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Meeting the moment: decision support amidst great environmental change and uncertainty

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Decision making is inherently a complex social and cultural process that is shaped by myriad influential factors both internal and external to the environments, people, and institutions affected. Natural resource management is no exception in this regard. As the Earth's climate rapidly changes, disturbances increasingly threaten forests across the globe, while the demand for resilient conditions and ecosystem services increases. As risks and threats to forests are building, so are assumptions, uncertainties, and stakes associated with management and mitigation outcomes. Decision support tools (DSTs) serve many functions in landscape and forest management, most centrally in helping decision makers and interest holders cope with complexity and uncertainty. Similarly, increasingly complex data, statistics, ecosystem dynamics, uncertainty, and technological advances have driven the evolution and integration of DSTs into forest and landscape management decision processes. We explore five factors driving DST development and integration into forest ecosystem management: environmental change, risk management, call for transparency, implicit and explicit social contracts, and technological advancement. We identify the challenges that DST growth and expanding deployment have addressed, as well as the emerging dilemmas that their current and future uses are likely to create. As environmental risks mount with changing climate, and computing capabilities continue to advance (e.g., statistical models, artificial intelligence), social norms and priorities are also changing. DSTs are expected to become central to forest and landscape management to help adjudicate the complexities of managed and unmanaged systems, the consequences of management actions and inaction, and their impact on environmental quality and forest resilience.

KEYWORDS
changing climate, environmental policy, forest management, landscape resilience, risk assessment, wildfire

Introduction

Decision support tools (DSTs) have been used for decades to enable users to make critical natural resource and ecosystem management decisions (Reynolds et al., 1999). In the most basic sense, DSTs are interactive computer-based programs used to acquire, store and present data, conduct analyses, and provide a quantitative foundation for evaluating tradeoffs and synergies among alternative management decisions (Reynolds et al., 2014). DSTs in natural resource management are simultaneously ecological, social and cultural constructs that can document the social contract associated with any decision. DSTs are commonly constructed through a co-development process among scientists, managers, interest holders, and partners, that reflects varied perspectives across a potentially broad array of sectors of the engaged community (e.g., Manley et al., 2023). As such, decision support intersects science, management, policy, and culture, and effective DSTs help managers and policy makers navigate this often tumultuous intersection.

Decision theory suggests that decision making is anything but a straightforward process with predictable outcomes based on available data (Groeneveld et al., 2017; Peterson, 2017). Rather, decision making is often a complex, messy, distinctly human process. Decisions are inherently laden with uncertainty, bias, diverse opinions and values, shared and individual risks and rewards, and the burden of associated consequences for those who bear them. Moreover, incomplete information can force a leap of faith that a selected path forward will be successful. Without decision support analytics, many decisions pertaining to complex systems will be unduly influenced by the individuals involved, and to factors both endogenous and exogenous to the decision-making process (De Vente et al., 2016; Zasada et al., 2017). Likewise, some decision-makers strive to retain the prerogative to make decisions based on their interpretation of the most important outcomes despite community engagement (Groeneveld et al., 2017). In fact, the greater the visibility and political impact of a decision, the greater is the incentive to control the narrative, the decision, and its expected outcomes. This paradox is relevant to DST development and its application because DSTs on the one hand must provide transparency, and on the other retain prerogative for decisions.

Over the past few decades, several factors have led to the broad application of DSTs to the management of forests and large landscapes. Firstly, climate change is precipitating more frequent and impactful disturbances, resulting in the degradation and loss of forests (Seidl et al., 2017). Secondly, regional and global demands for natural resources are approaching or have exceeded thresholds of sustainability (Biermann and Kim, 2020). Thus, conflicts arise in the establishment of management priorities at multiple scales (Ratner et al., 2017). Finally, the availability of sophisticated modeling capacities, computational power, and software applications are now widespread, driven by need (i.e., the risks and impacts posed by the prospect of scarcity) and opportunity (i.e., innovations in information technology) (Gonzalez et al., 2015). DSTs are now integral to decision making to elucidate and reconcile complex system dynamics, competing priorities, substantial uncertainty, high impact consequences, and resulting risks and tradeoffs. They reflect the social contract pertaining to how a problem or need is framed and how potential solutions are evaluated and crafted (e.g., Karadeniz et al., 2026). The more constraints on a system, and the smaller the margin for error within a system to be managed, the greater the potential for conflict and the consequences of failures (e.g., Homer-Dixon, 1991).

Here, we explore a fundamental shift in forest management with attendant DST integration into forest management planning and trade-off analysis. We focus our exploration on what we suggest are five core factors: (1) the profound influence of rapidly changing environments; (2) the need to reconcile near- and long-term risks; (3) the need for tractable decision processes; (4) navigating increased social engagement driven by perceived increasing risk; and (5) technological advances in data availability, statistical and simulation modeling, and computing capacity (Figure 1). As decision science and their applications continue to mature, science-management-community partnerships still remain an essential ingredient in decision support. These partnerships serve to identify and inform management with the best available information, to identify and prioritize knowledge, data, information and practice gaps, and to make new information applicable and accessible to decision making.

Factor 1: decision support at the nexus of environmental change

Ecosystems are inherently complex—shaped by co-evolution and biological, social, and cultural interdependencies. Prior to the 21st century, land management frameworks assumed gradual ecological change driven primarily by localized human activity (e.g., harvesting trees, domestic grazing, cultural burning, wildfire suppression) and population growth (e.g., land conversion from natural to agriculture to urban) (Millennium Ecosystem Assessment, 2005). Moreover, the historical global climate fluctuated within a narrow range of ± 0.5 °C for over a millennium (Salinger, 2005). However, accelerating modern climate change is now shifting the pace and scale of social-ecological dynamics (Malakar et al., 2023). By the end of the 21st century, global mean temperatures are projected to rise by an unprecedented 2 °C to 4.5 °C, driving extreme shifts in precipitation patterns and weather events (Salinger, 2005). This compounding environmental complexity will stress regional, continental, and global ecosystems, particularly those linked to food, timber, power, water supply and distribution, and investments that depend on non-declining yields. The resultant uncertainty associated with these changes will amplify the necessity and value of DSTs.

Anticipated environmental and social impacts have the potential to exceed the management systems and infrastructure and the coping abilities of communities and society, writ large (Malakar et al., 2023). For example, natural resource management, traditionally scaled to work at site, stand or small watershed scales, is now grappling with extreme disturbance dynamics precipitating large-scale mortality events over short periods of time, which are broadly affecting ecosystem conditions and services (Sun and Shi, 2020; Povak et al., 2023; Manley et al., 2025a, 2025b). Decision support functions are becoming essential mechanisms for grappling with multiple factors, multiple scales, substantial potential impacts, and significant uncertainty (e.g., Esen et al., 2026).

Continual changes to and losses of ecosystem functions and services challenge long-standing societal expectations and delivery of a sufficient and sustainable supply of goods and services traditionally provided by native forest ecosystems (Running et al., 2017). While scientists and managers seek an in-depth understanding of ecosystem processes, dynamics and capacities, managers are focused on sustainability under various future management and climate scenarios. In

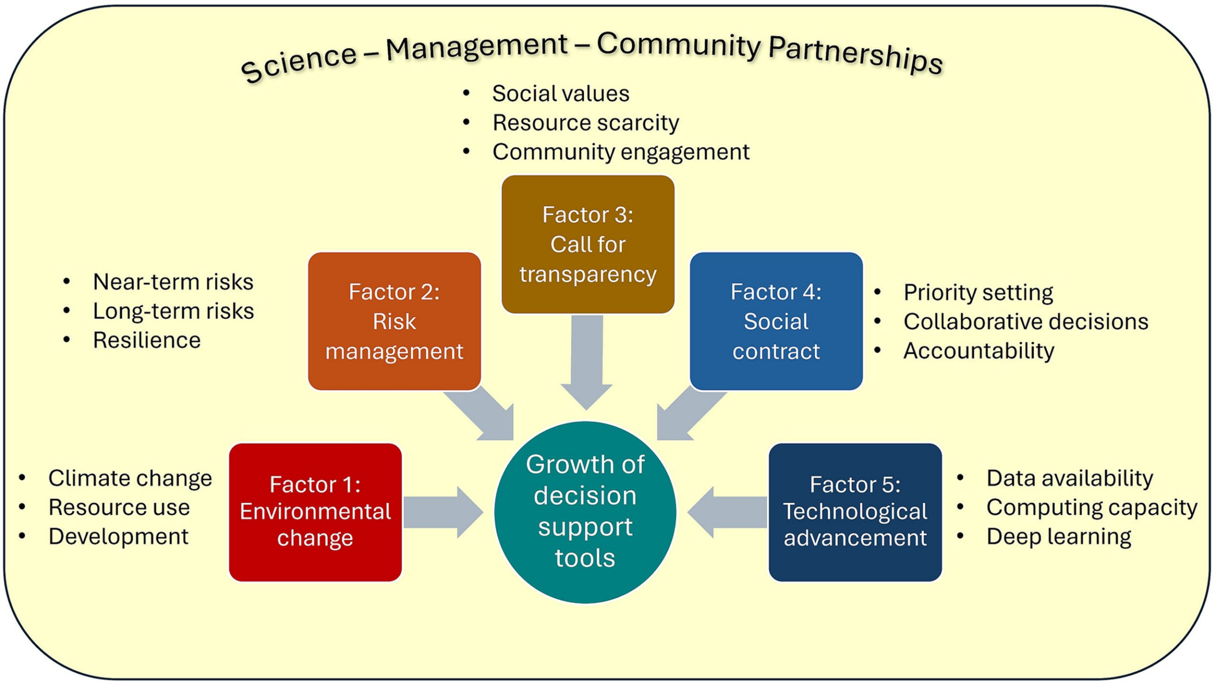

FIGURE 1
Primary factors driving advances and integration of decision support into forest management processes, all within the context of science-management-community partnerships.

this context, DSTs are playing a vital role in moving scientific information and understanding into accessible, practical applications, which greatly enhances the evaluation process (e.g., Kangas et al., 2000; Abelson et al., 2022; Furniss et al., 2023). The highly interconnected nature of ecosystems combined with rapid climate and weather changes suggest that long-standing top-down and bottom-up controls on ecosystems are changing rapidly as well, placing an even greater importance on the use of DSTs to enable scientists and managers to explore unconstrained "what if" future scenarios (Gustafson, 2013; Maxwell et al., 2022a; Maxwell et al., 2022b; Manley et al., 2023).

Factor 2: reducing risk versus enhancing resilience

Natural disasters worldwide cause widespread human and economic losses each year (Wallemacq and House, 2018). In many forested areas around the globe, drought and wildfires are increasing in their frequency, extent, and impact as climate changes (Oliveira and Martins, 2026). In the western United States, for example, burned area and severity have increased markedly in recent decades (Parks et al., 2025), and in California, nearly 25% of the over 13 M ha of forested lands in the state have burned in the last 10 years.[1] Fire dynamics are not the only disturbance processes getting pushed outside of multi-century norms, with drought, forest insects, and diseases contributing to stressors acting on forest ecosystems. These trends in risks to forested ecosystems are attributed to climate change combined with over a century of fire suppression, past management practices, expansion of the wildland–urban interface (WUI), and population growth (Hessburg et al., 2016, 2019; Hagmann et al., 2021).

The actions of these climate and disturbance stressors, among others, are pushing many systems to the brink of their resilience capacities, and beyond. Resilience is classically defined as, "The capacity of a system to absorb disturbance and reorganise while undergoing change as to still retain essentially the same function, structure, identity and feedbacks" (Walker et al., 2004). With the pervasive and substantial human impacts on ecosystems, these early descriptive definitions of resilience have morphed over the past two decades into more normative definitions of resilience, such as "The capacity to adapt or transform in the face of change in social–ecological systems, particularly unexpected change, in ways that continue to support human wellbeing" (Chapin et al., 2010; Biggs et al., 2015; Folke et al., 2016). For example, the impacts of drought and water stress on forested systems are challenging to mitigate, with efforts being directed primarily at balancing water availability and demand by reducing tree density through mechanical thinning or prescribed fire (Tague et al., 2019). Fire is equally challenging, in that the most effective means of managing the substantial risks posed by future wildfire is through the intentional use of fire, which also carries risks (e.g., O'Conner et al., 2016).

Here, we focus on the juxtaposition of current fire risk with future landscape resilience as a case study testing the resilience of forest ecosystems, and a common progenitor of the value of DSTs in risk and resilience tradeoffs in forest management. Understanding and considering current and longer-term risks of impact and loss in managing forests is an arena ripe for decision support tools. In short, extant fire risk-reduction strategies are primarily directed at short-term hazard and vulnerability

1 https://www.fire.ca.gov

mitigation (Calkin et al., 2023). Hazard refers to both the likelihood of fire in a location and its expected intensity (e.g., flame length), whereas vulnerability reflects the anticipated damage to a given asset or resource. Management of these hazards relies primarily on mechanical removal of living and dead woody materials (Prichard et al., 2021), designed to prevent wildfire spread into the WUI to increase public safety and reduce impacts to infrastructure. Furthermore, mechanical treatments in forests more distal to infrastructure are focused on reducing the impacts and enhancing the benefits of fire on forest conditions, habitat quality, and climate resilience (Hessburg et al., 2021). However, wildfire is a keystone disturbance that historically shaped vegetation structure and landscape patterns (see references in Agee, 1996; Hessburg et al., 2019; Hagmann et al., 2021), and in most dry forest ecosystems, it is essential to forest health. When allowed to operate as a functional disturbance process, fire creates and maintains forest conditions that are more likely to be resilient to future disturbances and climate change (Prichard et al., 2021; Stephens et al., 2021). However, the use of fire as a management tool carries the risk of increased hazards to infrastructure. The dominant fire management response today still emphasizes continued fire exclusion through prompt fire suppression, and fuel-reduction treatments near human communities to reduce hazard and vulnerability. This divergence creates a management conflict: reintroducing fire to natural landscapes can advance long-term resilience but may appear to conflict with immediate risk-reduction objectives for built environments.

Given the vast extent of western US landscapes with altered fire regimes (Hagmann et al., 2021) combined with scarce personnel and declining financial resources, DSTs have become central to prioritizing the location, type, and sequencing of forest management treatments (Hessburg et al., 2007; Calkin et al., 2011). Policies geared largely toward community protection in the WUI have dominated discussions in recent decades (Calkin et al., 2023), yet an exclusive focus on WUI defense inadvertently prolongs hazardous conditions elsewhere, increasing the probability of high-severity fires burning into communities. For example, Alcasena et al. (2022) found that combining treatments within the home ignition zone (a subset of the WUI) and the surrounding landscape led to the highest reductions in home exposure and loss to future fires. Fuel-reduction treatments outside the WUI can also provide long-term resilience goals.

Forest ecosystems provide and support a wide variety of ecosystem services that are widely recognized as critical to the sustainability and quality of life (Montreal Process, 2015). Global, national, and regional initiatives are being developed to support managers and policy makers with the integration of community protection (risk reduction) and landscape-scale restoration (enhanced resilience) across forested landscapes (e.g., Navalho et al., 2017; Bacciu et al., 2022; Creutzburg et al., 2022). For example, the long-standing Montreal Process Criteria and Indicators (Montreal Process, 2015) and the more recent Kunming-Montreal Global Biodiversity Framework (KMGBF, 2022) call out the critical importance of future forests to global sustainability. The Kananaskis Wildfire Charter is an example of associated action, recently adopted by the G7, as a means of slowing and potentially reversing the negative impacts of wildfire on forested ecosystems across the globe (Yadav et al., 2026). All of these commitments call for actions that also respect and support a wide array of social values that can present conflicts and tradeoffs, such as the right to development, intergenerational equity, biodiversity conservation, and economic opportunity and growth (e.g., CBD, 2022; Burgess et al., 2024). DSTs are now indispensable in identifying implementation options and tradeoffs where the stakes are high and in many cases consequences are irreversible.

Quantifying landscape resilience remains challenging because ecosystems are dynamic, conditions are nonstationary and multidimensional, and resilience is context and scale dependent. However, shifting toward a resilience-oriented framework offers multiple benefits. Treatments that restore heterogeneous forest structures, re-establish natural disturbance regimes in the context of changing climate, and reduce fuel connectivity can inhibit fire spread and reduce severity. Landscape-level outcomes resulting from these actions can help buffer vegetation conditions from impacts of changing climate and sustain a predictable flow of ecosystem services, such as water quality, wildlife habitat, carbon sequestration, and recreation. For example, large, severe fire events may be interpreted as a loss of resilience, but in some circumstances can also be integral to disturbance-prone systems and belie a necessary reset toward a more active and constructive disturbance regime (Povak et al., 2023). These complexities highlight the importance of investing in the development and application of DSTs to help reconcile priorities for restoration treatment locations and outcomes, document considerations and the decision process, and provide relevant measures of success. Tools such as the Ten Pillars of Socio-Ecological Resilience (TPOR; Manley et al., 2025a) provide a hierarchical socio-ecological framework that can be used to define, quantify, and track resilience outcomes. Complementary tools such as the PROMOTE model (Povak et al., 2024) integrate climate-change evaluations into planning by identifying monitoring, protection, adaptation, and transformation options based on both current and projected future resource conditions.

Factor 3: rational, transparent, and repeatable decisions

Decision support tools and applications to assist with various aspects of forest management began appearing in the 1970s, and were common by the 1980s. However, these early applications were typically developed to address relatively narrow, well-defined problems such as timber-harvest scheduling (Johnson et al., 1986; Barber and Rodman, 1990) or forest pest management (Mowrer et al., 1997; Reynolds, 2005). By the late 1980s, a 'whole ecosystem' management concept was born. It was adopted by national resource agencies in the US and elsewhere (Rauscher, 1999), along with the need for the associated practices of sustainable forest management and adaptive ecosystem management (Holling, 1978; Walters, 1986).

Since then, the requirements for forest management decision support began to change significantly from addressing narrow, well-defined problems to those that were much larger, more complex, and more abstract, such as improving forest ecosystem sustainability and social-ecological landscape resilience (Reynolds, 2005; Manley et al., 2025a). Meanwhile, human communities engaged as interest holders in land and forest management on public lands, were demanding more involvement in resource agencies' planning and implementation work (e.g., Schultz et al., 2012). In the US, federal oversight agencies such as the General Accountability Office (GAO) periodically reviewed the business practices of federal resource agencies, and they consistently identified the need for much more rational, transparent, repeatable decision processes (GAO, 2002, 2003, 2004, 2007). Federal agencies responded by establishing DSTs for some central functions, such as allocating annual budgets for forest fuels management in the US Forest Service and the US Department of the Interior. While fuels management was the specific focus of initial GAO reports (Reynolds et al., 2009), calls from oversight agencies for more transparent and repeatable decision processes quickly spread to many other aspects of environmental resource management in the US and beyond (Reynolds et al., 2003).

All the above factors inspired multiple innovations in DST form and function, and precipitated a new generation of forest management DSTs, such as the Ecosystem Management Decision Support System (EMDS; Reynolds et al., 2014). Indeed, a hallmark of second-generation forest DSTs (akin to EMDS) is their focus on rational, transparent, and repeatable solutions (Reynolds, 2005). For example, the need for transparency in DSTs became a compelling issue for the US Forest Service, an agency that stewards ~30% (~80 M ha) of the forested lands in the US. In response to the National Forest Management Act (1976) that required 10-year plans for all National Forests, the US Forest Service adopted the use of a computer program for modeling forest growth and management called FORPLAN that was used for over a decade to support the 10-year plans. However, these plans were also required to incorporate ecosystem management principles (Rauscher, 1999). Complex linear programming (LP) solutions such as FORPLAN were needed to track multiple resources, but were difficult to communicate given the complexity of the models. In the burgeoning era of environmental protection and regulation in the 1980s and 1990s (and up to the present day), the US Forest Service discovered that black-box LP solutions for large, complex, and abstract problems were neither politically nor socially viable. As a result, black-box FORPLAN solutions for forest planning were largely abandoned by the late 1990s, replaced initially by simpler, less sophisticated but more transparent modeling approaches, followed by the DST era that persists today, characterized by the development and application of complex, but also transparent and tractable, information systems.

Current challenges and future threats to environmental integrity and resilience call for DSTs that can be adapted to address complexities and concerns as they pertain to existing and emerging issues (e.g., see Povak et al., 2020, 2022, 2024; Churchill et al., 2022; Pascual et al., 2022; Furniss et al., 2023, 2024, 2025; Reynolds et al., 2023; Povak and Manley, 2024). Continued investment in a breadth and depth of DSTs (e.g., Smallmann et al., 2022; Lämås et al., 2023; Reynolds et al., 2023) will be essential to providing a collection of options to draw from as decision support needs arise and change over time. Increasingly, it is clear that decision support functions are being increasingly pushed and tested in response to social and cultural transparency and repeatability demands, as well as an increased computing capacity to address ecological complexities and uncertainties.

Factor 4: reconciling uncomfortable truths

Science-management-community partnerships are an essential component of DST development and implementation. Partnerships serve to ground problem definitions and solutions in real-world applications and constraints, and they serve to expand perspectives and deepen user understanding of complexities, uncertainties, ambiguities, and best available science. DSTs can then reflect this common ground, and make best available science readily applied to the target functions of the DST, be they assessment, planning, or management application (e.g., Churchill et al., 2022). However, it is well established across different disciplines that more information is not necessarily helpful in making decisions, and better information does not always lead to decisions that reflect the available information (Peterson, 2017). This phenomenon is particularly pervasive with regard to acting on the climate crisis in a manner that is aligned with scientific evidence (e.g., Wright and Nyberg, 2016).

Decision makers with land management responsibilities in this environment of rapidly changing climate are faced with the extremely challenging task of weighing, reconciling and communicating tradeoffs between short- and long-term values of security and benefit. Current conditions are measurable, relatable, and their benefits are tangible and potentially fungible. In contrast, future outcomes are fraught with uncertainty, and are commonly presented in the form of probabilities, as statistical surrogates for likely futures (Allen and Stein, 2013). Scientists and other experts are frequently engaged with managers and interest holders in land management decision processes to help identify expected or potential social-ecological outcomes associated with different courses of management action (Littell et al., 2012; Manley et al., 2025b). Highly certain short-term gains weighed against a set of probabilities of future benefits predictably will lead to a predominance of management approaches based on the status quo (Allen and Stein, 2013; Wright and Nyberg, 2016). Managers face substantial scrutiny and lack firm ground on which to venture away from the known and put near-term benefits at increased risk based on a statistical probability of improving future conditions across landscapes and socio-ecological systems (Hall, 2010).

Perhaps even more challenging is reconciling the likelihood of negative outcomes regardless of the management intervention (e.g., Povak and Manley, 2024), or management actions that are expected to be effective in reducing future impacts but have negative short-term consequences. For example, some would argue that old forests, as they existed historically in the western US, may no longer be viable—they may be ghosts of climates past. Attempts to protect them against threats posed by climate and fire may put the persistence of forests at even greater risk (Abella et al., 2007; Spies et al., 2006; Hill et al., 2023). Adoption of this rationale may suggest a shift in management strategies from conserving old forests to simply conserving forests writ large. Another example is carbon storage in temperate forests as a method for mitigating carbon emissions. Across the western US, dry temperate forests dominate forested landscapes, and fire suppression and other management policies and actions over the past century have resulted in forests with high densities of live and dead trees, and by extension, carbon (Campbell et al., 2011). Managing these forests in a manner that improves their probability of persistence into the future, as well as managing post-fire landscapes, is likely to involve reducing carbon in the near term in favor of long-term benefits of reduced risk of loss from fire (e.g., Scott et al., 2023; Hessburg et al., 2025; Manley et al., 2025b). Furthermore, new paradigms in climate-informed decision support applications acknowledge that management may not be practical in meeting ecosystem objectives in the long-run (Peterson St-Laurent et al., 2021; Williams, 2022; Povak et al., 2024).

The burden of reconciling uncomfortable truths and less desirable futures rests with both scientists and managers. Science has always served society, but the existential threats of a changing climate are steering investments in ecosystem sciences even more toward dual functions of near-term applied and foundational scientific contributions (McNie, 2013). Science-management-community partnerships are critically important to crafting effective responses to environmental challenges, and DSTs are an outgrowth of these partnerships (Figure 1). Understanding the challenges that these partnerships face is likely to translate into growth areas for future DSTs. For example, translating probabilities and uncertainties into relatable correlates that managers, interest holders, and policy makers can use is likely to enhance their ability to communicate and socialize options that involve some degree of short-term sacrifice to improve prospects for future resilience (Manley et al., 2024).

Factor 5: technological advances fueling decision science

Recent technological advancements have revolutionized the world of ecological sciences in terms of the amount and availability of high-resolution data, the ability to analyze these data and make predictions, and the availability of low-cost internet platforms for disseminating data and allowing for interactions with model outputs. On the one hand, the availability of open-source web-based tools, computing environments, and platforms has provided unprecedented access to information to facilitate the decision-making process. However, it also carries the risk of developing black-box tools created outside of the co-development process that may undermine the social-cultural foundation of decision support.

Remote sensing and data availability

DSTs are only as useful as the quality of the data representing the system. With recent advances in remote sensing technology and big data analytics, researchers and practitioners have access to more high-resolution earth system data than ever before. With the launch of LANDSAT 1 in the 1970s bringing spaceborne observations to the world, we are able to track the evolution of ecosystems over a significant period of time when the planet has undergone tremendous changes resulting from forest clearing, exotic species invasions, unprecedented wildfire events, historic droughts, and the onset of climate change (Steffen et al., 2011; Kuwae et al., 2024). Further advancements in the field of aerial and ground-based LiDAR (Light Detection And Ranging) systems capture forest canopy characteristics across large areas down to sub-meter resolution (Beland et al., 2019). Commercial platforms such as Google Earth Engine and Microsoft Planetary Computer, as well as data curated by federal, state, and local governments provide access to a seemingly infinite amount of spatio-temporal data through high level scripting languages or graphical user interfaces (GUIs) making it easy for even novice users to access them. However, with access comes great responsibility. For example, some datasets may tout their ultra-high resolution (e.g., <10-m), but undisclosed model error and biases may hamper their utility and provide a false sense of accuracy. It is incumbent upon scientists and developers to provide users with a clear understanding of the products available, identify the strengths and weaknesses of individual datasets, and carefully tailor the data application to match the specific task.

Statistical learning models

Artificial intelligence (AI) and machine learning algorithms (ML) have greatly increased the ability to model ecosystem dynamics (Cutler et al., 2007; Olden et al., 2008; Kattenborn et al., 2021; Frazier and Song, 2024). These models can ingest huge volumes of data and quantify interactions and non-linear behavior that are characteristic of ecological systems. Many of these models are robust to their parameterization or can be auto-tuned through exhaustive parameter searches with minimal input by the modeler. These applications have allowed for mapping forest attributes where field data are sparse, detecting complex patterns in remote-sensing data, modeling nonlinear relationships (e.g., tipping-points), identifying drivers of observed patterns, and generating predictions are beyond the reach of conventional modeling (Wang et al., 2025). However, many view these models, again, as black boxes indicating they produce results without a clear understanding of how they were developed. It is therefore incumbent upon scientists to translate these methods in ways that are approachable for non-specialists to remove potential hurdles to their adoption in the DST process. Methods from the field of explainable AI have helped make these models more transparent to highlight their strengths in modeling high-dimensional, non-linear, non-stationary data (Ryo et al., 2021). In short, AI/ML can be used to improve inferences about system behavior, but alone cannot supply the values, objectives, constraints, or legitimacy needed for decision support.

Platformized web-based DSTs

Prior to the age of the internet, DSTs were often conceived, developed, and disseminated among a small group of interest holders. Model outputs were often in the form of reports with static maps displaying spatial outputs of the analysis. As technology advanced, model outputs could be stored on the web to reach a wider audience. But not until recently could web-based applications be leveraged to allow for an open-source native GIS experience where maps could be displayed, downloaded, and explored to change priorities and test alternative parameters for sensitivity and tradeoff analyses. For example, wSADfLOR (Marto et al., 2019) is a web-based DST focused on forest management in European forests, which integrates forest inventory, growth and yield modeling, simulation, forest management and planning, and decision making with a Pareto frontier tool. In the US, platforms such as the open-source Planscape tool and the proprietary Vibrant Planet Platform have been developed with a more generalized approach (Ager and Safford, 2026; Safford et al., 2026). These web-based DST platforms resulted from co-development processes designed to transcend bespoke functionality to offer more generalized access to data, methods, tools and visualizations that can more efficiently and expeditiously serve a larger user base. These systems offer a huge level change in the utility of DSTs in ecosystem management, with their functionality being applicable across broad geographies owing to the similarity in issues affecting forests across the globe (e.g., across the western US; Hessburg et al., 2019): increases in forest fuels, impacts of large wildfires, reductions in water availability due to drought, expansive mortality from insects and disease, growth of the wildland urban interface, and other impacts of climate change (Povak and Manley, 2024; Povak et al., 2024).

Discussion

The fate of forests around the globe has never been more precarious, the ability to understand their condition and future threats has never been better, and the capacity to conserve and manage them sustainably has never been more important—this is the territory where DSTs can have tremendous impact. With roots firmly embedded in the interface between ecology, sociology, and technology, DSTs are uniquely positioned to help cope with the significant changes affecting the world's natural areas by reducing near-term risks to their functions and values, while improving their long-term resilience and the supply of ecosystem services crucial to our future prosperity.

We explored the five factors driving change in forested ecosystem management and how those factors are simultaneously driving the growth and integration of DSTs in land management decision making. With rapid growth comes inevitable growing pains in the form of collateral constraints (e.g., complex algorithms reduce transparency) that require attention and innovation to overcome. One could argue that advances in DSTs are a predictable response to the challenges and opportunities posed by environmental and social change. However, we posit that alternatively looking at how environmental and social change are shaping DSTs provides novel insights into the connections and interactions among the moving parts that make up complex socio-ecological systems. It also provides unique context for postulating how DSTs will need to evolve under these pressures, and the implications for future socio-ecological decision making and forest management. So what might the future hold? In the following sections, we foray into this question.

Everything everywhere all at once

As the 2022 film by this title encapsulates, DSTs exist because in complex systems, "Every decision creates a new path; every choice ripples through the multiverse," a reality personified by the character Evelyn Wang. The connection among the five factors driving DSTs (Figure 1) belies a compelling dynamic of complexity. Each factor has shaped and pushed the evolution of decision support processes and tools, directly and through bi-lateral and multi-lateral interactions. On one hand, the sequence of five factors is a prevalent dynamic driving DST development and increasingly integrated applications. The challenges posed by change (F1) and associated risk (F2) are commonly followed by intensified social and institutional engagement (F3), greater shared decision making (F4), and leveraging technological advances (F5) to enhance decision support functions and tools for future management challenges.

Synergistic interactions also occur between various non-linear pairings of the five factors (Figure 1), such as increasing impacts from climate change (F1) cascade to increase risk from severe fire (F2) requiring shared decision making (F4) in order to spread the responsibility of protecting and adapting forest resources. As social-cultural engagement increases (F3), so too does the demand for better information (F5), to help reach consensus on a path forward across diverse interest holders (F4). Conversely, increasing risks to high value ecosystem services (F1) are likely to drive technological advances (F5) in search of pathways toward lower risk and greater resilience (F2). The prospect of unavoidable future loss (F4) can weaken or strengthen social engagement (F3) depending on the coping mechanism [surrender to the inevitable (weakened) or coming together to enhance adaptive capacity (strengthened)]. Each factor, their interactions, and the self-reinforcing sequence of reaction to change all act on decision support forms, functions, and processes. It is likely that these socio-ecological interactions and feedbacks will speed up to keep pace with change and shifting threats, further propelling DSTs into new realms, and amplifying their importance.

Change is inevitable, learning is critical

Uncertainty can be challenging to quantify, particularly when modeling multiple socio-ecological responses under future climate projections. Modeled products that do not include a measure of uncertainty can lead to false sense of certainty. Thus, analytic approaches to estimating multi-model uncertainty propagation are increasingly important for DSTs, given their impact on decisions and associated consequences, as well as the erosive effect that uncertainty can have on the ability to reach consensus. Quantitative representations of iterative modeled outputs can be generated using creative statistical techniques tailored to the ensemble of models being used (e.g., Povak et al., 2013; Young and Holsteen, 2015; Wagena et al., 2019).

Once uncertainty is quantified, particularly when employing multiple models, the resulting certainty estimates can be stultifyingly poor. What can managers and interest holders do with all that uncertainty? High uncertainty, particularly when risk is perceived to be high, can trigger a wide range of human responses. One option is based on simple principles for maximizing positive outcomes, following the direction and magnitude of central tendencies, despite their uncertainty, relying on these representations as “best available information” that can be used as a guide to rational decision making (Von Neumann and Morgenstern, 1944). However, there is evidence that people often assess gains and losses estimated with high levels of uncertainty relative to a given reference level (e.g., current or historical baselines) rather than conditions associated with outcomes (i.e., ‘prospect theory’; Kahneman and Tversky, 1979; Tversky and Kahneman, 1974), and that individual reference levels often vary based on perceptions and beliefs (Meyfroidt, 2011). Two extremes can result from this phenomenon. One potential response, more likely when uncertainty and risks are high, is paralysis in the decision process—the inability to make a decision for fear of making the wrong decision, thereby stalling the ability of actions to proceed. The other potential response, more likely when uncertainty is high but risks are lower, is the perception of unconstrained decision space, meaning that all options are viable because there is little confidence what will happen in any circumstance.

Alternatively, high uncertainty may precipitate a philosophy of “learning as you go” as a counterbalance to more extreme ‘all-or-nothing’ options for dealing with uncertainty. The concept of adaptive management (Holling, 1978) is commonly referenced in “learn as you go” approaches, particularly in public land management (e.g., Rist et al., 2012) where uncertainty regarding multiple resource outcomes is unavoidable. In simplistic terms, adaptive management is accomplished through various forms of monitoring. As such, it requires a commitment to monitor change and drivers of change over time, reviewing and acting on new information as it becomes available, and maintaining a flexible management approach as conditions are altered through disturbances. Environmental monitoring is classically underfunded in public land management, despite broad recognition of its value.

Passive and/or active adaptive management offers a defensible and productive path forward in the face of high uncertainty, and ideally will bolster investments monitoring as a standard operating procedure. Systematically monitoring change based on a well-designed and implemented monitoring strategy perhaps is the most affordable insurance on investment one can garner. Monitoring provides a means of reducing uncertainty over time, such that short-term actions can be more cautious or exploratory given that monitoring (combined with research) will shrink information gaps and provide greater clarity regarding productive management approaches (e.g., Sparrow et al., 2020).

Two primary avenues of monitoring investments are likely to expand to reduce uncertainty and improve decision outcomes: surveillance and targeted monitoring. Surveillance (retrospective) monitoring refers to post-hoc data collection for documenting status and trends, whereas targeted (prospective) monitoring is structured around specific hypotheses to evaluate management outcomes (Nichols and Williams, 2006). Surveillance monitoring can provide early indicators of positive outcomes and early warnings of unfavorable trends (e.g., Manley et al., 2006; Hutto and Belote, 2013). It can also provide a wealth of information on covariance patterns among ecological, social or cultural outcomes, which in turn can improve model estimates and reduce uncertainty. Retrospective monitoring also serves as a safety net, by providing a means of detecting unexpected changes and their potential drivers—early detection is commonly key to reducing and mitigating impacts of negative change—early detection of positive change can help expedite investments that improve or secure resilience. Retrospective monitoring provides a means of validating general trends, providing empirical data to reduce uncertainty around the outcome of management actions and modeled estimates.

Targeted monitoring is used to observe expected outcomes that are of high interest, either because positive outcomes are expected and highly desired, or because negative outcomes would be very costly and potentially irreversible. In the spirit of active adaptive management (Holling, 1978; Walters, 1986), prospective monitoring can be designed to test hypotheses by orchestrating management in a manner that establishes and systematically collects response information on replicates of different treatments. Monitoring then serves to compare outcomes and efficiently refine management treatments over time (i.e., information being collected is highly structured and more definitive (fewer fixed effects) than an unstructured approach would yield). For high value resources, structured management implementation and monitoring can pay high dividends in reducing uncertainty for targeted concerns in shorter time periods (Nichols and Williams, 2006; McCarthy and Possingham, 2007).

Defining resilience in a non-analog future

High rates of change combined with substantial uncertainty are pushing operational definitions of resilience to more practical, normative definitions that recognize the interdependence of social and ecological systems. Specifically, definitions are expanding to include wellbeing and sustainability as outcomes of resilience processes (Malherbe et al., 2024). Normative definitions of resilience have migrated even further in some instances to focus specifically on the capacity of social-ecological systems (SES) to sustain human wellbeing in the face of change (Biggs et al., 2015; Folke et al., 2016). The shift from a strictly objective definition of resilience (i.e., based on state variables of the system) to one that includes subjective judgements regarding the maintenance of desirable ecosystem services and functions and coping with change precipitated the inclusion of adaptive capacity as a central concept that bridges descriptive and normative perspectives.

Adaptive capacity is defined as, "the combination of the strengths, attributes, and resources available to an individual, community, society,or organization that can be used to prepare for and undertake actions to reduce adverse impacts, moderate harm, or exploit beneficial opportunities" (IPCC, 2012). Malherbe et al. (2024) elaborates on how resilience definitions are progressing in these two (likely complementary) lines of reasoning: the classic descriptive perspective characterizes systems as *dynamic states* and the emerging normative perspective pivots to *dynamic pathways*. Both rely on adaptive capacity as the process that allows systems to maintain and achieve desired outcomes. He posits that operationalizing dynamics states and pathways is the next frontier in resilience science (Serfilippi and Ramnath, 2018; Haider and Cleaver, 2023), which in turn can be applied to setting objectives and evaluating outcomes with DSTs that reflect multiscale and temporal dynamics, and emergent properties that are not observable at smaller, stand-level scales.

The ability to anticipate the direction, magnitude, and timing of change as key facets of adaptive capacity will continue to be a valuable commodity over time, particularly in the context of a normative perspective of resilience where movement toward or away from dynamic pathways is of paramount importance. Status and change of conditions, functions, and services as they relate to resilience would then become focal features of surveillance and targeted monitoring in adaptive socio-ecological systems. Decision support systems and their functions could then be explicitly built around these critical adaptive capacities, and help adjudicate the diverse value judgments of expected outcomes and merits of management investments toward future states. Operationalization will require engagement across interest holders and decision makers to identify desired outcomes of treatments. Furthermore, engagement from the science community will be essential to provide side boards on what is possible and how to most effectively and reliably measure and portray status and change relative to dynamic resilient pathways (Quinlan et al., 2016).

Next generation DSTs

DSTs remain at the cutting-edge of data science and resource management, and their evolution has largely tracked major milestones in technological advancements. As such, the ability to broadly disseminate 'platformized' web-based DSTs gives users unfettered access to new data and tools. Although there still exists a learning curve to proper implementation of structured user journeys architectured by the developers of the tools, technology is likely to also provide a bridge to overcome these hurdles.

One area of expected future growth for DSTs will be an increasing reliance on large language models (LLMs). Web-based chat interfaces like Claude AI, and ChatGPT have largely become mainstream in modern life. As highly generalist applications, these models can interpret, synthesize, and resolve complex problem statements through human-like reasoning. In addition, through the use of Retrieval-Augmented Generation (RAG) frameworks, LLMs can be further tuned and informed via access to local databases relevant to specific ecosystem management applications (Ehrlich-Sommer et al., 2025; Xie et al., 2025).

One possible future avenue of integration of LLMs into decision support will be to facilitate unstructured interactions within web-based DSTs. Traditional web-based DSTs guide users through a rigid, linear pipeline of curated steps, including data selection, normalization, weight assignment, and spatial optimization. Integrations of LLMs with RAG frameworks would allow users to perform spatially explicit treatment prioritization using a series of prompts that help define the problem, the decision space, and desired outputs without needing to follow pre-established workflows. For example, rather than clicking through several screens of a graphical user interface as is commonly the case today, a user could simply ask: "I am interested in identifying management opportunities to reduce wildfire risk around my community, conserve areas with large carbon stocks, and benefit spotted owl habitat where it currently exists. Please avoid roadless areas, favor carbon protection away from communities, and avoid working in sensitive areas and steep slopes with limited access." The DST could then interpret these prompts through its access to spatial, tabular and other (potentially) unstructured data formats within the DST database as well as through its access to the broader knowledgebase. It could then pose follow-up questions to the user to fine-tune the analysis, and/or output spatial maps and reports specific to the user's prompt. This immense flexibility drastically reduces the friction between the user and the software, unlocking landscape prioritization schemes outside of programmatic pathways. However, this fluid environment removes traditional software guardrails. Because these interactions are fundamentally ungoverned, they can easily operate outside the data's intended boundaries. Consequently, both developers and users will bear an increased responsibility to rigorously evaluate the underlying assumptions, logical consistency, and uncertainties inherent in AI-generated outputs.

Another potential avenue of development for future DSTs is the implementation of landscape simulation modeling (LSM) into the decision-making process. LSMs encapsulate whole ecosystem dynamics through empirical, semi-empirical, or mechanistic models that quantify key structures and processes integral to ecosystem dynamics (Costanza and Voinov, 2004). Such models can then be used to test treatment outcomes across large landscapes and multiple scales to better understand temporal and multi-spatial responses and interactions (Liu, 2018, 2023), and their ramifications of local management decisions on broader ecosystem resilience and potential ecosystem service outputs. Models such as Landis-II (Maxwell et al., 2022b), LSIM (Ager et al., 2020), LDSIM (McGarigal et al., 2018), FireBGC (Keane et al., 2011), and REBURN (Povak et al., 2023; Prichard et al., 2023) are currently being used towards these goals, although their direct implementation to evaluate treatment effects as a DST module is limited due to the complexities surrounding parameterizing (Furniss et al., 2022) and running them at scale in real time. However, as processing barriers become less restrictive over time and as modelers continue to develop methods for parameterizing to new geographies, the ability to run LSMs through a web-based interface as a tool to quantify expected management outcomes and leverage multiple model runs to diagnose tradeoffs among management scenarios are likely to become much more accessible to DST end-users. Such integrations could help tackle the complexities introduced by temporal and multi-scale interactions (Liu, 2018, 2023), make progress toward measures of anticipation and adaptive capacities (Boyd et al., 2015; Malherbe et al., 2024), streamline the comparison of alternatives in the context of environmental protection laws and policies, and provide users a clearer understanding of potential positive and negative impacts expected from management. For example, LSMs can be used to determine the large-scale and long-term implications for community wildfire protection strategies compared with those aimed at broader landscape restoration goals and help elucidate tradeoffs between expected losses from future fire and potential gains/losses in ecosystem services, such as carbon capture and storage, air quality, water quantity and quality, wildlife habitat, and others (e.g., Alcasena et al., 2022).

The future of transparency

The rapid evolution of DSTs brings many valuable and important social benefits, but it carries with it important caveats and potential pitfalls. Advances in deep learning, machine learning, and artificial intelligence can effectively identify dependencies among data that are pertinent to environmental management, and derive intuitive explanations of modeling results, but these algorithmic solutions often lack transparency, particularly for users that are unfamiliar with the analytics. Data and models alone are not decision support tools, but rather they provide the quantitative building blocks used to communicate information about system states and trajectories to inform management solutions. The "tools" that result from decision processes are just one of many outcomes, and shorting decision processes risks undermining the trust needed to parlay the DST process into effective tools and, ultimately, positive changes on the landscape. Transparency is the currency that serves as connective tissue that runs between data, tools, and implementation. It operates through the community of individuals engaged in all steps of the decision support process, including scientists, managers, and interest holders, whereby the final roadmap for treatment implementation results from the ongoing learning within and across member groups to develop a shared understanding of management needs.

The counterbalance to less transparent, hyper-analytical capabilities in DST processes is likely to be a strong emphasis on the co-development of explanatory materials and tools generated by the same technology. Perhaps ironically, AI also has the potential to offer parallel products in the course of tool development that provide intuitive explanations to a variety of DST users and interest holders with diverse backgrounds. Foundational work on application of explanatory tools to support DSTs is already rapidly expanding DST capacities, such as Hoffman et al. (2018), and Minh et al. (2022). AI explanations specific to supporting non-subject-matter experts in particular have been explored by Miller (2019), Jiang and Senge (2021), and Mamun et al. (2022). More recent work on human-centered AI explanations have been addressed by Schwalbe and Finzel (2024).

Building better social contracts

Despite fantastical possibilities and tangible progress toward revolutions in data availability and accessibility, the human element remains relatively constant, and it will remain a strong influence on the form and function of DSTs, particularly in how they attend to social values, norms and contracts.

Organizing data and building trust

Managers are often required to balance and consider many different data streams, from purely scientific to local economic and social values and needs (e.g., Marques et al., 2021). DSTs can aid natural resource managers in meeting their social responsibilities by turning complex ecological data into clear, practical insights (Abelson et al., 2021). Further, DSTs can combine all of these considerations into a "common language" that enables all to observe where ecosystem limits and tipping points lie—and what happens if those boundaries are crossed. The process of building a DST also acts as a diagnostic test. If data are missing or of poor quality, the DST framework can flag it early. This allows teams to pause and improve their data before moving forward. Instead of delaying progress, this pause often amplifies trust and prevents groups from wasting time and money on flawed plans.

Collaborative planning and designing scenarios

By using collaborative frameworks, DSTs open up the planning process and bring together people who might start out with very different viewpoints or world views. This cooperative approach turns open discussions into concrete "what-if" management scenarios (e.g., Abelson et al., 2022). The DST can then simulate these ideas, clearly showing the trade-offs, benefits, and results of each path (Rodríguez-Fernández et al., 2025; Poudel et al., 2026).

When interest holders see these results visually, they can evaluate competing interests more fairly. It helps them find solutions that match partner and interest-holder values while remaining technically and financially realistic. Seeing these trade-offs often inspires groups to fine-tune their ideas and create even better alternatives or management scenarios. Ultimately, incorporating complex data, values, and concerns—like mapping or modeling habitat zones—in a DST often reduces the emotion associated with a dialogue, thereby shifting the focus toward productive collaborative, data-driven problem solving.

Fairness, accountability, and meeting legal rules

In modern land management, DSTs often provide the evidence-based justification needed to satisfy strict legal and policy requirements, such as those embodied in national and international frameworks (Montreal Criteria and Indicators; Montreal Process, 2015). These functions in DSTs use mapping and statistical tools to ensure resource allocation and activities are consistent with environmental obligations and guardrails. For example, when deciding where to target specific wildlife conservation or fund habitat development or restoration, DSTs help managers identify where treatments will most benefit species or habitats of interest. This step-by-step approach ensures agency and manager decisions are data-driven, repeatable, defensible, and open to public review. It proves to the public and the courts that the decisions were fair, transparent, and based on the best science available.

Long-term monitoring and community stewardship

Once a co-created plan is put into action, DSTs can keep partners engaged by setting up a continuous feedback loop. DSTs can serve to monitor real-world conditions over time, letting managers compare resulting conditions and ecosystem properties against the project's original forecasts. Furthermore, DSTs can house crowd-sourced data from citizen science apps and community volunteers. This helps local communities build their own monitoring skills while keeping communication open between government agencies and the public. Because these tools process data quickly, managers and partners can spot negative impacts on values or environmental trends early, share those worries openly, and adjust their strategies on the fly. At their core, well-designed DSTs are powerful tools for building community, finding common ground, and keeping management plans effective over the long haul.

Conclusion

Natural resource science spans a broad array of topic areas, including landscape ecology, fire ecology, forest ecology, biodiversity conservation, social-ecological systems, and climate change. The conduct and results of this research no longer simply live within the pages of journals—it is a partnership between scientists, managers, communities, and policy makers. Research studies are increasingly designed and implemented to facilitate their application into DSTs and other pipelines to inform decision makers and support changing conditions on the ground in real time. This connection between knowledge generation and application ensures that scientists are answering the most critical questions, and that results can be readily incorporated into planning and tangible actions. In tandem, managers are striving to access and apply the best available scientific information—translated into concepts, terms, and values that anyone can understand, discussed as needed, and moved expeditiously to effective actions. DSTs have a central role to play in facilitating all of these functions so that society can keep pace with, adapt to, and cope with impacts and threats affecting forested ecosystems, landscapes, and human communities across the globe.

Given the complexities and uncertainties associated with managing natural resources over the long term, DSTs can no longer function as static, off-the shelf resources for planners. The next generation of DSTs must be flexible and adaptive as new data become available, as environmental conditions continue to change and impact ecosystem function and stability, as novel or unexpected events alter landscapes and communities, and as social and political perceptions and priorities change and alter desired outcomes. Much progress has been made towards these goals, but as advancements in data science continue at a breakneck pace, the field of decision science is fertile ground for innovating to meet the many current and future challenges facing the resilience of social-ecological systems.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

PM: Conceptualization, Project administration, Writing – original draft, Writing – review & editing. NP: Conceptualization, Writing – original draft, Writing – review & editing. KR: Conceptualization, Writing – original draft, Writing – review & editing. PH: Conceptualization, Writing – review & editing.

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The author(s) declared that Generative AI was not used in the creation of this manuscript.

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