade-offs and synergies in ESs changes, as well as the strength of their relationship (cf. maps illustrated in Figure 22 and the Appendix v, Supplementary table 6).

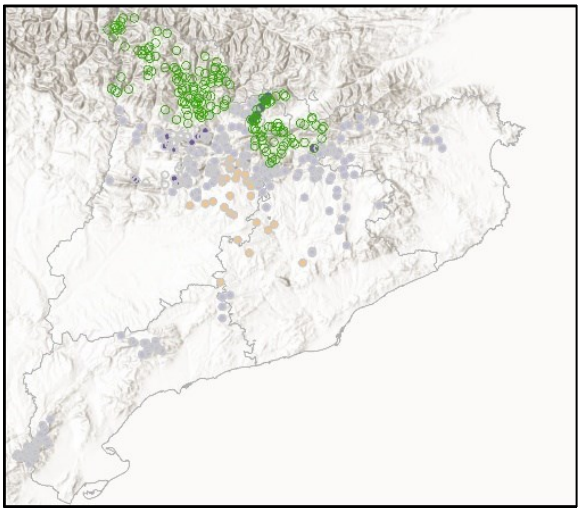
By applying this method separately for each NFI interval, it was possible to study temporal variability in the ESs interaction. For instance, in the first period, there was a strong and statistically significant spatially clustered synergy between timber and scenic beauty (Figure 22A1), while, in the second period, the relationship was found to be less significant (Figure 22A2). Conversely, potential fire risk and scenic beauty, at the greatest extent within the study area, was found weak and non-significant in the first period (Figure 22B1), but in the second period, the great majority of the stands exhibited a statistically significant trade-off (Figure 22B2). Mushroom production and timber exhibited a significant synergy, sparsely distributed in space, during the first period (Figure 22C1) while in the second period the relationship became stronger and more spatially clustered (Figure 22C2). A strong synergy was found in both periods in timber-carbon relationship (Figure 22D1 and D2).



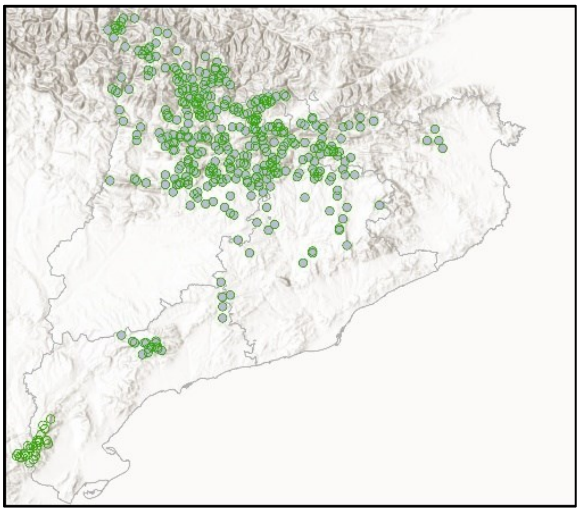
A1
Scenic beauty-Timber 1990-2000



A2
Scenic beauty-Timber 2000 - 2010



B1
Fire risk – Scenic beauty 1990 – 2000



B2
Fire risk – Scenic beauty 2000 – 2010

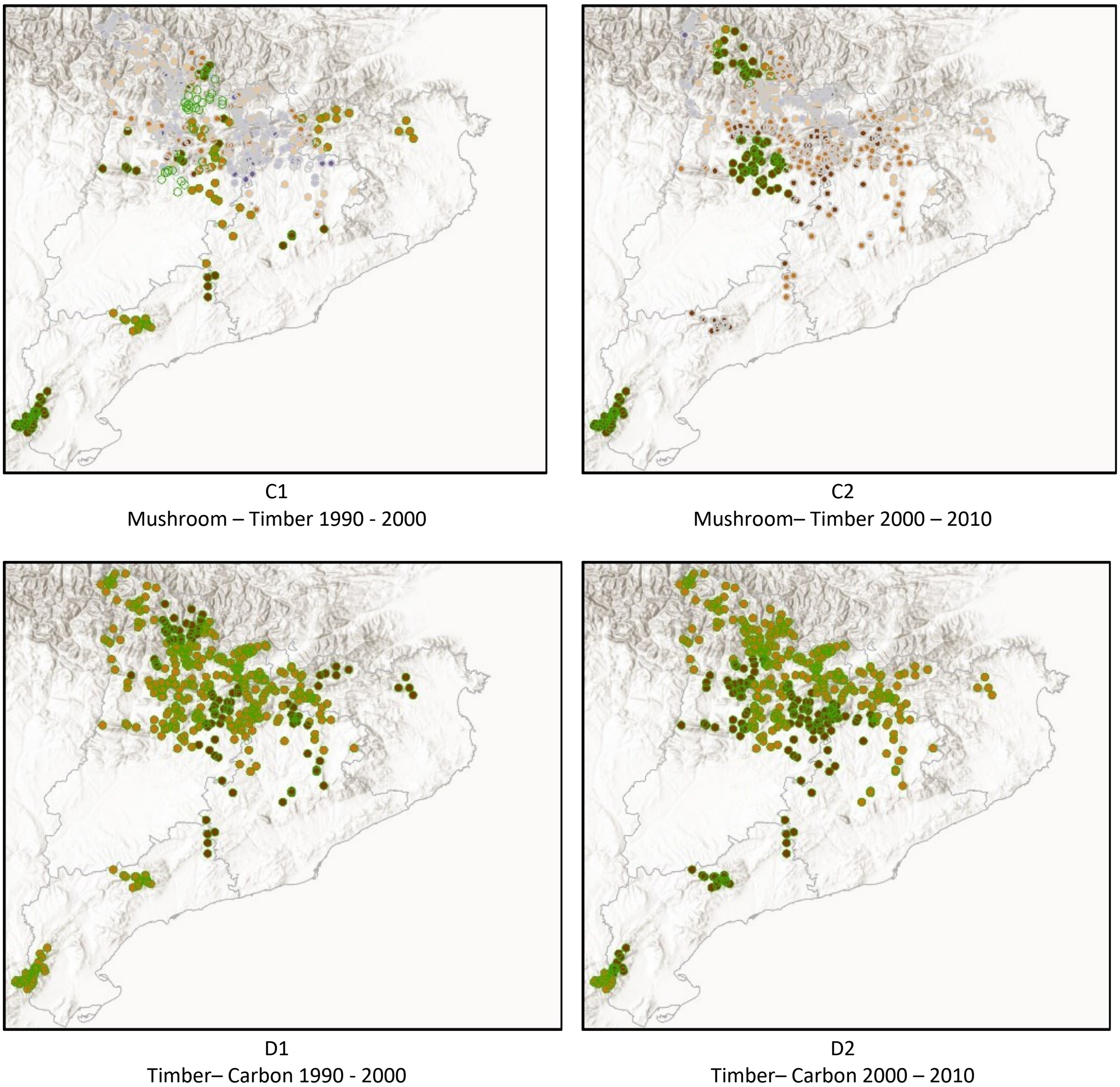


Figure 22. Trade-offs and synergies between changes in ES pairs: Warm colors indicate same direction of change (synergies), cold colors indicate opposite directions of change (trade-off). Color intensity shows the strength of the relationships. Green outline color indicates statistical significance.

3.2. Case study II. Adaptive simulation experiment

3.2.1. Effects of management and climate change on timber production

The simulation experiment, conducted with SORTIE-ND and GOTILWA+ using adaptive harvest configurations, aimed to illustrate how current management recommendations, represented by the ORGEST models Ps09 and Ps08, would perform under the future climate conditions. Notably, there were significant differences among the simulations.

First, in the no-management alternative (Ps00) (Figure 23A), the stand basal area in SORTIE-ND decreased steadily with climate change pressure in all sites by ~10 m^2 ha^{-1} in total. In GOTILWA+, however, the climate change scenarios RCP 4.5 and RCP 8.5 provoked a sudden tree loss in mesic and xeric sites, which resulted in a decrease of around 60 percent of total basal area, while the humid site was not affected by climate change.

Second, the thinning adjustments varied significantly between simulators: while SORTIE-ND extended thinning intervals as a function of severity of climate change scenario, GOTILWA+ shortened them (Figure 23B, 23C). For instance, when applying the Ps08 management alternative (Fig. 23B), SORTIE-ND simulated rotation periods ranging from 80 years (humid site, RCP 0.0) to 200 years (xeric site, RCP 8.5), while GOTILWA+´s rotation periods ranged from 50 years (humid and mesic sites, RCP 8.5) to 90 years (xeric site, RCP 0.0). In Ps09 management alternative (Fig. 22C), the rotation period varied between 65 years (humid site, RCP 0.0) and 165 years (xeric site, RCP 8.5) in SORTIE-ND, while in GOTILWA+, it ranged from 50 years (humid and mesic sites, RCP 8.5) to 100 years (xeric site, RCP 0.0).

Third, the values of timber production indices also varied across site, simulators, and climate change scenarios. Total timber production, referred to as the total harvested timber per rotation, in both simulators increased as function of site humidity and management: the largest yield corresponded to the humid site and more intensive thinning regime (Ps08), with GOTILWA+ simulating 30% higher values than SORTIE-ND (Figure 24A).

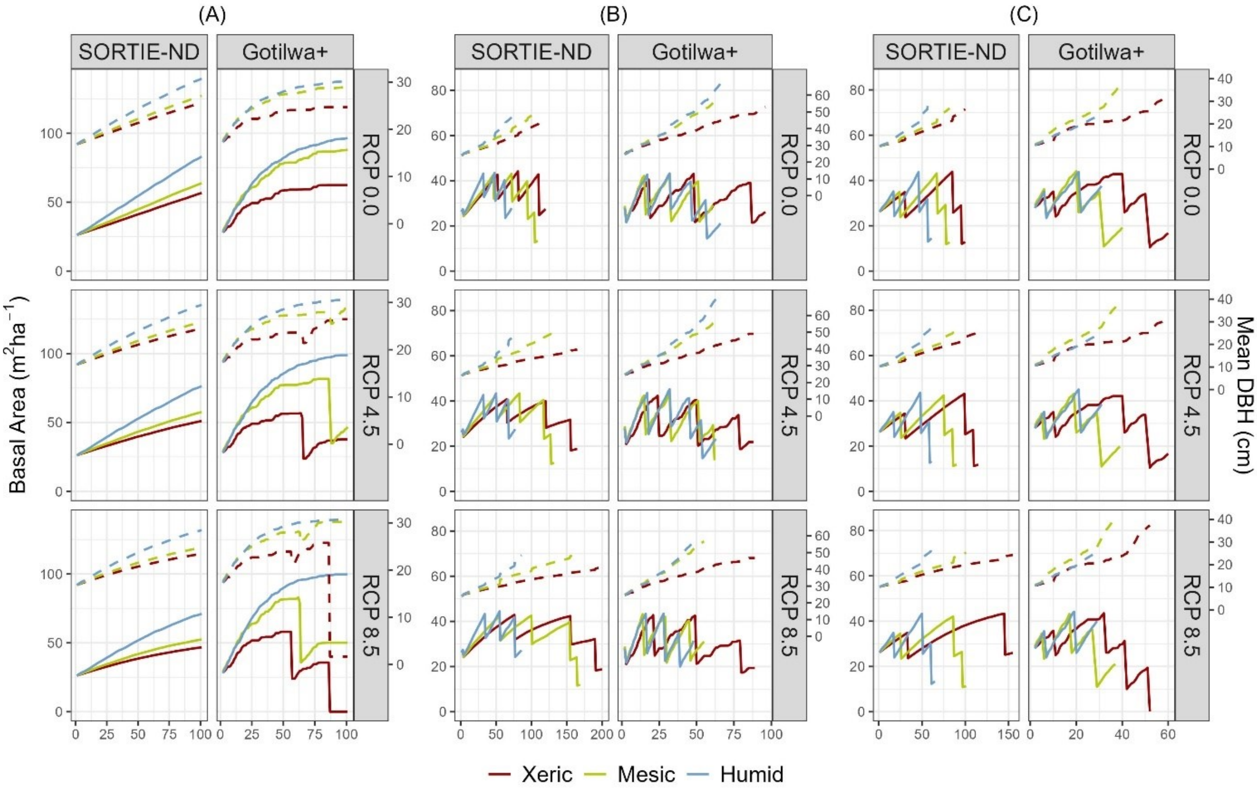


Figure 23. Simulations of humid, mesic and xeric stands: (A) without management, (B) low intensity, high frequency management Ps08, (C) high intensity, low frequency Ps09. The graphs show the basal area (BA) with a continuous line, and the mean DBH with a dashed line, along the simulation period under three climate change scenarios. The values show the means of the 10 simulation replicates.

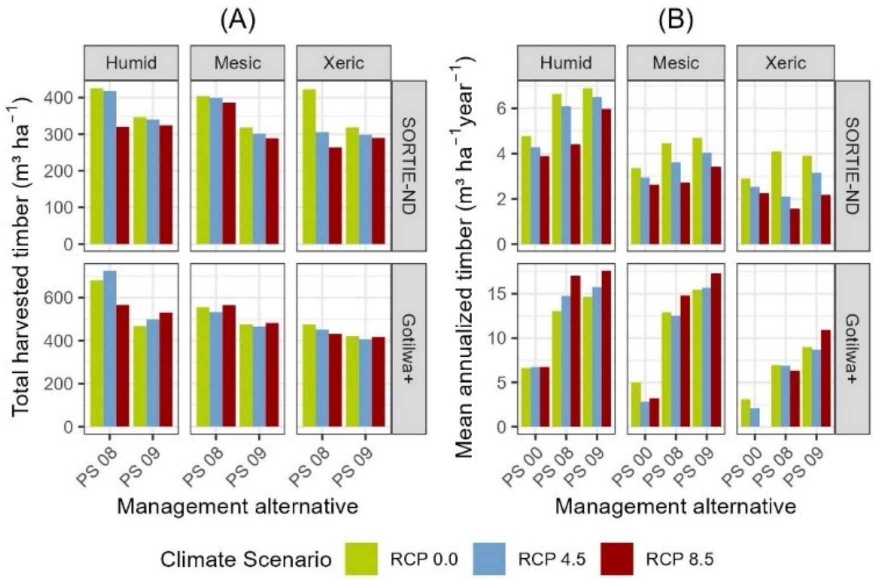


Figure 24. Timber production across sites, management alternatives and climate change scenarios: (A) Total timber volume harvested at the end of the simulation period; (B) Annualized timber production, calculated as the mean cumulative timber per rotation period. The values are averaged from 10 simulation repetitions.

The mean annualized timber had higher values due to management in all but xeric site under RCP 4.5 and RCP 8.5 climate change scenario in SORTIE-ND (Figure 24B). The simulation of the humid stand in SORTIE-ND demonstrated the highest timber production under the RCP 00 scenario, especially when management practices were applied, leading to an approximately 25 percent increase in timber volume compared to no management. In the mesic and xeric sites, this difference was around 15-20 percent. In GOTILWA+, the annualized timber production, simulated under both management alternatives, was more than double at all sites and under all climate change scenarios compared to the no management option. The Ps09 management alternative under the RCP 8.5 scenario yielded the highest timber production value.

3.2.2. Factors influencing variations in simulation outputs

The results of variation partitioning, applied for each simulator, showed that timber production in SORTIE-ND outputs was mainly explained by site conditions, followed by climatic scenario and management alternatives (Figure 25A). In contrast, timber production simulated in GOTILWA+ was mainly explained by management alternatives and site conditions (Figure 25B), while climate change scenarios did not show significant explanatory power (Figure 25B).

When assessing the combined results from both simulators, the variations observed in timber production were primarily explained by the simulator identity (Figure 25C). VP indicated that ~38% of the variance in the values of timber production was attributed to the simulators alone (p = 0.001), and an additional ~28% was jointly attributed to both the simulators and the management alternatives. Site alone explained ~11% (p = 0.001) of the variation in timber production outputs, and ~7% combined with the simulator (Figure 25C).

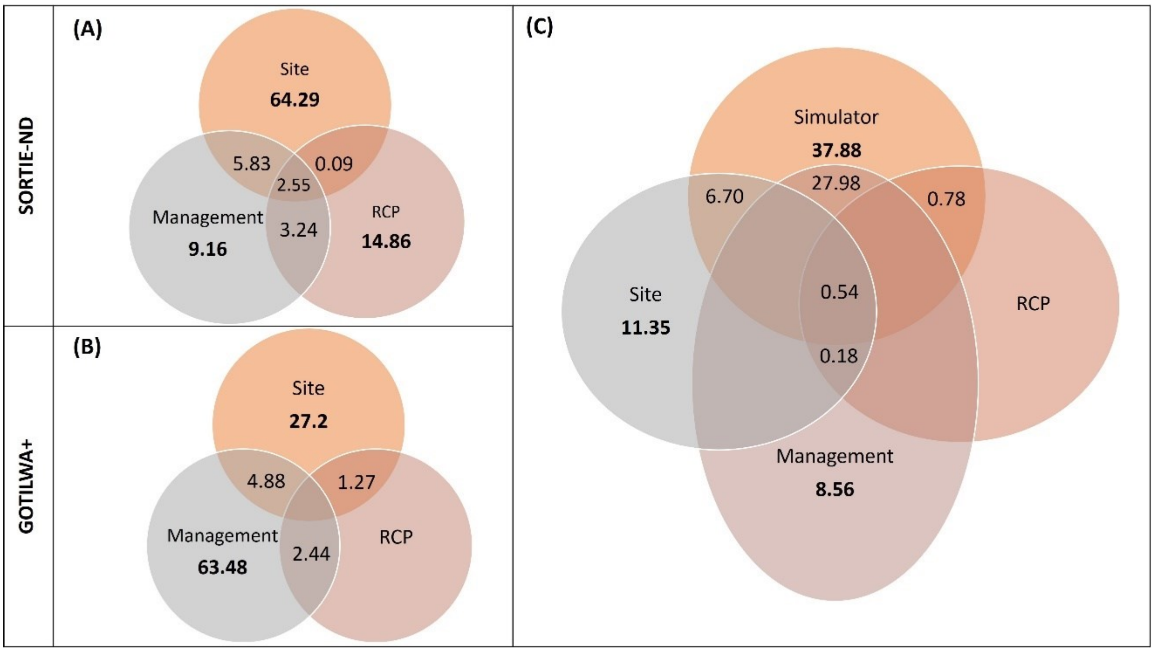


Figure 25. Venn diagrams illustrating variation partitioning between simulators, sites, climate change scenarios, and management alternatives. A and B display the variance of site, management alternative, and climate scenarios on the annualized timber production projections for each simulator, while C shows the variance in the simulations from both simulators. The numbers represent the percent of variance explained by each factor, where zero values did not contribute to the variation in the results and were omitted from the diagrams. E.g. (C) shows than that the RCP factor in the combined results of the two models explains less than when applied separately in each model.

3.3. Case study III. Decision-making and VR

3.3.1. Virtual 3D stands

A Python module was developed for the purpose of generating 3D scenes from simulation outputs, each portraying the state of the forest stand for a specific simulated year. These scenes are essentially X3D files that are integrated into the X3DOM framework. This framework, supported by HTML5, facilitates the visualization of scenes within a web browser. The scenes are generated based on species identity, tree height, and tree coordinates – information extracted from the simulation outputs. The 3D representations of each tree consist of actual images stored on the web server, allowing for scene visualization directly in the web browser. An illustrative example of a 3D stand is presented in Figure 26A, showcasing a forest stand 15 years after thinning and the Figure 26B depicts the simulation of a mixed stand with no management considerations.

Additional JavaScript functions were implemented to enable information retrieval at both individual tree level (including species identity, DBH, and height), and stand level (including BA, mean DBH, and ES indicators).

A B

Figure 26. Example of 3D simulation of the stand. (A) 25 years after thinning, and (B) 80 years of simulation without management.

3.3.2. Opinion questionnaire results

The pilot opinion survey, announced in March 2022, collected data from 18 participants. The respondents were between 28 and 49 years old. Gender distribution was 56% female and 44% male respondents. The participants' attitude toward technology was rated 3.54 out of 5 in average, while the preference for video games, which was selected as an indicator for a) technology adoption and comfort, and b) the user experience expectations, revealed an average of 2.28. Most of the participants indicated little familiarity with VR technology: 39% stated that they had an idea what VR is, and 50% tried VR headsets at least once.

The question regarding user preferences for visualising management alternatives revealed an inclination towards 3D and VR visualisations, as shown in the figure below.

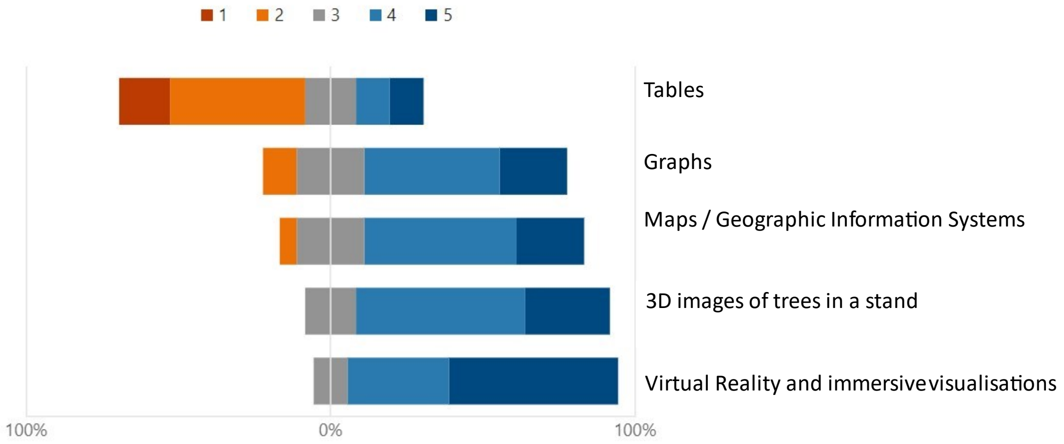


Figure 27. Responses regarding visualisation preferences

However, regarding the applicability of VR, participants favoured educational use and engagement of public over forest management decision-making.

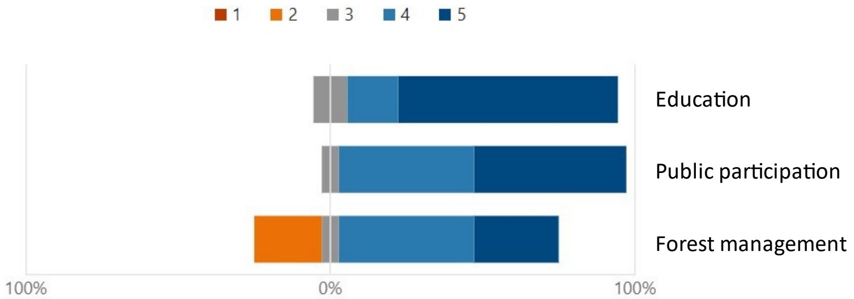


Figure 28. Responses regarding applicability of 3D and VR visualisations

When the participants were asked about the utility of VR, most of the participants agreed that VR can improve the interpretation of climate change and management impacts on forests.

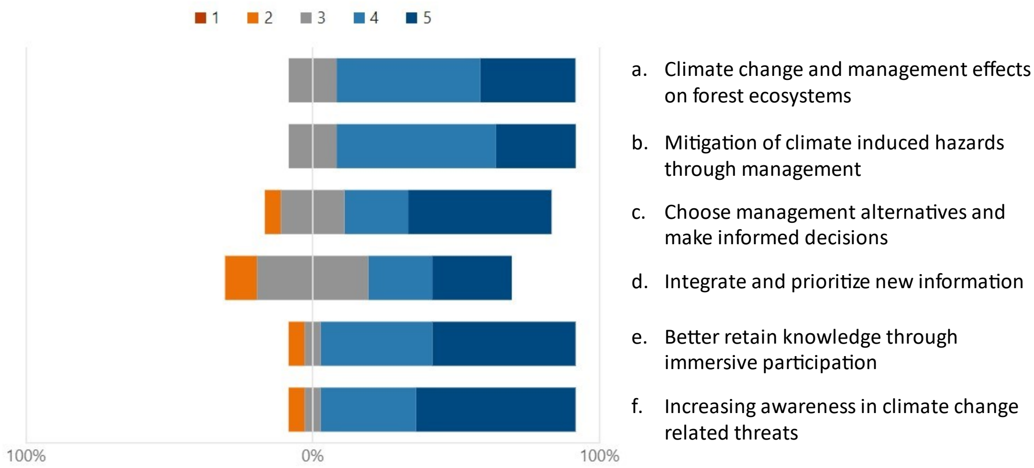


Figure 29. Responses regarding the utility of 3D and VR applications

3.4. Case study IV - DSS framework

3.4.1. Description of the system

The Decision Support System (DSS) adopted a 3-tier implementation (Figure 30). The data tier comprises information in diverse formats, in line with the user preferences. This includes a NoSQL database implemented in MongoDB, which stores forest stand data derived from the National Forest Inventory (NFI) in a hierarchical structure (see Appendix iii). Additionally, data are organized within a file system, accommodating both user preferences and model requirements (e.g., SORTIE-ND default outputs are in text delimited or XML formats). The data tier interacts with the business tier of the system, which encompasses various modules. These modules include the ESs module, management module, 2D visualizations module, 3D visualization module, and the Controller - a component that binds all modules together and establishes communication with the presentation layer, as well as with the external tools such as SORTIE-ND and the web server. The presentation tier is responsible for Human-Computer Interaction (HCI) and incorporates the Graphical User Interface (GUI). Additionally, it establishes connections with the web browser for the 3D visualization module, contributing to a comprehensive and user-friendly system interface (Figure 30).

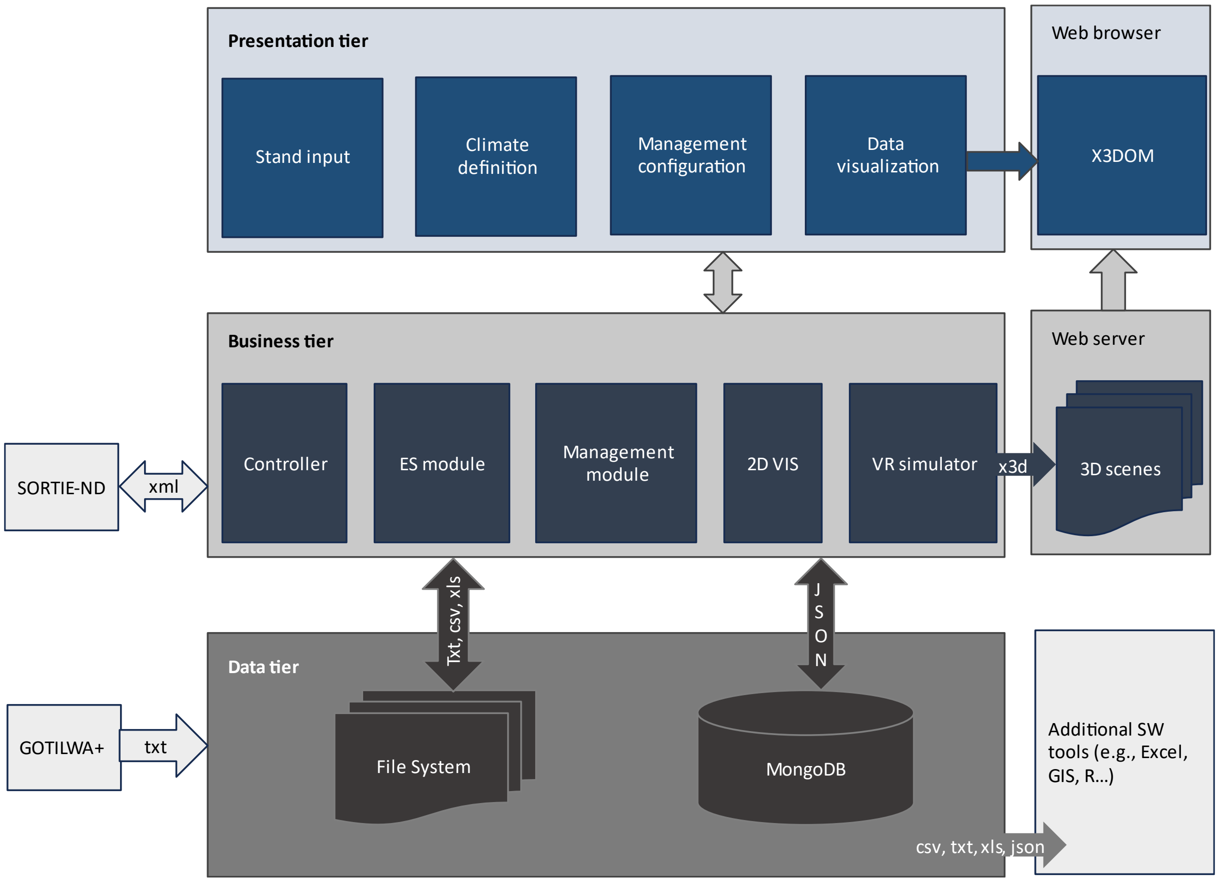


Figure 30. DSS implemented infrastructure and data exchange.

The HCI is a key aspect of the system, designed and customized to align with user requirements. In Figure 31, a simple use case illustrates the user's interaction with the GUI with the aim of simulating a forest stand. The flowchart delineates potential user choices and decisions guided by the GUI. This scenario exemplifies the basic use case, providing insight into the system's core functionality.

The use case initiates with the user inputting stand and tree data through the *stand definition interface*. If climate change is considered, the user transitions to the *climate definition interface*. Subsequently, if management is considered, the user is directed through the *management interface*. The subsequent decision is either to proceed with the simulation or define another stand. Upon completion of the simulation configuration, the system generates a configuration XML file for the SORTIE-ND forest dynamics model. If the user considers calculating ecosystem services, the system establishes a connection between SORTIE-ND outputs and the ESs module. The final step involves visualizing the outputs, which can be done either in 2D through the integrated GUI or in 3D through the web browser (consult Figure 30).

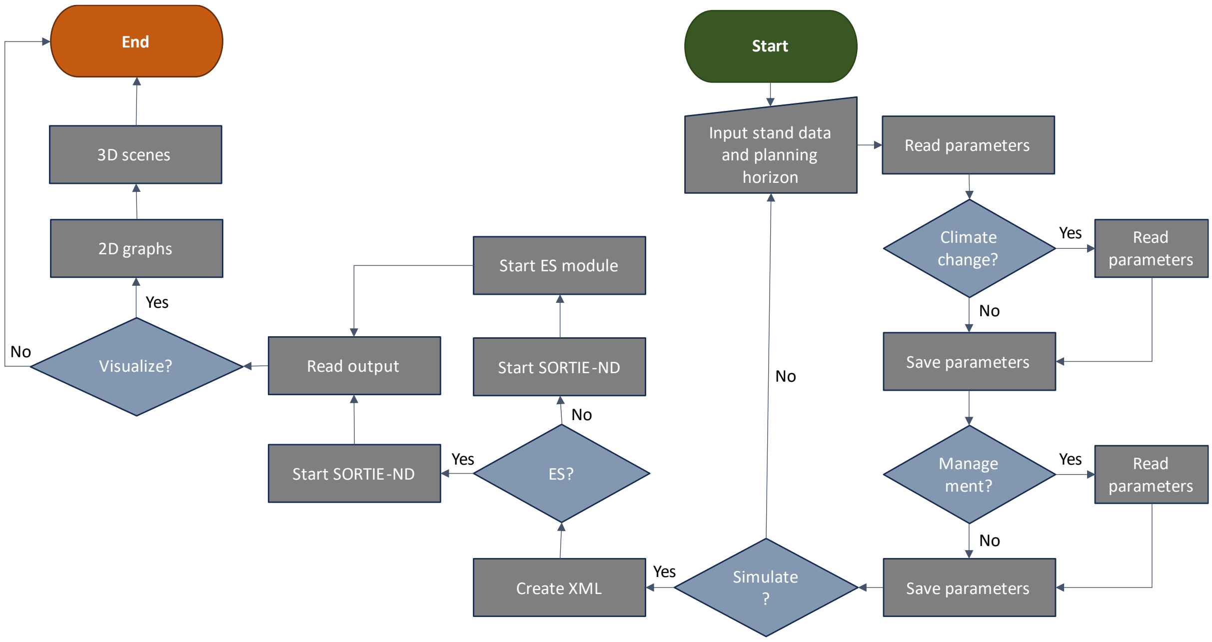


Figure 31. DSS flowchart: use case scenario using the system's user interface.

The interfaces can receive data from various sources (e.g., Figure 32 shows management configuration trough an Excel template). Stand data can be input via the interface (Figure 32 and 33), uploaded in tabular formats (e.g., Excel, TXT, CSV), or accessed through the MongoDB interface for NFI-based data. This flexibility applies to management and climate change data as well. The GUI allows defining one stand at a time, while external data can be uploaded for multiple stands.

	A	B	C	D	E	F	G	H	I
1						Amount to cut per DBH class			
2	management	thinning_year	thinning_type	apply_to_species	tallest_first	15-25	25-35	35-45	45-100
3	light	10	percent of basal area	All	no	33	25	25	25
4	light	20	percent of basal area	All	no	20	20	20	20
5	light	20	percent of basal area	All	no	10	10	10	10
6	heavy	45	percent of basal area	All	no	33	33	33	33
7	heavy	65	percent of basal area	All	no	33	33	33	33
8	heavy	85	percent of basal area	All	no	40	40	40	40
9	heavy	95	percent of basal area	All	no	50	50	50	50
10	heavy	105	percent of basal area	All	yes	100	100	100	100
11									

Figure 32. Example of management configuration input through an Excel file template

The DSS can be used to either project forest dynamics or to assess ESs. The strictly required stand data to simulate forest dynamics are plot geographical coordinates (latitude and longitude) and mean annual temperature and total annual precipitation. To calculate ESs indicators, in addition to coordinates and climate, topography in terms of elevation, aspect and slope is required. If climate change is considered, the system allows to either define precipitation and temperature trends within the interface, or upload detailed precipitation and temperature monthly timeseries, according to a provided template.

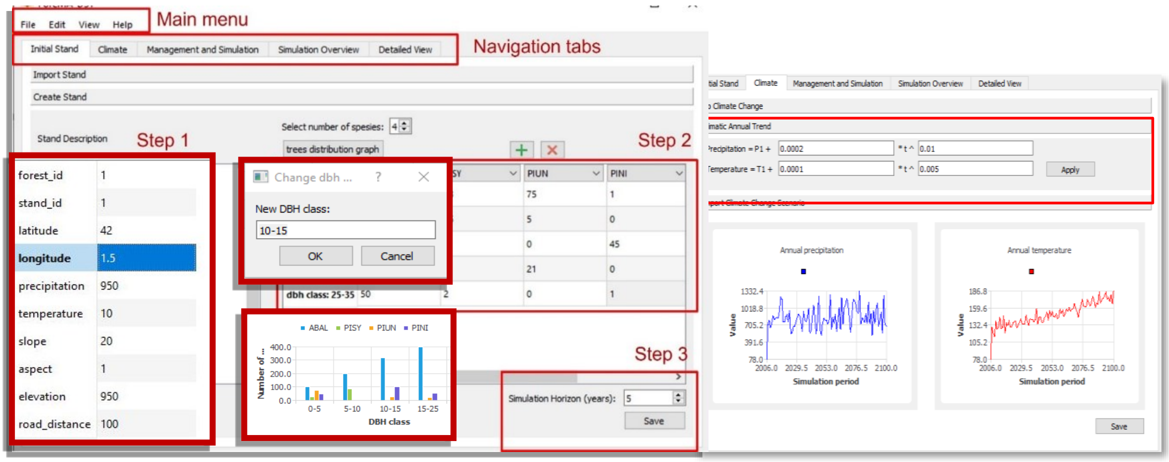
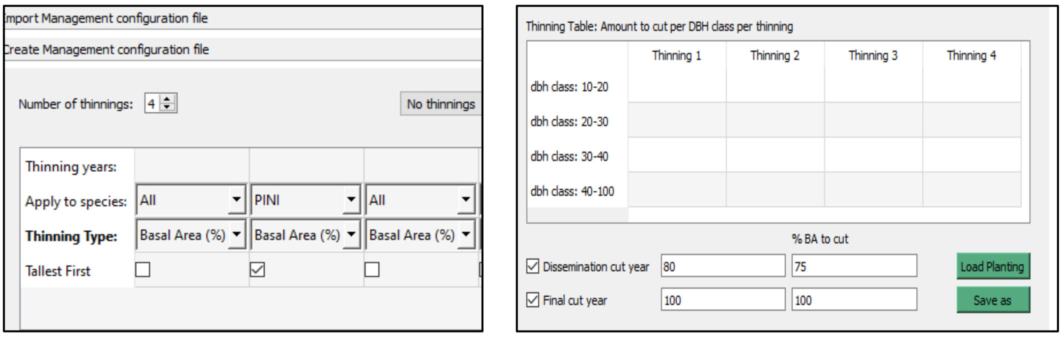


Figure 33. Input data interface

The management interface allows definition of configurations in line with SORTIE-ND requirements (Figure 34). Users may also upload a configuration file using the provided template (Figure 32). The simulation is initiated via the interface, offering options to simulate only forest dynamics or both forest dynamics and ecosystem services.



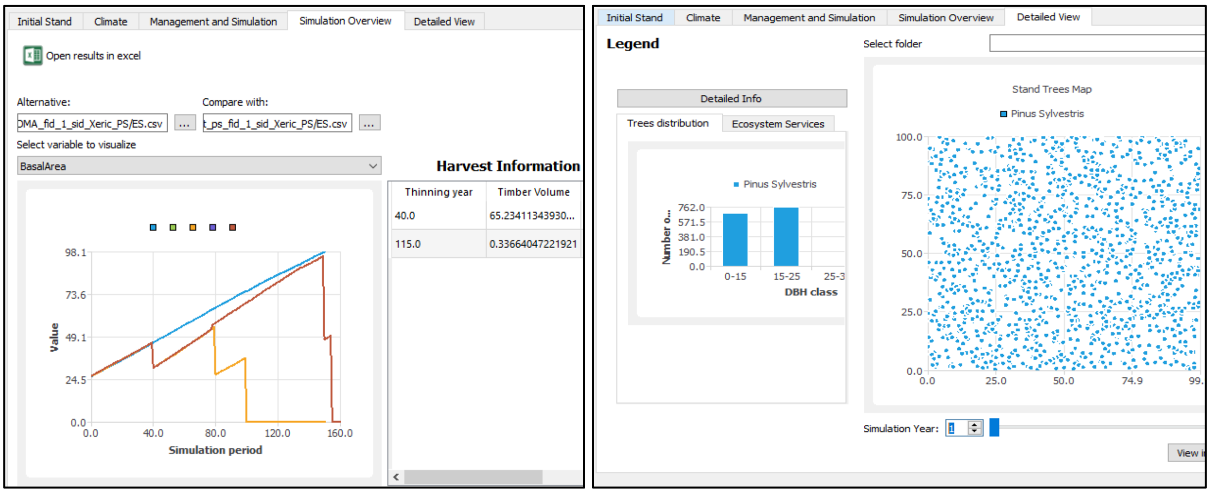
A B

Figure 34. Management alternative definition: (A) select number of thinnings, choose the species for management application, specify the removal type (based on % of BA or number of trees), and (B) assign the respective values for each thinning and DBH class. The management alternative can include or exclude final cutting, and regeneration by planting can be uploaded as a separate file.

After the simulation, the output data are organized in a file structure. The output folder is named after the stand. When climate change scenarios and management alternatives are applied, directories are created for each scenario and alternative. Simulation outputs are organized into folders, containing i) simulation overviews of forest characteristics, and ESs aggregated at a stand level per each year of the simulation, ii) harvest data of timber volume per DBH class, and iii) detailed tree level information per stand for each year of the simulation.

These simulation outputs are then visualized in the GUI through the visualization module that includes three types of visualizations: simulation overviews represented as time series graphs of stand averages

(Figure 35A), 2D visualizations of spatial tree distribution with accompanying DBH distribution histograms, and tables displaying ES values (Figure 35B). Furthermore, 3D stand visualization (Figure 29) can be generated through the interface and displayed in the web browser.



(A) (B)

Figure 35. Visualisation of the outputs: left, simulation overview; right, tree distribution in the stand

3.4.2. Usability evaluation

Usability evaluations were performed at different stages of the DSS development. The first evaluation, at the initial development stage, aimed at identifying fundamental usability issues. After implementing the necessary changes, the second evaluation was conducted to ensure that the modifications contributed to improved usability.

The first usability test was performed in-situ and involved 10 participants with an academic forestry-related background. The gender distribution among participants was 30% female and 70% male. Regarding background and familiarity with forest modelling, 50% reported being unfamiliar, 40% were familiar, and 10% were somewhat familiar. The System Usability Scale (SUS) results indicated a score of 66.7, reflecting an average degree of system usability. Responses to the overall satisfaction questions revealed unanimous satisfaction among participants with the ease and efficiency of task completion. Concerning satisfaction with system functionalities, 70% expressed satisfaction, while 30% suggested the need for some adjustments. In the open question section, feedback uncovered areas for system improvement. Suggestions included incorporating more ecosystem services, adding input sources such as TXT, CSV and Excel files, and providing explanatory text in visualizations. Responses to questions about system drawbacks indicated perceptions of rigidity and academic orientation in forest management implementation. Conversely, positive aspects highlighted the system’s ease of use, speed, simplicity in learning, and didactic nature. In summary, participants advised for a system improvement through enhancing flexibility in data input, accommodating input from various sources, and incorporating additional ecosystem services.

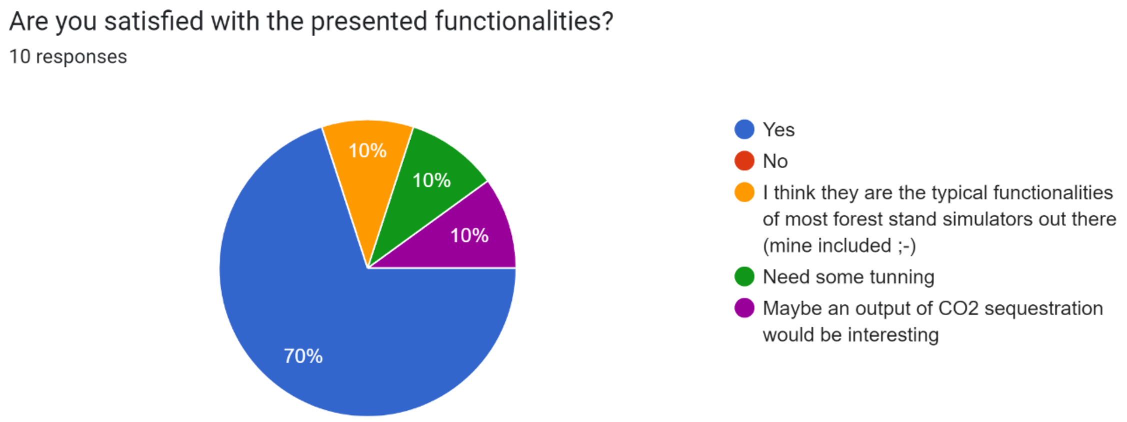


Figure 36. Responses to the users' satisfaction with the presented functionalities of the system (first usability test)

The second usability test was conducted online, involving potential stakeholders. The 19 respondents with diverse backgrounds, can be broadly categorized as forestry technicians and administration officials. The gender distribution reflected 35.3% female and 65.5% male participation. Familiarity with forest modelling indicated that 61% had no familiarity, 22% had little familiarity, and 17% were familiar with forest modelling concepts. In terms of system usability, the SUS score was 60.79. The general satisfaction question indicated that 84% of participants were satisfied (61% satisfied, 23% very satisfied), while 10.5% (two respondents) answered neutrally, and 5.4% (one participant) not at all. Responses to the question about expected functionalities varied, with 42% stating that the presented functionalities met their expectations, 42% expressing neutrality, and 16% disagreeing. Satisfaction with the presented functionalities revealed an overall satisfaction of 89%. Open-ended questions yielded suggestions for improvement, including adding more tree species, incorporating ORGEST management configurations, and enhancing flexibility to integrate results into GIS software systems.

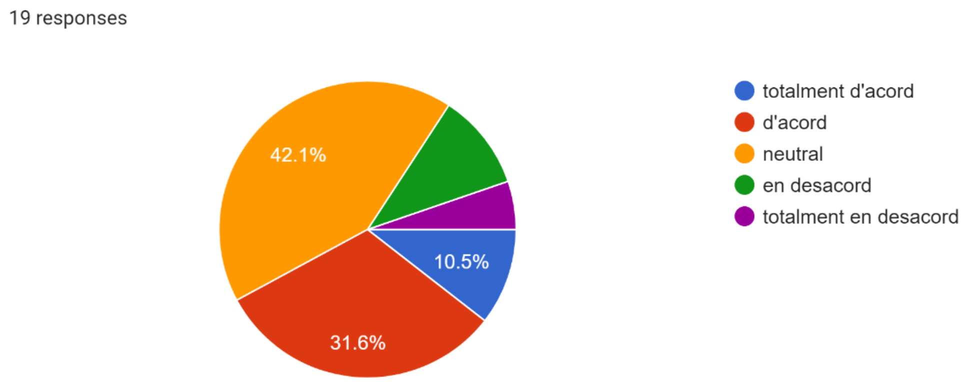


Figure 37. Responses to the users' satisfaction with the presented functionalities of the system (second usability test)

4. Discussion

4.1. Case study I. Current forest assessment: Patterns and drivers of ES dynamics

The first case study addressed the first objective of the thesis, which is to establish the requirements for incorporating geographically oriented strategic planning into the Decision Support System (DSS) framework. The first research question aimed to identify the spatial and temporal patterns characterizing recent changes in forest ESs to ascertain if these changes exhibit temporal stability. Temporal stability can have important implications in forest management: if changes occur consistently, projections become more reliable, and global methods may suffice in analyzing ESs dynamics. The hypothesis posited that if changes demonstrate temporal variations, traditional global methodologies might prove inadequate for such assessments. Furthermore, the drivers behind these changes may themselves exhibit spatiotemporal variations, thus influencing the heterogeneity in ESs supply.

Temporal variations

The temporal assessment of ESs showed non-stationarity, primarily in those ESs related to biomass production. This outcome aligns with the larger-scale study conducted by Astigarraga et al. (2020), which explored temporal trends in forest demography. Their results similarly revealed non-stationary in the temporal patterns characterized by an overall increase in forest productivity. While the overall values of ESs increased over time, when comparing their rate of changes between inventories, the second period showed a deceleration. A study conducted by Vilà-Cabrera et al. (2017), based on the NFI2 and NFI3, reported an increased rate of growth of the “new forests” in Catalonia, with 25% higher rates of growth than the rest of the forested lands. New forests refer to the forest conversion of the abandoned farmlands in the past century (Vilà-Cabrera et al., 2017). One can hypothesise that these new forests reached a state of equilibrium between NFI3 and NFI4, that resulted in the deceleration of ES changes in the second period compared to the first. However, more analyses are required to support this hypothesis, especially considering that the Spanish NFI does not provide the stand age information.

The literature consistently reports a lack of temporal consideration in ES assessments (cf. Boesing et al., 2020; Snäll et al., 2021; Willemen, 2020), likely stemming from insufficient temporal and spatial monitoring (Holland et al., 2011). Utilizing data from NFI systematic surveys, the present study examined the temporal dynamics and spatial distribution of forest ESs. Mapping the rate of ESs temporal changes revealed spatial heterogeneity in the distribution of acceleration, deceleration, and stationarity patterns. Further analyses of the factors driving these changes provided insights into these spatial distributions.

Spatiotemporal patterns of the main ES drivers

To uncover the factors driving temporal variations in ecosystem services and their spatial changes involved applying a Geographically weighted Random Forest algorithm (GRF, Georganos et al., 2021; Georganos and Kalogirou, 2022). The specific questions addressed here were: What are the main drivers underpinning the changes in ecosystem services? How do they differ across the study area? Do these drivers change in time? How?

The ESs drivers were selected based on literature, were forest and stand attributes are the direct drivers and population and infrastructure are the indirect drivers (M.E.A., 2005). GRF was chosen for two main reasons: first, it provides a spatial non-stationarity analysis, by considering each location and its neighbourhood dynamics; second, it can deal with collinearity issues and non-linearity of data.

Studies assessing ESs often operate at an administrative unit level, such as a municipality (e.g., Qiu et al., 2018; Roces-Díaz et al., 2018). This approach aligns with the overall goal of the ESs concept, which is to foster collaboration across diverse domains, integrating economic theory, policymaking, and ecological research (Costanza et al., 1997; Fisher et al., 2008; Hausmann et al., 2016; Kindler, 2016; Thorsen et al., 2014). The use of administrative units, in this context, can facilitate this integration. However, continuous geographical phenomena often transcend arbitrary boundaries set by administrative units. To address this, some studies used more meaningful geographical delineations such as watersheds, or boundaries of eco-regions (e.g., Roces-Díaz et al., 2021), employing global statistical methods for their assessments. The global methods estimate the average effect of a variable on an outcome in a specific geographical region. The contribution of the present study lies in employing local spatial statistics able to analyze data across geographical space, accounting for their inherent spatial dependencies and variations. In short, it explores how the relationship between variables changes across different areas. Within the regression framework, this translates into spatial diversity of the regression coefficients.

The study revealed that forest attributes played a prominent role in driving changes in all ecosystem services, which is also supported by similar studies (e.g., Felipe-Lucia et al., 2018). Interestingly, although forest management is a recognized direct driver, it displayed weak predictability in ESs changes with the GRF approach. It is important to note that forest management directly impacts forest structure and composition, thus acting as a “latent variable” in this context. Additionally, the management categories outlined in the National Forest Inventory (NFI) lack specificity. For instance, the “soil improvement” category encompasses various practices such as fertilization, understorey removal, or prescribed burning, each exerting distinct effects on the stand. Similarly, the “stand improvement” category includes pruning or thinning without specifying intensity (ICONA, 1995). Therefore, the management variable showed a limited predictive power. Another aspect to consider is that GRF, like many other ML algorithms, primarily focuses on predictive power rather than explanatory insights. The method chosen to identify the best predictor prioritized enhancing accuracy over reducing variation, posing challenges for drawing assumptions about the explanatory power of the predictors. Essentially, the results show which variables most effectively predict changes in ESs. This analysis, conducted over two periods, aimed to observe how the predictors evolved over time. For instance, in examining carbon storage maps between NFI2 and NFI3, key predictors included basal area (BA), leaf area index (LAI), temperature anomaly, mean and standard deviation of diameter at breast height (DBH), along with initial carbon values. An interesting observation was the clustering of predictors, a pattern that varied based on the specific ecosystem service being considered and the time interval under examination. For example, C storage drivers exhibited a clustered pattern observed in both time intervals, but the spatial distribution and the number of drivers varied between intervals. Scenic beauty was explained by one driver at a time, which was different from one period to another. Potential fire risk drivers showed a clustering in the first period, but in the second period they exhibited spatial heterogeneity. While the drivers of mushroom production exhibited a spatial heterogeneity in both periods. The drivers were related to both stand and site attributes; however, they depended on the specific ESs and examined temporal window. In a recent study examining drivers of ESs, Felipe-Lucia et al. (2018) similarly found that numerous forest attributes contribute to multiple ESs changes.

Taking as an example the drivers of C storage in the first period, Leaf Area Index (LAI) showed great predictive power in water-rich Pyrenees stands, aligning with a recent study by Li et al., (2022) that identified a global pattern in LAI and soil moisture. Stand Basal Area (BA) was the strongest predictor over a large spatial extent, which aligns logically with the fact that BA is strongly correlated with the biomass production (Castedo-Dorado et al., 2012). In the second period, fewer main predictors were identified compared to the first period. This reduction might suggest a more consistent or uniform pattern of change during the second period.

Understanding ESs drivers offers ecological insights with practical management implications. However, the focus of the study is not explaining these potential drivers; it is about demonstrating how their composition, pattern, and distribution can vary depending on the specific timeframe being studied. The choice of the time window can have consequences on the geographically oriented management decisions. Therefore, it is important to understand the dynamic nature of ecosystem processes in both space and time. It is also essential to use spatially explicit methods, i.e., geographically weighted approaches to analyse continuous phenomena. Previous ES studies relying on the National Forest Inventory (NFI) data considered spatial heterogeneity by dividing the study area into distinct regions (cf. Roces-Díaz et al., 2018 and 2021). In contrast, GRF views the study area as a continuous surface, offering a more nuanced understanding of predictors-response interaction across geographical space.

Interaction between ESs

Besides understanding the main drivers of ESs changes, forest management planning aims to identify areas of conflict or co-production in multiple ESs. Traditional methods, often employing snapshots in time, and global approaches at the fragmentation of geographical space, do not fully capture the continuous spatial nature of these services. Moreover, ecosystem services operate on various scales and timeframes, necessitating a cross-scale approach. To address this, Multi-scale Geographically Weighted Regression (MGWR) was employed to explore how ES pairs interact across space and time.

MGWR analysis revealed spatial and temporal variations: biomass related ESs showed a strong and positive relationship indicating synergies. For instance, timber production and C storage had strong positive statistically significant relationships across space and time. The repeatedly co-occurring ESs over space and in time are called ES bundles (Saidi and Spray, 2018) and are crucial in policy making and sustainable forest management. However, it is important to note that the way the ESs indices are calculated may affect the interpretation of bundles. Here, C storage (a regulating service) is determined by the total biomass of trees, that is directly linked to standing timber (a provisioning service), and hence shares the same underlying mechanisms.

Other ESs pairs showed more localized effects. Mushroom production and timber production revealed synergistic relationship, however, the statistical significance was restricted to specific geographical areas, which changed from one period to another. Similarly, scenic beauty and timber production showed a strong and significant geographically clustered relationship in the first period, while the second period exhibited synergies in few stands. Scenic beauty and fire risk probability displayed weak negative, statistically significant relationships. In practical terms, since potential fire risk serves as a proxy for fire regulation service, this association can also be seen as synergistic.

In conclusion, all the studied ecosystem services demonstrated synergies, aligning with findings from previous assessments in the region (Morán-Ordóñez et al., 2020; Roces-Díaz et al., 2021). However, the spatial distribution of relationships between pairs of ecosystem services varied considerably depending on the specific time window and the pair of ecosystem services being examined. Unlike traditional approaches, using correlation analyses over hard boundaries, MGWR offered a more detailed insight into ES relationships by considering spatial and temporal dynamics, thus, revealing localized effects of ESs associations. This study showcased the effectiveness of geographically weighted methods in acknowledging and addressing spatial heterogeneity, enhancing our understanding of spatial and temporal variations in ecosystem services dynamics. Similarly, sustainable forest management (SFM) requires recognizing location-specific processes to identify where limited resources can be most impactful. Therefore, leveraging local spatial statistics holds significant promise in facilitating geographically oriented forest management to promote sustainability.

4.2. Case study II. Future forest assessment: Adaptive simulation experiment

Addressing the second objective of the thesis, which focuses on facilitating adaptive management through forest modelling while assessing future uncertainties, the second case study involved a simulation experiment. This experiment was based on two recognized models in the literature, parameterized for forest species in Catalonia.

The second case study corresponds to the alternatives' generation decision-making stage. In this stage, if spatial planning is considered, the landscape is divided into management zones, each associated with proposed management alternatives. Subsequently, these alternatives are implemented in forest simulation tools to project their impacts on forest dynamics and ESs. Forest simulation tools, particularly those addressing climate change, are often developed in research environments and tend to offer fixed management configurations. The simulation tools considered in the context of this study required configuring management parameters, such as thinning timing and intensity, prior to initiating the simulation. Since adaptive management acknowledges the impacts of climate change on forests, the simulation tools also should adopt this perspective. This case study approached adaptive management by a goal-driven simulation, where the management configurations are adjusted to the evolution of stand in respect to previous interventions and climate change impacts. Based on the ORGEST management objectives, outlined in the management models Ps08 and Ps09 (cf. Methodology section), the rules for the simulation algorithm were set in respect to expected DBH and BA. However, the algorithm can be easily modified to include multiple objectives, in line with SFM principles.

The aim of this case study was to assess the feasibility and the requirements of integrating process-based forest modelling in the DSS. The research questions addressed in this case study aimed at evaluating the effectiveness of current management recommendations in an adaptive management simulation, and at assessing the robustness of these simulations.

Effects of current management recommendations

The simulation experiment considered ORGEST management models Ps08 and Ps09, corresponding to light and heavy thinning, respectively. Both models were developed to increase timber production and reduce fire risk (Piqué et al., 2017). The experiment (Figure 12) was conducted in two simulators i.e., SORTIE-ND (Canham et al., 2005) and GOTILWA+ (Nadal-Sala and Sabate, 2013). In SORTIE-ND, thinning intervals were extended as a function of climate change and site aridity. One potential explanation is that these factors, combined with stochastic mortality (represented by a 2% loss in basal area per year), extended the time needed to reach the BA and DBH thresholds of the ORGEST management models. On the other hand, GOTILWA+ model simulated rotation periods that were nearly three times shorter than those of SORTIE-ND. Potential explanation is that increased CO_2 by climate change and reduced competition by thinning contributed to the increased tree growth. These results are also supported by experimental studies suggesting that thinning reduces competition for resources among trees and promotes growth (D'Amato et al. 2013; Aldea et al. 2017; Vilà-Vilardell et al., 2023). Thinning effects of reducing drought vulnerability (cf. Sohn et al., 2016) was depicted in GOTILWA+, where the widespread drought induced mortality was prevented by both management alternatives in the mesic and xeric sites. The indicators used for timber production examined in this study (total yield, annual and annualized timber production) increased as a function of site humidity and management alternatives. The largest total yield corresponded to the humid site and more intensive thinning regime (Ps08) which is consistent with studies examining the effect of different management treatments on timber productivity (e.g., Alonso Ponce et al., 2017). Moreover, reducing competition through thinning is a well-accepted measure to improve the impact of water deficit on the remaining trees (Tague et al., 2021; Vilà-Vilardell et al., 2023), not only by increasing productivity (Olivar et al., 2022), but also by reducing vulnerability to sudden and widespread drought induced mortality, in regions where climate is expected to become drier (Martinez-Vilalta et al., 2019).

Overall, the adaptive simulation experiment presented a goal-driven approach that relies on the forest attributes to guide the timing of the management interventions. Using the ORGEST management guidelines as an example, the results of the simulations were in accordance with ORGEST models when growth was simulated using current climate. However, when combined with climate change scenarios, the outcomes became divergent in both simulator and site considerations. SORTIE-ND extended rotation periods up to 200 years in the xeric site and RCP 8.5 climate change scenario. Conversely, GOTILWA+ reduced rotation periods to 60 years in the same simulation settings, thus, mitigating massive diebacks.

Drawing conclusions and implications in management planning based on these results would be challenging, given the different outcomes produced by the simulation tools. It is important to note that both modelling approaches are used in forestry research and have been validated against field data (Ameztegui et al., 2015; Nadal-Sala et al., 2013). Moreover, this study is not aiming to compare the structural differences between modelling approaches. The goal was to understand the implication of an adaptive management approach in forest simulation studies. The main message conveyed by this study is the necessity of integrating adaptive approaches into the simulation tools. Nevertheless, it also raises concerns about the uncertainties of the simulation outputs, emphasizing the relevance and need for further investigation addressed in the subsequent research question.

Variations in simulation outputs are primarily subject to modelling approaches rather than climate change scenarios

Forest management plans are inherently uncertain, especially in the context of global changes. Typically, forest management simulation studies rely on a single simulation tool and report future uncertainties primarily through climate change scenario analyses. The management simulations conducted using two modelling approaches yielded contrasting outputs. While the simulations of SORTIE-ND suggested enlarging the rotation periods and the thinning intervals to reach the specified goals under climate change perspective, GOTILWA+ suggested shortening them.

Both models stem from distinct spectra: one focuses on light competition and annual averages of monthly climate data, while the other is based on detailed eco-physiological processes, incorporating weather data spanning hourly to daily averages. This fundamental differences naturally anticipate divergent outputs. Nevertheless, the ranges of values produced by the outcomes of both simulators fall within the range of reported NFI data (cf. Palahí et al., 2003). This emphasizes our still limited understanding of natural processes leading to uncertainties in future projections. Nevertheless, the concern is raised on how the choice of the simulation tool may affect management decisions. Variation partitioning revealed that the simulator had the greatest impact on variations in timber production projections, followed by site and management factors. This finding confirms the initial hypothesis and is in line with previous research conducted at larger scales (cf. Petter et al., 2020). However, there is an important take away from this study: the choice of the simulation tool holds more significance than the climate change scenario in projecting forest response to climate change and management. Contrary to the common practice of focusing only on climate change uncertainty when reporting simulation outputs, this case study emphasizes the need of additionally considering uncertainties originating from the simulation tools.

4.3. Case study III. Decision-making and VR

To address the third objective, a VR application was developed followed by the administration of an online opinion survey. The survey evaluated the effectiveness of immersive visualizations in conveying management implications, specifically in participatory decision-making contexts. This case study corresponds to the third phase of decision-making that entails evaluating management alternatives involving stakeholders' participation. 3D visualizations and VR have been usually applied to create virtual forest environments applying a static approach, i.e., where the virtual forest scenes are built to showcase selected management and/or climate change scenarios (e.g., Chandler et al., 2022; Huang et al., 2020; Queiroz et al., 2018). This case study employed a quasi-3D modelling method for reconstructing trees based on images, a time-efficient technique used for real-time rendering. This approach enabled simultaneous visualization of virtual forest stands based on mathematical models' simulations. As a result, stakeholders can assess not only predefined management alternatives but also simulate scenarios of their own. Similar approach was applied in previous literature to enhance education in forest management (cf. Fabrika et al., 2018). This case study employed a quantitative survey to collect public opinion on the effectiveness of VR and 3D modelling in forest management decision-making. The respondents were selected based on proximity, providing a convenient approach for conducting a pilot survey. As a result, most respondents were found to have a similar research-oriented background. The survey findings suggest that VR applications hold a potential in decision making, although respondents agreed on its better suitability for educational purposes. Despite that, aspects such as immersive comprehension enhancement, that indicate suitability criteria for education, received lower ratings. Overall, 3D and VR methods were preferred over 2D visuals for understanding forest simulation complexities. For more comprehensive results and to draw more accurate conclusions, a larger sample size is required. Additionally, conducting a pre- and post- VR tool utility survey would help understand perception changes, especially considering the unfamiliarity of many respondents with the VR concepts.

4.4. Case study IV. DSS framework

To address the fourth objective of the thesis, the insights of the previous case studies were utilized to design a holistic DSS. Operational criteria that translate sustainable forest management principles into the DSS development were defined as a) addressing multiple ESs across scales, b) adapting management configurations to the climate change impact on the future forests, c) addressing robustness of the future projections of forest dynamics and increasing transparency in communicating these projected impact and d) facilitating stakeholder participation in decision-making through immersive visualizations and user-friendly interfaces.

Similar to Vacik and Lexer (2014) thinking, the design of the DSS was perceived as a collection of tools aiding different decision-making stages. Attempting to integrate all the tools into one comprehensive system can be complex and possibly unnecessary, as commented by Reynolds (2005). The technological needs assessment and usability evaluations led to an architecture that combines both integration and composition approaches (cf. Holsapple, 2003). Participants in the usability evaluation surveys showed preference to combining software solutions, such as spreadsheets and GIS. To integrate these tools is a challenge, given that they are often commercialized, standalone applications. Therefore, the architecture was implemented through a *composition* approach, that allows the outcomes of one component to be utilized in another component (Burstein and W. Holsapple, 2008). Based on the insights from the case studies, the components of the DSS were identified as follows: a database, a model base comprising two forest dynamics models and five ecosystem services models (ES module), a management module, a 3D visualization component, and graphical user interfaces. However, the minimum requirements for the basic functionalities included one forest simulator (i.e., SORTIE-ND), the ES module, and the management-oriented user interfaces. The implementation (cf. Figure 30) followed a modular approach, allowing performing tasks of different scales and complexities. For instance, for education purposes the system can function without connecting the database. A simple use-case (e.g., Figure 31) involves inserting stand-specific data through the interface to a) visualize its present state, b) quantify ecosystem services, c) simulate future alternatives considering climate change and management, and d) generate VR forest scenes in real time. Another scenario involves uploading a spreadsheet containing multiple stands and predefined management options (Figure 32). This particular case was required during system usability evaluation and was integrated into the DSS. The DSS can be further combined with other external tools or software to enhance its capabilities and overall utility. This is enabled by the compatibility between file formats among all the identified components.

During the needs assessment phase, it became evident that input data arrives in diverse formats and from various sources. While relational databases and database management systems based on SQL (e.g., Oracle, PostgreSQL, MS Access etc.) are widely accepted for their structured relationships between entities, they pose challenges when dealing with diverse output formats from different software solutions within the DSS. For instance, SORTIE-ND generates outputs in XML format, 3D visualizations in X3D and HTML, and climate and climate change data comes in tabular formats, making integration into a single schema complex, especially considering the substantial volume of simulation outputs: for instance, the simulation experiment employed in this study generated 540 simulation cases, each associated with at least 100 files per case. To handle the scalability and variety of data sources more effectively, a NoSQL database was employed. NoSQL can manage heterogeneous data by providing flexible schema designs, unlike the rigid structure of SQL databases. This flexibility allows handling diverse data formats and large volumes of simulation outputs, making them suitable for managing complex and varied datasets within the DSS. Recent research has assessed NoSQL databases for decision support (cf. Llano-Rios et al., 2020); however, to the best of current knowledge, this is the first implementation within the context of forest management DSSs.

The main priority in developing a software system lies in its usability. The literature review has outlined concerns and challenges related to the practical implementation of existing DSSs (Linkevičius et al., 2019; Walling and Vaneeckhaute, 2020). To address these challenges, the developed DSS integrated multiple ESs, implemented management-oriented simulations, and introduced real-time Virtual Reality (VR) visualizations to facilitate the interpretation of simulation outputs. To ensure system usability, usability evaluation surveys were conducted at the beginning and at the end of the development process, involving diverse user groups. The first usability evaluation focused on forestry experts and aimed to define DSS functionalities for intuitive, comprehensive support in forest management decisions. The second evaluation involved potential end-users from diverse backgrounds. Despite improvements made after the initial evaluation, the second assessment resulted in a lower System Usability Scale (SUS) score. This discrepancy might be attributed to the evaluation being conducted online due to COVID-19 restrictions, preventing users from interacting with the system and fully comprehending its capabilities. Moreover, as the initial evaluation involved participants with scientific backgrounds, the human-computer interaction (HCI) issues were prioritized over limitations in forest modelling, as the participants were more familiar with the modelling issues. The second group highlighted restrictions in considering tree species, the limited number of ESs, and the inflexibility of management regimes, emphasizing forest modelling issues rather than HCI. The feedback from potential end-users directly reflected the gaps found in the existing decision support literature concerning the integration of policy requirements. These included widening the range of the considered ESs, facilitating flexibility in data sources and formats, and enabling simulations adaptable to management goals. Consequently, based on user recommendations, the DSS considered the inclusion of two forest simulators to account for more species, adopted an adaptive management approach to offer flexibility in management configurations, and incorporated the ORGEST forest management guidelines.

4.5. Potential limitations

Data limitations

National Forest Inventories (NFI) currently serve as valuable source of data for studying and modelling spatiotemporal trends in forest dynamics (e.g., Astigarraga et al., 2020; Ruiz-Benito et al., 2014), or modelling natural disturbances (González-Olabarria and Pukkala, 2011; Selkimäki et al., 2012). Forest inventories employ sampling techniques to select representative plots. This method introduces sampling error. Fortin et al., (2016) in their uncertainty assessment based on the Spanish NFI2 and NFI3, found that sampling uncertainty accounted for the largest share of total uncertainty in their models. In most cases, sampling variance contributed to over 60% of the total variance. In addition to the sampling error, measurement errors are also common, but often overlooked (Berger et al., 2014). Measurement errors occur when the measurement instrument fails to accurately record a measurement. For instance, in the Spanish NFI2 tree height consistently appeared underestimated due to calibration issues with the measurement tool (Trasobares et al., 2022). Human-induced errors are also prevalent in this context. For instance, Castelo et al. (2018) reported that 16% of the same trees were misidentified as different trees during consecutive measurements in forest inventories. Recognizing data constraints and finding ways to minimize their impact is vital for better insights into forest ecosystems. Remote sensing technologies have the potential to enhance the quality of forest inventory data (Hilker et al., 2008; Lister et al., 2020).

Modelling limitations

Our understanding of forest systems and their interactions with the environment is still evolving, with many processes and mechanisms remaining poorly understood or difficult to quantify (Botkin, 1993). Therefore, modelling approaches often rely on simplifying assumptions to handle complex phenomena (Monserud, 2003). For instance, SORTIE-ND assumes a maximum potential growth influenced by competition and annual temperature and precipitation, while GOTILWA+ includes various plant processes (i.e., photosynthesis and stomatal conductance) and considers CO2 fertilization and hydraulic failure. SORTIE-ND considers neighbourhood dynamics and mixed species interactions, while GOTILWA+ ignores spatial heterogeneity and considers only single species stands. Current parameterization of these models is done in different sites. SORTIE-ND in the pre-Pyrenees pine forests (Ameztegui et al., 2015), while the GOTILWA+ model in sub-Mediterranean (Gracia et al., 1999). The context-specific parameterization of these models should be considered when extrapolating their outputs to different regions or larger scales. Regarding forest dynamics, both models consider mainly growth and mortality, with natural regeneration being substituted by planting. Moreover, there is a poor consideration of natural disturbances, at least in the versions used in the study. Addressing these limitations by assessing and communicating the uncertainties in the simulation outputs is essential for informed decision-making.

4.6. General discussion

In the context of global changes, there is a strong demand for effective tools to guide forest management decisions. These tools should integrate scientific knowledge, societal values, and policy requirements while making use of available technological advancements. Although scientific tools and policy instruments to address sustainability challenges exist, they need to be translated into operational criteria for management-oriented decision support tools.

Given the dynamic nature of management objectives, that evolve continuously in response to societal and policy demands, the adoption of an adaptive approach is imperative, particularly in the long-term forest management planning context. Adaptability in decision-making involves revising plans at different stages to accommodate new information. To navigate between decision-making stages effectively, it is important to ensure compatibility between spatial and temporal scales. The National Forest Inventory (NFI) data is a valuable resource applicable across multiple management levels (cf. Andersson 2005) and can be aggregated across spatial and temporal scales (Case Studies I, II, III, and IV). Adaptive management approach is particularly relevant in dealing with climate change scenarios, where future uncertainties impede the implementation of fixed solutions (Case study II).

The sustainability concept, first denoted at international policy level in 1987 (cf. Brundland report), was further defined as the act of balancing social, economic, and ecological needs (cf. Agenda 21, UN SDGs). To address this sustainability triptych, Ecosystem Services (ESs) framework (MEA 2005) was adopted by both policymakers and the scientific community. Assessing forest ESs dynamics across spatial scales and time windows (Case Study I) can help setting management goals in accordance with the available forest resources, as denoted in the New EU Forest strategy (European Commission, 2021, p. 4). The traditional way of assessing ESs at the administrative unit level may overlook spatial patterns in ESs that transcend administrative boundaries. Case study I demonstrated that the use of local geospatial statistics in addressing ESs in a continuous space can depict interactions and nuanced relationships. Furthermore, temporal scales play a crucial role in drawing conclusions about the changes in ESs (Willemen, 2020). Case Study I, based on data from the NFI, emphasized the temporal variability of these changes, advocating for the incorporation of spatiotemporal considerations in large-scale assessments. Another pertinent aspect discussed in ES analysis is the discrepancy between their operating spatial scales. Case Study I addressed this challenge by employing multi-scale geographically weighted regression that can handle cross-scale data simultaneously.

The need for climate change mitigation urged the development of process modelling approaches that enable projections under uncertain future climate conditions. These models are essential in forest management decision-making to develop and evaluate management alternatives. However, they are usually built within scientific settings, often resulting in a rigid implementation of management prescriptions. To facilitate decision-making, the simulation of future alternatives should align with management objectives (Case Study II). Additionally, it is crucial to communicate uncertainties related to these future projections to stakeholders, ensuring transparency in the decision-making process (de Pellegrin Llorente et al., 2023). Case Study II showed that the forest models were the primary sources of uncertainty in projecting future management alternatives, especially in long term, and advocated the adoption of a multi-modelling approach.

Engaging stakeholders in decision-making process is one of the key aspects in the Sustainable Forest Management (SFM) concept. Policy requirements aim to ensure accessibility, transparency and understanding of the potential impacts of management prescriptions, empowering stakeholders to make informed decisions. However, the challenge lies in developing tools that effectively convey scientific findings to stakeholders and encourage their active involvement in decision-making (Case study III and IV). Immersive visualizations have shown a potential in education and in conveying complex data (Radianti et al., 2020). Case study III expanded on this by exploring their potential for aiding decision-making.

The escalating policy demands, and the improvement of the scientific knowledge increased the complexity of computer-based decision support systems, potentially impeding their adoption among practitioners (Linkevičius et al., 2019, Vacik and Lexer, 2014). To promote their applicability, the literature proposed either broadening their scope (e.g., Reinolds, 2005), or narrowing it (cf. Gordon, 2006). The present thesis proposed a framework that translated SFM principles into operational steps. These steps included setting geographically oriented management goals considering multiple ESs interactions (case study I), generating adaptive management alternatives (case study II), and engaging stakeholder in decision making (case study III). Ultimately, these steps were integrated into a holistic Decision Support System (DSS) (case study IV). The system development combined both integration and synthesis of its components, comparable with Vacik and Lexer's (2014) "toolbox" vision of DSS.

The path toward defining operational criteria and developing the DSS was not linear; it involved iterative processes and continual adjustments based on user feedback and the requirements derived from the specific case studies. The first version of the DSS (cf. Cristal et al. 2019) integrated the SORTIE-ND forest dynamics model with empirical ESs models and provided a management – oriented user interface. This system underwent usability evaluation at the initial stage of its development, revealing users' further requirements. Despite the good performance of the overall usability of the system, the users' feedback suggested that the application of management prescriptions, based on the SORTIE-ND implementation, was rigid and research oriented. After the adjustments, the subsequent evaluation revealed that external tools are necessary to make the system broadly accepted. At the same time, the case studies showed adherence to the users' feedback. For instance, the case study II demonstrated the practicality of adaptive management simulation approach in a goal-oriented forest management. Additionally, case study IV stressed the importance of considering supplementary analytical tools, which were addressed through data compatibility and a compositional design architecture. As a result, the DSS development adopted an adaptive approach, aligning with user needs and SFM principles. To enhance clarity in presentation, the methods were systematically outlined, starting with identifying and operationalizing the integration of SFM principles into decision-making. To facilitate the translation of these principles into operational criteria, forest management decision-making was divided into distinct phases, each addressed with a case study (Table 20).

The approach undertaken in this thesis serves to bridge policy, decision-making, and stakeholders' engagement. Alongside introducing a holistic DSS framework (Case study IV), it addresses essential limitations in implementing SFM in decision-making by:

1. Assessing cross-scale ESs in time using NFI data and local geospatial statistics (Case study I),
2. Simulating adaptive to climate change management prescriptions (Case study II),
3. Combining forest growth models' outputs to convey uncertainties stemming from underlying assumptions in modelling (Case study II),
4. Developing real-time immersive visualizations to facilitate interpretation of forest simulations (Case study III).

Table 20. Mapping decision-making stages to forest planning levels and addressing literature gaps in accordance with SFM principles through case study objectives.

Decision-making stage	Forest planning level	SFM objectives (EU Forest Strategy)	Identified gaps	Case Study (CS) objectives
Problem setting	Strategic planning (landscape scale)	Balance social, economic and ecological needs Management based on biogeographic regions.	Limitations in accounting for spatiotemporal variations in multiple and multi-scaled ESs	CS I: Geospatial ESs assessment based on NFI data, considering varying scales and the continuity of the geographical space.
Alternatives generation	Strategic/ tactical planning (stand scale)	Adapt management to the changing environmental conditions.	Lack of adaptability in the simulation tools, especially those designed in the research settings	CS II: management configurations “adapted” to the forest response to climate change scenarios.
Decision stage	Strategic/ tactical	Enhancing stakeholder participation	Limitations in communicating uncertainty of the outputs. Lack of proof of the utility of immersive visualizations in decision-making	CS II: Use of multiple forest models alongside climate change scenarios CS III: Develop a VR application based on simulation outputs; conduct user opinion survey on its usability in decision-making

Besides the alignment with the generic SFM principles (Table 20), Table 21 details the results obtained in each case study in respect to the New EU Strategy 2030.

Table 21. Mapping EU Forest Strategy 2030 with DSS operational indicators developed in this dissertation.

EU Forest Strategy 2030	Description	Operational indicator	Case study
2.1. Promoting sustainable forest bioeconomy for long-lived wood products	*"… promoting forest management practices, production tools and processes that are **better adapted to different future forest resources**" (p.5)*	Geographically oriented management; Rule-based forest simulations	Case study I & II
2.3. Promoting non-wood forest-based bioeconomy, including ecotourism	*"promote the elaboration of coordinated and integrated regional, national and subnational programmes on the sustainable production of **non-wood forest products**" (p. 9)*	Non-wood ESs	Case studies I & IV
2.4. Developing skills and empowering people for sustainable forest-based bioeconomy	*"promote cooperation and connect pupils, students, teachers and stakeholders on the role of forests"* (p. 9)	Easy visualizations of climate change and forest management impacts on forests	Case study III
3.2. Ensuring forest restoration and reinforced sustainable forest management for climate adaptation and forest resilience	*"all forests should be increasingly managed so that they are sufficiently biodiverse, **taking into account the differences in natural conditions, biogeographic regions and forest typology**"*	Geographically oriented management	Case study I
Section 4. Strategic forest monitoring, reporting and data collection	*"FMPs should **include forest-related risk assessment and management, as well as better integrate biodiversity-related data**"*	Inclusion of multiple ESs and risk indices	Case studies I & IV
Section 5. A strong research and innovation agenda to improve our knowledge on forests	*" providing evidence-based and **practically feasible guidance for climate change mitigation and adaptation** in line with biodiversity objectives" p. 22*	Rule-based forest simulations	Case studies II & IV

5. Conclusion

This doctoral thesis aimed to integrate Sustainable Forest Management (SFM) principles into decision-making through a practical Decision Support System (DSS) development. To achieve this goal, key pre-conditions were identified at the thesis outset. First, to address the three pillars of sustainability, i.e., ecological, social, and economic dimensions, the Ecosystem Services (ESs) approach was considered. Second, to enable adaptive decision-making, integration of decision stages was approached by harmonizing scales and using National Forest Inventories (NFIs) data. The methodological approach revolved around three sustainability facets, which were identified and explored through dedicated case studies for each decision-making stage. These are: geographically oriented strategic management, adaptive management, and stakeholder engagement. Finally, insights from the case studies were employed as a basis for shaping the criteria and requirements essential for creating the DSS.

Attaining geographically oriented management in the first objective of the thesis, involved assessing multiple ESs at continuous spatial scales, implementing methods that uncover spatiotemporal patterns, rather than presuming them. The findings indicated an overall increase in ESs supply within the study area for the 25-year period. However, as hypothesized, ESs derived from forest attributes exhibited a global deceleration during the second half of the studied period. The spatial distribution of accelerating and decelerating patterns did not exhibit specific trends, but when their drivers were examined, a clear spatial grouping within bioregions was observed, that underpinned multiple forest attributes. Confirming the initial hypothesis, their importance and spatial distribution changed over time. As anticipated, the cross-scale interactions of the five studied ESs revealed synergistic relationships that changed in magnitude over time, showing localized patterns when their operational scales differed and globalized when the scales were similar. Overall, the first study stressed the importance of using spatial modelling and cross-scale interactions to understand ESs dynamics in space and time in order to better design geographically oriented management interventions. It also showed the importance of considering temporal grain when reporting ESs and their changes. The conclusions drawn for the DSS design were primarily related to the structure of the data schema, emphasizing the consideration of temporal dimensions and the need for data harmonization. Additionally, it stressed the importance of implementing an ES module able to quantify these services based on NFI data.

As part of the second objective, to facilitate an adaptive management approach in decision-making, the second case study showcased the viability of current management recommendations under future climate conditions. As hypothesized, the outcomes from two process models based on different underlying modelling assumptions yielded divergent results. However, the interpretation of these results under adaptive simulation approach revealed ambiguity, indicating that our scientific understanding of forest responses to climate change is still evolving. To address these limitations, is advisable to employ multiple forest modelling approaches rather than relying solely on one. The overconfidence on a single model may lead to suboptimal management decisions. Therefore, it's essential to transparently communicate this uncertainty to stakeholders to build trust and avoid misinterpretations of the projected outcomes. These insights contributed to the DSS design primarily regarding the creation of an adaptive simulation module and the incorporation of regional management guidelines; and subsequently, regarding the integration of simulations from various predictive models, and allowing visualization of their collective contribution to the overall variability of projection.

To address the third objective, regarding involving stakeholders in decision-making, the third case study coupled forest simulations with rendering immersive visualizations in real-time. Insights from the opinion survey unveiled a preference toward 3D and VR technologies in educational contexts rather than in the decision-making process, aligning with the initial hypothesis. The third case study contributed to the DSS through the development of the VR module of the system.

Addressing the fourth and final objective, regarding the DSS implementation, the insights from the case-studies and the user feedback, received during system usability evaluations, shed light into the basic requirements of a functional DSS. The gained insights, as hypothesized, emphasized the challenge of creating a fully integrated complex system, which could hinder its usability. Therefore, a composition approach, enabling component interaction through compatibility of data exchange was followed. The three case studies also revealed the need of an adaptive database design, accommodating the diversity and the growing amount of simulation outputs, implemented through the NoSQL database. The minimum model requirements for a functional DSS included the incorporation of multiple ESs and risk models, alongside at least one forest growth model. With continuous advancements in models and tools that aim to tackle the growing complexities of forest management problems, decision-makers might find it challenging to choose and implement the appropriate one. Ultimately, decision-makers may choose tools they are most accustomed to, potentially favouring familiarity over the best-suited tool for the task. To overcome this challenge, the adaptive design approach, incorporated user feedback throughout different stages of system development. The proposed framework offers solutions to usability issues by flexible data handling, support for adaptive management, intuitive visualizations, and compatibility with external tools, aiming to encourage broader adoption of DSS in forest management.

In conclusion, this work operationalized SFM principles into integrated decision-making in forest management planning. Integrating decision-making stages offers a holistic perspective on both opportunities and conflicts in managing forests for multiple objectives. This study showed how this integration can be supported by novel technological tools and combined into a holistic DSS. Moreover, it demonstrated the importance of considering geography as a continuum when analysing multiple ESs across scales. This approach can aid in shaping policies aligned with ecosystems' needs. The adaptive management concept, operationalized here through goal-oriented forest simulations, can facilitate both strategic and tactical management planning levels. However, an important take-away is that due to our still evolving understanding of forest responses to climatic changes, simulation outputs must be taken with precaution when developing management plans. To increase the credibility of scientific outputs, uncertainty levels from both forest modelling and from climate change scenarios have to be reported. To prevent misconceptions arising from underlying modelling assumptions, is advisable to employ multi-modelling approaches, potentially considering ensemble modelling for future use, along with transparently communicating their limitations to the stakeholders. In addition, emphasis should be placed on creating easily comprehensible visualizations and user-friendly interfaces. These tools should enhance stakeholder and public engagement, not only in the final stage of choosing predefined alternatives but also in the stage of generating these alternatives. This aligns with the core principles of sustainable forest management. Overall, the insights drawn from this thesis serve as a valuable resource, providing not only a practical framework for policy shaping and decision-making but also functioning as an educational tool that helps explain the complexities involved in achieving sustainability within forest management.

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The 10 theses

1. Decision support tools in forest management should be able to accommodate different planning levels, thus, facilitating adaptive decision-making.

2. Integrating various levels of management planning should involve harmonizing spatial scales across each level and enabling multi-scale analyses in both spatial and temporal contexts.

3. Although administrative boundaries offer convenience in ESs analyses, strategic forest planning must prioritize the geospatial context of forest attributes and associated ESs.

4. The analysis of ESs needs the use of geographically explicit methodologies that account for the heterogeneous spatiotemporal dynamics, emphasizing continuity over hard boundaries and acknowledging neighborhood dynamics as integral factors shaping ESs supply.

5. Effective strategic planning in forest management requires acknowledging the diverse spatial and temporal scales of ESs and employing cross-scale analyses to identify areas of conflict or co-production, ensuring more precise and informed geographically oriented decision-making.

6. To address adaptive management, forest simulation tool should allow the flexibility of adjusting harvest regimes in anticipation of the climate change and associated disturbances effects on forest structure and composition.

7. The management alternatives should account for various sources of uncertainty in future projections, including forest simulation tools. These uncertainties should be clearly communicated to stakeholders and the public to increase transparency and reliability of scientific outputs.

8. Effective decision support tools should facilitate stakeholder and public involvement by improving usability and aiding comprehension of complex outputs using accessible visual representations.

9. Decision Support Systems need to accommodate diverse data sources and be compatible with additional software tools that can expand their capabilities and potentially enhance their utility.

10. Overall, decision support systems in forest management should adhere to established policies while should also aid in future forestry policy development. This alignment ensures that decisions made using these tools contribute to effective and sustainable forest management.

Appendix

i. Systematic review on ES research

Supplementary material 1: Studies in Europe assessing forest ecosystem services based on NFI data: their scope, main objectives and methods applied.

Authors	Scope and Objectives	Method/Tools
Krumm et al., (2011)	- Study how forest structure (BA and N) varies with management, slope and aspect. - Model forest protection indicator - Study the effects of structural changes on forest protection	ANOVA Regression trees
Wernsdörfer et al., (2012)	- Define homogeneous forest strata. - Model forest dynamics (2006-2009) for these strata. - Unveil Patterns and drivers of forest dynamics	Forest stratification Markov transition matrix
Benito-Garzón et al., (2013)	- Create growth and mortality models based on NFI data - Combine with distribution models - Model the effect of growth and mortality on species distribution	Random Forest
Vayreda et al., (2013)	- Categorize species into pine and broadleaves (from the Spanish NFI) - Assess the response of sapling abundance and ingrowth rate to the spatial variability of climate, forest structure and disturbances	Generalized Linear Models (GLM)
Henttonen et al., (2017)	- Develop models of stem volume, basal area and height increment, based on Finnish NFI (1971–2010), for each of the NFI regions - Study effects of tree and stand attributes on stem volume, basal area and height increment	Additive Models (GAM)
Ruiz-Benito et al., (2017)	- Develop models of tree growth, mortality and abundance of saplings based on NFIs from Spain, Germany, Wallonia, Finland and Sweden - Study the effects of functional diversity on demographic responses to environmental variation in European forests.	nonlinear maximum likelihood
Acácio et al., (2017)	- Develop models for forest cover change in various oak forest types - Assess spatial patterns of persistence and land cover change	multinomial logistic regression analysis; spatial autocorrelation/association
Schelhaas et al., (2018)	Model diameter increment based on 10 NFIs in Europe	sigmoidal relationships with theoretical growth curves (Gompertz function)
Jevšenak and Skudnik, (2021)	Model species specific, non-parametric tree basal area increment based on Slovenian NFI tree level data.	Random Forest
Di Cosmo et al., (2020)	Model basal area increment of major forest species based on Italian NFI	mixed-effects model
Di Cosmo and Gasparini, (2020)	model tree mortality in Scots pine and European beech Study the effects of drought and competition on tree mortality	logistic regression
Astigarraga et al., (2020)	Study Patterns and drivers of forest dynamics in Spain	Mixed models SEM

Trasobares et al., (2022)	Model species specific diameter and height increment and survival rate from Spanish NFI	Mixed models
Thom and Seidl, (2022)	- Assess spatiotemporal changes in forest structure and composition from German NFI - Unravel the drivers of forest change	Spatial semi-variograms; Boost regression trees

Authors	**Scope and Objectives**	**Method**
Krumm et al., (2011)	- Study how forest structure (BA and N) varies with management, slope and aspect. - Model forest protection indicator - Study the effects of structural changes on forest protection	ANOVA Regression trees
Wernsdörfer et al., (2012)	- Define homogeneous forest strata. - Model forest dynamics (2006-2009) for these strata. - Unveil Patterns and drivers of forest dynamics	Forest stratification Markov transition matrix
Benito-Garzón et al., (2013)	- Create growth and mortality models based on NFI data - Combine with distribution models - Model the effect of growth and mortality on species distribution	Random Forest
Vayreda et al., (2013)	- Categorize species into pine and broadleaves (from the Spanish NFI) - Assess the response of sapling abundance and ingrowth rate to the spatial variability of climate, forest structure and disturbances	generalized linear models (GLM)
Henttonen et al., (2017)	- Develop models of stem volume, basal area and height increment, based on Finnish NFI (1971–2010), for each of the NFI regions - Study effects of tree and stand attributes on stem volume, basal area and height increment	Additive Models (GAM)
Ruiz-Benito et al., (2017)	- Develop models of tree growth, mortality and abundance of saplings based on NFIs from Spain, Germany, Wallonia, Finland and Sweden - Study the effects of functional diversity on demographic responses to environmental variation in European forests.	nonlinear maximum likelihood
Acácio et al., (2017)	- Develop models for forest cover change in various oak forest types - Assess spatial patterns of persistence and land cover change	multinomial logistic regression analysis; spatial autocorrelation/association
Schelhaas et al., (2018)	Model diameter increment based on 10 NFIs in Europe	sigmoidal relationships with theoretical growth curves (Gompertz function)
Jevšenak and Skudnik, (2021)	Model species specific, non-parametric tree basal area increment based on Slovenian NFI tree level data.	Random Forest
Di Cosmo et al., (2020)	Model basal area increment of major forest species based on Italian NFI	mixed-effects model
Di Cosmo and Gasparini, (2020)	model tree mortality in Scots pine and European beech Study the effects of drought and competition on tree mortality	logistic regression
Astigarraga et al., (2020)	Study Patterns and drivers of forest dynamics in Spain	Mixed models SEM
Trasobares et al., (2022)	Model species specific diameter and height increment and survival rate from Spanish NFI	Mixed models
Thom and Seidl, (2022)	- Assess spatiotemporal changes in forest structure and composition from German NFI - Unravel the drivers of forest change	Spatial semi-variograms; Boost regression trees

ii. Mushroom production model parameters

Supplementary material 2. Parameters for the models of mushroom production (source: de-Miguel et al., 2014)

Model parameters	Marketed	Edible	Total
β_0	−0.858	1.455	1.538
β_1	1.988	1.670	2.988
β_2	−0.846	−0.871	−1.512
β_3	0.171	0.458	0.719
β_4	−8.313	−1.602	−4.064
β_5	1.849	1.642	1.866
β_6	−0.913	−0.986	−1.016
β_7	0.575	0.626	0.382
β_8	−0.009	0.000	−0.006
β_9	0.000	0.073	0.092
$s(b_{0j})$	0.505	1.058	1.655
$s(b_{0k})$	1.382	1.181	1.322
$s(b_{4j})$	2.104	2.448	1.503
$s(b_{4k})$	1.504	0.848	2.429
$s(b_{6j})$	0.348	0.510	0.547
$s(b_{7j})$	0.000	0.000	0.064
$s(b_{7k})$	0.000	0.000	0.078
$s(b_{8j})$	0.002	0.000	0.000
$s(b_{8k})$	0.001	0.000	0.000
$s(\varepsilon_{ijk})$	1.489	1.548	1.419
CF	2.301	2.124	1.857

iii. JSON formatting example

Supplementary material 3. Snapshot of JSON file representing the NoSQL database


```
{ "stand_id": 22354
  {"year": 2020,
   "X_UTM": 356383.63
   "Y_UTM": 4698018.58
   "baseline_ppt": 856.23
   "baeline_temp": 9.02
   "trees": [
     {
       "X": 56,
       "Y": 46,
       "dbh": 8.5,
       "height": 8.2,
       "species_name": "Pinus sylvestris",
       "species_code": 21
     },
     ...
     {
       "X": 98,
       "Y": 22,
       "dbh": 30,
       ...
     }],
     "climate_timeseries": [
     "climate_name": "RCP00"

      {"year": 2020{
         "month": 01{
         "ppt": 750.47,
         "temp": 5.1,
      }
         ....
      }
     },
     ...
     {"year": 2100{
         "month": 12
         "ppt": 500.31,
         "temp": 2.5,
     }
         ....
```


iv. ES module snapshot

Following is a fragment of the ES DSS module implemented in Python 3.4

Supplementary material 4. Fragment of the EcosystemServices class in Python

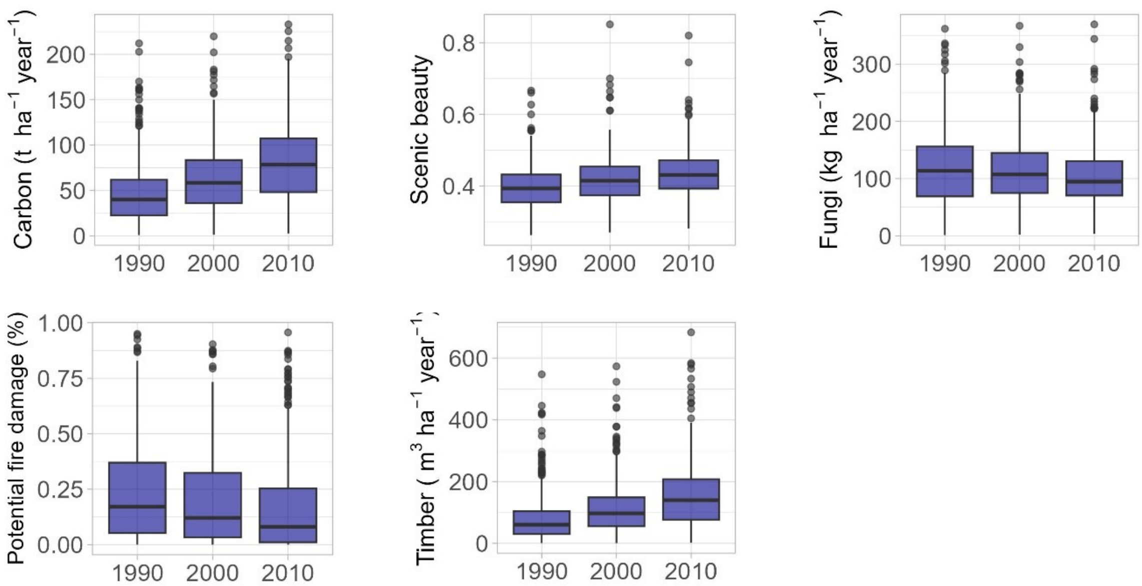
```
class EcosystemServices:
    """
name: EcosystemServices
:returns biomass, carbon storage in trees, co2, standing timber volume,
harvested timber volume, roadside prices in euro, mushroom production (wild,
edible and total), scenic beauty index, potential fire risk.
method: Ecosystem Services are calculated using statistical models
    """
    def __init__(self, slope, aspect, elevation, dbh, species, heights,
*out_file):
…
    def biomass(self):
        """Calculate the biomass of the trees per species, for the stem,
branches and roots
            :return biomass, carbon, co2, self.stem_mass_total
            --------------------------------------------------------------------
            Source: R. Ruiz-Peinado et al., "New models for estimating the
carbon sink capacity of Spanish softwood species", Forest Systems 2011 20(1),
            --------------------------------------------------------------------
            """
        dm = [float(d) for d in self.dbh]
```

```
        ht = [float(h) for h in self.heights]

       sp, thick_abal, thin_abal, thick_pisy, thin_pisy, thick_piun, thin_piun,
medium_pisy = ([] for _ in range(8))

        thick_pini, thin_pini, medium_pini = ([] for _ in range(3))

        sp_c = [0.0189 if x == '0' else 0.0154 if x == '1' else 0.0203 if x ==
'2' else 0.0403 for x in self.species]

        self.stem_mass = [c * d ** 1.838 * h**0.945 if c == 0.0403 else c * d **
2 * h for d, h, c in zip(dm, ht, sp_c)]

        # root biomass calculation
        sp_root = [0.101 if x == '0' else 0.130 if x == '1' else 0.193 if x ==
'2' else 0.0189 for x in self.species]
        root_mass = [r* d ** 2.445 if r == 0.0189 else r * d ** 2 for r, d in
zip(sp_root, dm)]

        # thick and thin branches
        for s in self.species:
            i = self.species.index(s)
            d = float(self.dbh[i])
            h = float(self.heights[i])
            if h<=0.0:
                h=0.1
            if s == '0' and d != 0:
                w = 0.0584 * d ** 2
                thick_abal.append(w)
                w2 = 0.0371 * d ** 2 + 0.968 * h
                thin_abal.append(w2)

            elif s == '1' and d != 0:
                w_medium = 0.0295 * (d ** 2.742) * (h ** -0.899)
                medium_pisy.append(w_medium)
                w_thin = 0.530 * (d ** 2.199) * (h ** -1.153)
                thin_pisy.append(w_thin)
                if d > 37.5:
                    w = 0.540 * (d - 37.5) ** 2 - 0.0119 * (d - 37.5) ** 2 * h
                    thick_pisy.append(w)
            elif s == '2' and d != 0:
                w = 0.0379 * d ** 2
                thick_piun.append(w)
                w_thin = 2.740 * d - 2.641 * h
                thin_piun.append(w_thin)
            elif s == '3' and d != 0:
                thin_pini.append( 0.0720*d**2)
                medium_pini.append(0.0521*d**2)

                if d > 32.5:
                    w = 0.228 * (d -32.5) ** 2
                    thick_pini.append(w)

        masses = [sum(self.stem_mass), sum(root_mass),
                  sum(thick_abal), sum(thin_abal),
                  sum(thick_pisy), sum(thin_pisy),sum(medium_pisy),
                  sum(thick_piun), sum(thin_piun),
                  sum(thick_pini), sum(thin_pini), sum(medium_pini)]
        biomass = sum(masses)
        carbon = biomass/2
        co2 = carbon * 44 / 12
        self.stem_mass_total = sum(self.stem_mass)

        return biomass, carbon, co2
```

v. ES provision

Supplementary table 5. Summary statistics of calculated ESs per forest stand, based on NFI data

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	NFI
Carbon	727.34	22368.62	40081.87	47633.04	61716.29	212126.98	
Scenic beauty	0.26	0.35	0.39	0.40	0.43	0.67	
Fire risk	0.00	0.05	0.17	0.24	0.37	0.95	NFI2
Mushroom production (total)	8.87	301.48	439.55	498.22	622.75	1861.82	
Standing timber	0.97	30.32	60.37	80.91	104.34	547.29	
Carbon	983.58	35919.15	58414.20	63923.14	83474.91	219849.89	
Scenic beauty	0.27	0.37	0.41	0.42	0.45	0.85	
Fire risk	0.00	0.03	0.12	0.20	0.32	0.90	NFI3
Mushroom production (total)	14.86	321.32	462.76	535.69	645.75	1897.90	
Standing timber	0.90	55.53	97.25	114.25	148.76	573.19	
Carbon	2512.94	48044.28	78525.29	81711.76	107287.66	233032.04	
Scenic beauty	0.28	0.39	0.43	0.43	0.47	0.82	
Fire risk	0.00	0.01	0.08	0.17	0.25	0.96	NFI4
Mushroom production (total)	23.19	320.02	465.84	543.40	629.52	2169.89	
Standing timber	2.38	76.75	139.84	155.45	207.70	683.11	



Supplementary material: Boxplots of calculated ESs per forest stand, based on NFI data

Supplementary table 6. Trade-offs between ESs in space and time: pairwise regression based on MGWR