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ORIGINAL ARTICLE

A review of optimization and decision models of prescribed burning for wildfire management

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Abstract
Prescribed burning is an essential forest management tool that requires strategic planning to effectively address its multidimensional impacts, particularly given the influence of global climate change on fire behavior. Despite the inherent complexity in planning prescribed burns, limited efforts have been made to comprehensively identify the critical elements necessary for formulating effective models. In this work, we present a systematic review of the literature on optimization and decision models for prescribed burning, analyzing 471 academic papers published in the last 25 years. Our study identifies four main types of models: spatial-allocation, spatial-extent, temporal-only, and spatial–temporal. We observe a growing number of studies on modeling prescribed burning, primarily due to the expansion in spatial-allocation and spatial–temporal models. There is also an increase in complexity as the models consider more elements affecting prescribed burning effectiveness. We identify the essential components for optimization models, including stakeholders, decision variables, objectives, and influential factors, to enhance model practicality. The review also examines solution techniques, such as integer programming in spatial allocation, stochastic dynamic programming in probabilistic models, and multiobjective programming in balancing trade-offs. These techniques' strengths and limitations are discussed to help researchers adapt methods to specific challenges in prescribed burning optimization. In addition, we investigate general assumptions in the models and challenges in relaxation to enhance practicality. Lastly, we propose future research to develop more comprehensive models incorporating dynamic fire behaviors, stakeholder preferences, and long-term impacts. Enhancing these models' accuracy and applicability will enable decision-makers to better manage wildfire treatment outcomes.

KEYWORDS
fire modeling, fire uncertainties, model complexity, prescribed burning practicality

1 | INTRODUCTION

Global warming intensifies wildfires, resulting in approximately 400 million hectares burned globally each year (Nolan et al., 2022). This escalating threat leads to billions of dollars being spent annually on wildfire management. To mitigate these risks, prescribed burning (Rx) has been an important tool for reducing the severity of wildfires (Moritz et al., 2014; Waters et al., 2023). It is widely recognized as one of the most effective treatments for managing surface and ladder fuels (Casals et al., 2016; Prichard et al., 2021; Taylor et al., 2013; Zema & Lucas-Borja, 2023). Numerous studies have demonstrated the positive effects of prescribed burning on mitigating wildfire risk (Jose et al., 2023; Prichard & Kennedy, 2014; Wu et al., 2023). In addition, it has the benefits of maintaining ecosystem balance (Clark et al., 2024; Regmi et al., 2023), controlling pests and diseases (Kramer et al., 2023; San Emeterio et al., 2016), and managing habitats for humans and animals (Harper et al., 2018; Regmi et al., 2024). However, this method is not without controversy. Concerns about prescribed burning's side effects, including significant risks like escaping fires, which can lead to severe consequences, as evidenced by the May 2022 fire in New Mexico (Gabbert, 2022), have stirred questions among decision-makers. Prescribed burns may also inflict ecological damage, such as destroying vulnerable plants or wildlife, particularly in the event of escaped fires (Hong et al., 2023; Peris-Llopis et al., 2024). Other outcomes to consider in applying the prescribed burning include smoke production, changes in soil properties, effects on plant growth, and impacts on native species (Armas-Herrera et al., 2016; D'Evelyn et al., 2023; Valkó et al., 2014; Valor et al., 2015). Despite these considerations and the common trade-offs among prescribed burning outcomes, decision-makers face the challenging task of managing its use and striking a balance among these outcomes to ensure its suitability for their objectives (Bradford & D'Amato, 2012; Granath et al., 2018; Schollaert et al., 2024).

Considering the various strengths, weaknesses, and challenges associated with prescribed burning, the decision-making process surrounding its use is inherently complex and multifaceted (Finney, 2005; Scasta et al., 2023; Swain et al., 2023). This process involves strategic, operational, and tactical components (Howard et al., 2020; Martell, 2015). Strategic decisions focus on long-term resource needs, including fire management personnel, equipment, burn size, and costs (Behrendt et al., 2019a). Operational decisions are guided by the anticipated effectiveness of prescribed burns and predictions of fire loads. While the boundary between strategic and operational decisions can sometimes blur, they are typically distinguished by their respective time frames. Tactical decisions, in contrast, involve the detailed planning and execution of prescribed burns (Taylor et al., 2013). To effectively manage the complexities involved in planning prescribed burns, risk management has become a critical component of the decision-making process. Risk-based decision-making quantifies the likelihood and consequences of various risks, informs decision-making, aligns risks with stakeholders' needs, and assesses uncertainties (Morgan et al., 2022). This approach facilitates the integration of analyzed risks and uncertainties into optimization models, enabling the identification of optimal or near-optimal decisions that balance trade-offs among conflicting objectives (Calkin et al., 2021; Wilson et al., 2011; Wibbenmeyer et al., 2013). In addition, machine learning techniques have been employed to estimate the impact of prescribed burning on wildfire risk reduction, providing quantitative evaluations of the risks and effectiveness of these treatments (Jain et al., 2020; Penman et al., 2014; Pérez-Rodríguez et al., 2020; Thapa et al., 2024; Zema et al., 2024).

Despite the complexity associated with prescribed burning, no existing study has comprehensively addressed all the critical components necessary for developing effective decision-making and optimization models. This study aims to fill this research gap by thoroughly reviewing and summarizing these critical components, focusing on stakeholders, decision variables, objectives, and factors that influence overall practicality. Specifically, we aim to address the following research questions: (i) what optimization and decision models have been proposed in the field of prescribed burning management, and how applicable are they to wildfire management practices? (ii) what are the specific formulations used in decision and optimization models within prescribed burning management, encompassing stakeholder considerations, objective functions, variables, and the factors taken into account, as well as the solution techniques utilized? (iii) what are the general assumptions made in the formulation of prescribed burning management models, and what are the implications and methodologies for relaxing these assumptions to advance the models' realism and practical applicability?

The remainder of the paper is organized as follows: Section 2 outlines the methodology employed in this study. Section 3 presents our review and analysis of the collected papers. Section 4 summarizes the findings from the reviewed literature and concludes with insights gained from this work. Finally, Section 5 discusses potential directions for future research.

2 | REVIEW METHODOLOGY

To conduct this review, we adhered to the methodology developed for conducting systematic literature reviews and meta-analyses in environmental science research by Mengist et al. (2020). Specifically, we used a modified PSALSAR (problem formulation, search strategy, appraisal, synthesis, analysis, and reporting) protocol tailored to forest fuel management systems. Our review encompasses six steps: (i) formulate the problem into research questions; (ii) define and search for studies; (iii) select studies; (iv) extract and categorize decision and optimization models along with their assumptions; (v) analyze models and assumptions, discuss results, and draw conclusions; and (vi) compose the report.

2.1 | Literature collection and filtering

The study aims to identify and analyze optimization and decision models related to prescribed burning by conducting a literature review of three databases: Google Scholar, USDA Treesearch, and Science Direct. The search focused on newer articles to reflect the current state of prescribed burning implementation and its evolving environments. We used multiple keywords in the search, such as "prescribed burning," "wildfire mitigation," "optimization," "decision," "trade-offs," "stakeholders," and "preference," to refine the search and identify articles that optimized treatment outcomes or made decisions on trade-offs.

The preliminary search, after removing duplicates, yielded a total of 471 papers within our study's scope. We focused on studies conducted from 2000 to 2023. We then conducted a two-step filtering process on the collection. Figure 1 provides an overview of the collecting and filtering process for the literature in our study. The purpose of the filtering process was to identify papers that contributed to the strategic or operational planning of prescribed burning in terms of modeling, solution techniques, and assumptions. The selected papers had to meet at least one of the three following criteria: (a) contribute to wildfire mitigation, (b) model fire behavior or influencing factors and their effects on fire behav-

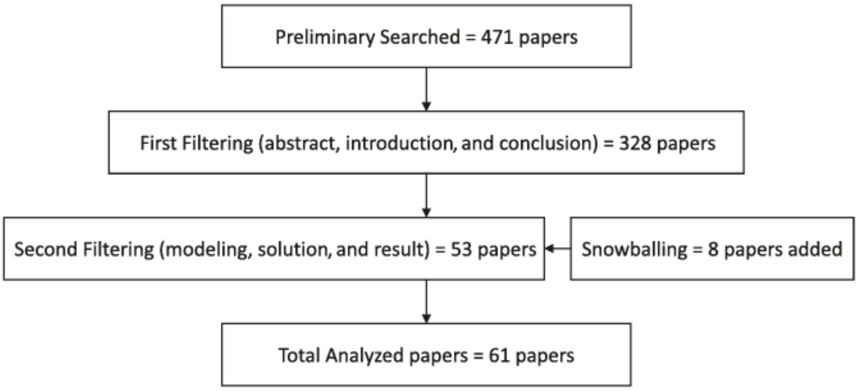

FIGURE 1 The process of collecting and filtering literature.

ior, and (c) focus on strategic or operational planning of prescribed burning.

In the first filtering step, we manually screened the 471 collected papers to examine their relevance to this study by reviewing the abstract, introduction, and conclusion sections in detail. This filtering step led to excluding 143 papers that did not properly fit our study, leaving 328 articles for further analysis. In the second filtering step, we conducted a more detailed review of the model formulation, solution, and result sections for the remaining articles to determine their suitability for inclusion in the final selection. Finally, we selected 53 papers for this review based on their relevance, contribution to the literature, and overall quality. Furthermore, upon reviewing the selected papers, we identified eight additional relevant studies through a snowballing approach. In total, 61 papers were included in this review, covering a range of modeling approaches to prescribed burning, thereby providing a comprehensive overview of the state-of-the-art in this field.

2.2 | Overview and statistics

Our search and filtering resulted in a total of 61 papers published between 2000 and 2023. We discovered that the variables in the optimization models are multidimensional, and many influencing factors add uncertainty to the modeling. We categorized the models based on the category in preview studies and their focused criteria before proceeding (Alcasena et al., 2018; Elia et al., 2014; Holland et al., 2017; Mason & Lashley, 2021; Minas & Hearne, 2016; Vega-Martínez et al., 2023). Our review identified four main criteria in the optimization models and one distinct category in the decision models: (a) spatial-allocation models are designed to strategically determine the most effective locations for prescribed burns. They may consider factors such as areas with high fuel accumulation, regions prone to wildfire risks, or zones critical for ecological diversity and habitat conservation; (b) spatial-extent models focus on optimizing the acreage of prescribed burning utilized considering the constraints of available resources and land management objectives; (c) temporal-only models concentrate on optimizing the timing and frequency of burns to attain desired outcomes, which might involve scheduling burns during favorable weather conditions or limiting burns during sensitive periods for wildlife; (d) spatial–temporal models integrate both spatial and temporal variables to formulate a more comprehensive prescribed burning strategy. They synchronize the where and when of prescribed burning application to balance prescribed burning impact, fire risk mitigation, and resource management effectively.

Figure 2 visually represents the quantity of research papers produced for each criterion related to optimization and decision models for prescribed burning in the last 25 years. Publications are experiencing a general upward trend, possibly because to the rising risk of wildfires caused by climate change (Ellis et al., 2022). The number of publications on temporal and spatial allocation is steadily rising, reflecting the impact of burn location and time as fundamental factors in prescribed burning planning. There was an upward trend in spatial–temporal studies after 2010, which suggests an increase in the complexity of prescribed burning strategies. The number of spatial-extent studies has remained stable across all time intervals, likely due to the common understanding that the implementation of prescribed fire has not yet reached its upper limits, and that more prescribed burns are necessary.

3 | FORMAL REVIEW/ANALYSIS

The formulation of optimization models for prescribed burning management is inherently complex due to the significant uncertainties involved in the impacts of prescribed burning. The primary function of prescribed burning is to mitigate the risk of wildfires, but achieving this objective depends on a variety of factors, including climate conditions, fuel load, terrain, vegetation, weather patterns, and the behavior and stochastic nature of fires (Agee & Skinner, 2005; Clarke et al., 2019; Prichard et al., 2010). These variables can significantly affect the success of prescribed burning, making their careful consideration and integration essential when planning and executing burn operations.

In this section, we conduct a comprehensive review and analysis of the optimization and decision models presented in the selected papers. We evaluate the logic behind model

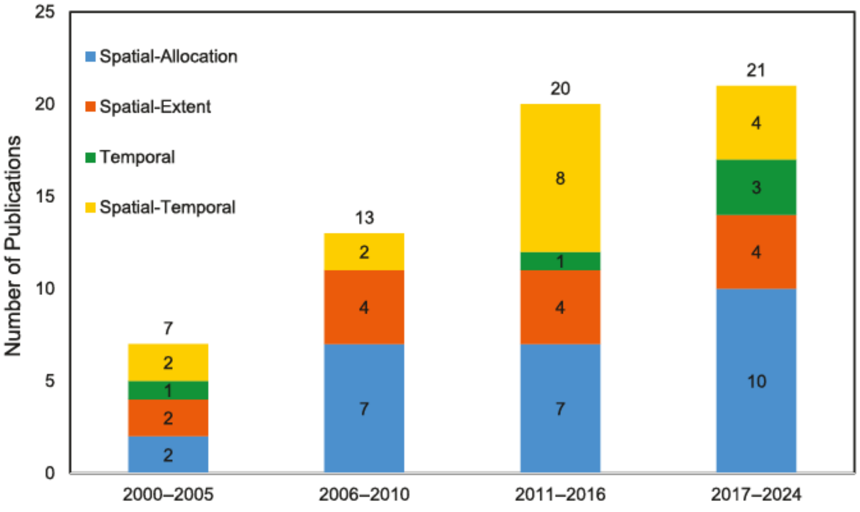

FIGURE 2 Number of papers published from 2000 to 2024.

formulations and the components involved. Specifically, we extract models to identify their objective functions, decision variables, considered impacts and perspectives, solution techniques, and assumptions. In addition, we discuss potential relaxations or challenges associated with these assumptions to refine the models and better reflect real-world scenarios. We also review case studies to assess the effectiveness of prescribed fire and the performance of the models based on study outcomes, along with insights drawn from the conclusions of each reviewed study. Lastly, we present suggestions from the reviewed studies on advancing the modeling and planning of prescribed fire.

3.1 | Spatial-allocation models

Spatial-allocation models are an essential tool for understanding and mitigating wildfire risks, particularly through the strategic application of prescribed burning treatments. These models integrate various factors, allowing researchers to optimize Rx treatments amidst complex and dynamic landscapes. By taking into account fire behavior, environmental conditions, ecological impacts, and economic considerations, the spatial optimization models discussed in this paper underscore the importance of these elements in devising effective and efficient wildfire risk management strategies. A summary of the factors considered in the spatial-allocation models, as reviewed in this paper, is provided in Table 1.

3.1.1 | Fuel load

In their research, Hof et al. (2000) developed a spatial optimization model to maximize the delay of wildfire ignition through the spatial application of treatments. They identified the treated cell using a discrete decision variable, with available resources limiting the total number of treatment cells. The authors assumed that the Rx effect extends across the entire allocated cell, which might not be suitable for large cells. Furthermore, they assumed that there was no cell-to-cell fire spread and that burn time depended solely on the fuel level of the ignition cell. Their research explores spatial optimization approaches to fire (and possibly fuel) management problems with a timing-oriented model formulation. By simulating fire behavior under different treatment strategies, they demonstrated that the wildfire ignition time was spatially sensitive to the prescribed fire treatment. Similarly, Ager et al. (2013) proposed a model to prioritize forest restoration for Rx by allocating Rx treatments to minimize wildfire risk and maintain low hazard to old-growth ponderosa pine (PPOG). The objective is to maximize the number of PPOG in the landscape, using a binary decision variable to decide whether Rx treatments are applied to stands. The model was able to identify the optimal result that balanced the two objectives in the case study, resulting in a flame length of 4 m, with the PPOG saved being greater than the loss in the untreated area. The authors assumed that wildfires within a stand are independent of other adjacent stands and that all stands have an equal probability of wildfire in the case study, which may not fully aligned with practical fire behavior. One study has relaxed this limitations on fire spreading in their framework, Elia et al. (2014) used the spatial allocation index (SAI) to estimate fuel load and human presence in wildland–urban interface (WUI) areas for the spatial allocation of fuel treatment. The decision variable is the SAI indicator, which determines the need for Rx treatments with the objective of minimizing the SAI values across all locations. The SAI accounts for the fuel load and human presence in the area, including population density, urban density, and road density. The SAI outcomes provide a more targeted allocation of fuel intervention over a large area and at a large scale using precise data from fuel sampling and land cover maps. Through a case study in Taranto province, the SAI analysis identified 44% of the WUI area as optimal for treatment. This approach guides management and decision-making in prioritizing efforts to prevent fire spread in WUI areas, addressing some limitations identified in earlier studies, and offering a comprehensive solution for

TABLE 1 Factors considered in spatial-allocation models.

Focus	Factors/Attributes			Reference
Fuel load	Fire ignition, spreading, duration			Hof et al. (2000)
	PPOG, Flame length			Ager et al. (2013)
	Population, Urban density			Elia et al. (2014)
	Ignition probability, Value-at-risk			Rytwinski and Crowe (2010)
Fire stochastic	Climate condition	Physical condition		Wei et al. (2008)
		Value-at-risk, landscape condition		Belval et al. (2015)
		Economic values		Konoshima et al. (2008)
			Fuel condition	Konoshima et al. (2010)
			Fuel regrowth	Perello et al. (2024)
			Vegetation	Lagos et al. (2024)
	Loss of fire			Wei (2012)
	Geographic condition			Kim and Bettinger (2008), Yemshanov et al. (2021)
Stakeholders' preference	Ecosystem health	WUI, Pine straw production		Costanza and Moody (2011)
		Fire stochastic		Sturtevant et al. (2009)
		Site productivity		Hiers et al. (2003)
		Koala habitat, Estate, Species complex		Mollasalehi (2015)
	Economic impact, Cultural heritage, Fauna species, Human life loss			Gazzard et al. (2019)
	Fire resilience of ecosystems, Rx impact, Rural communities protection			Alcasena et al. (2018)
	Forest fairness, Area fairness, Curing fairness			Chen et al. (2022)
	Heat load index, LANDFIRE index, SBRE ecological zone			Phelps (2021)
Trade-offs	Fire risk, Harvest volume			Thompson et al. (2017)
	Rx cost	Fire suppression cost		Heines et al. (2018)
			Loss of fire, House loss	Florec et al. (2019)
			Weighted MC	Minas et al. (2015)
		Loss of fire, Wildfire prevention education cost		Butry et al. (2010)

Abbreviations: MC, management cells; PPOG, old-growth ponderosa pine; WUI, wildland–urban interface.

the spatial allocation of fuel treatments. In a similar vein, Rytwinski and Crowe (2010) addressed the challenge of optimally locating fuel breaks in forests to limit wildfire spread and minimize damage. They developed a decision support model using a simulation-optimization approach, accounting for uncertainty in future fire ignition and spread. The model's objective is to minimize fire risk by adhering to a constraint on the total area designated for fuel breaks. A stochastic simulation model of fire spread illustrates the spatial relationships between fuel breaks and their effectiveness in reducing fire risk. Despite the computational burden of the model, the authors emphasize the significance of spatial relationships in fire-risk reduction and efficient decision-making regarding fuel-break locations through its evaluation on a 220,000 ha forest and comparison to a spatially blind greedy heuristic.

3.1.2 | Fire stochastic

Diverse uncertain factors, including topography, fuel availability, and meteorological conditions, all contribute to the complexity of wildfires as natural phenomena. These uncertainties complicate the planning of prescribed burns, particularly when considering the probabilities of ignition, growth, and spread. Despite the uncertainties in the Rx impact in wildfire mitigation, it is acknowledged as an essential tool for managing forest fuels (Reinhardt et al., 2008).

To confront the challenge of planning Rx in the face of uncertainties stemming from weather conditions, several studies have proposed diverse models and optimization techniques. For instance, Wei et al. (2008) employed conditional probability to minimize the total expected loss due to wildfires, taking into account a limited budget constraint. Their model incorporated the possibility of fire spreading to adjacent cells, posited that high-intensity fires could be downgraded to low-intensity fires, and considered the impact of wind direction on fire spread. The test case validated the mitigation effect of spatially allocated prescribed fires on the expected wildfire loss, taking into account that fire spread is primarily driven by wind direction. With a similar focus on modeling the wildfire spreading, Belval et al. (2015) introduced a mixed-integer program designed to explore integrating spatial fire behavior and suppression placement decisions into a mathematical programming framework. The model computes both fire arrival times and fire line intensities based on the direction that a fire spreads into a cell as a response to spatially explicit suppression placement. The model's ability to determine efficient suppression placement decisions is illustrated using test cases that examine trade-offs between suppression cost and area burned. Integrating fire suppression with prescribed fire optimization, Wei (2012) investigated the impact of wildfire ignition probability distribution on the optimal spatial layout for Rx fuel treatments. They employed a mixed-integer programming (MIP) model to maximize the total expected loss while adhering to a budget constraint limiting the number of treatable cells with Rx. The model used a binary variable to track the Rx decisions in cells and two continuous parameters to estimate the probability and duration of wildfires. The authors assumed the impact of Rx in mitigating wildfires and a uniform attribute value for each cell. The study revealed that Rx effectiveness on wildfire mitigation is more pronounced when allocated in a contiguous area, adhering to regular, intuitive spatial patterns. Another study validated that regular and clumped Rx patterns are most effective in wildfire simulations (Kim & Bettinger, 2008). Continuing the effort in modeling the fire spreading among adjacent cells, Yemshanov et al. (2021) proposed a network optimization model to determine the optimal spatial location for Rx treatments in a grid arrangement. The objective was to minimize the number of fire-spreading cells while being constrained by the total treated area. They used a simulation model to estimate the probability of ignition and fire spreading among cells. A binary decision variable was used to assess the potential for fire spreading between two cells. However, this study did not consider the effectiveness of Rx, presuming it eliminates wildfire risk from treated and connected cells. Furthermore, the authors made a practical assumption that the Rx budget constraint is proportional to the treated area, as the size of an Rx is a primary factor in estimating its costs (Stevens et al., 1997).

Two studies used stochastic dynamic programming to handle the uncertainties in fire behavior in the spatial pattern optimization model (Konoshima et al., 2008, 2010). The initial study used the spatial fire behavior model with the stochastic dynamic optimization model to identify the optimal Rx spatial pattern that maximizes the anticipated net value. This analysis considers factors such as fire danger, wood harvest value, and Rx cost. Utilizing backward induction, the authors addressed the objective formulation, with a risk-neutral land manager as the decision-maker to evaluate the trade-offs between costs and gains. The decision variable represents the action to be taken in the management unit, selected from a combination of harvest and treatment options. The authors initially assumed flat terrain conditions in the first study but later relaxed this assumption in their subsequent study to better model real-world conditions. The study assumed a 10-year effectiveness for prescribed burning (Fiedler & Keegan, 2003; Loehle, 2004), which was specific to the region studied. The longevity of Rx effects varies across regions depending on influencing factors, typically ranging between 4 and 10 years posttreatment (Boer et al., 2009; Kobziar et al., 2015; Reilly et al., 2016; Susaeta & Carney, 2023). To enhance the applicability of Rx models, the longevity of Rx can be represented by a function incorporating regional parameters such as vegetation type and climate conditions (Cullen et al., 2024; Fonseca et al., 2022; Hood et al., 2020). The second study integrated the physical fire and dynamic spatial optimization models to analyze the trade-offs between on-site value and wildfire risk mitigation. The risk-neutral forest manager served as the decision-maker, with the objective of maximizing the expected net value. Climate conditions and weather probability were incorporated into the optimization function, influencing fire behavior and interactions among harvest, fuel treatment, and climate conditions. However, they made an assumption of cell-to-cell fire spreading to allow for a more detailed examination of the trade-offs. This assumption could be further relaxed by incorporating the calibrated Rothermel model, which would provide a more accurate representation of real fire dynamics (Pereira et al., 2024). Both studies validate the effectiveness of the proposed models through test studies, emphasizing that the treatment outcome were significantly influenced by wind and slope conditions. In a recent effort to use fire simulation for addressing uncertainties, Perello et al. (2024) introduced a complex dual-objective model for prescribed fire allocation, aiming to maximize wildfire mitigation and minimize conduction costs. Simulated via the PROPAGATOR framework, the model integrates key factors such as fire ignition, weather conditions, and fuel regrowth to better reflect real-world dynamics. Wildfire risk is defined as the area of wildfires occurring after prescribed burns, influenced by these factors and the spatial allocation of treatments. Prescribed fire costs are assumed constant and normalized within the objective function, facilitating balanced decision-making. Case results showed that optimized burn locations minimized these objective values, and expanding strategically burned areas reduced the overall wildfire-affected regions. By using real data on fire behavior, topography, and weather, the model provides a practical approach for prescribed fire allocation in both emergency and planning phases. In addition, the assumption of deterministic fuel regrowth can be improved by incorporating a stochastic process with assigned regrowth probabilities, further enhancing the model's realism and applicability.

Taking a distinct approach, Lagos et al. (2024) proposed a game-theoretical model for allocating prescribed fire. The treatment planner acts as the defender, strategically using prescribed burns to reduce the impact of wildfires, with nature as the attacker causing fire ignitions. The objective is to minimize the maximum total expected wildfire-burned area through a bi-level integer programming model. This model addresses two major uncertainties in fire dynamics: weather conditions and wildfire ignition. Weather scenarios are incorporated into the objective function, along with the probability of each scenario. Wildfire ignition is treated as a lower-level decision, given that most wildfires are human-caused and difficult to predict. A case study compared the performance of the proposed bi-level model with a single-level model, showing that the bi-level model performed better in mitigating expected fire loss and burned area under a constrained treatment budget. This study presents a valuable approach for modeling wildfire ignition without requiring probabilistic information, which could be particularly useful for modeling ignition in small regions targeted for prescribed fire.

3.1.3 | Stakeholders' preference

Given that stakeholders have firsthand experience of the consequences, their participation is essential for accurately evaluating the effects of prescribed burning (Rx) and ensuring successful management. Hence, it is crucial to comprehend their varied interests and concerns. Within this particular framework, researchers have utilized several approaches to investigate stakeholder preferences and limitations. The choice of methodology mostly depends on the requirements of the stakeholders engaged in fire management and the particular objectives and circumstances of the study (Velasquez & Hester, 2013).

To identify the important factors for stakeholders, Costanza and Moody (2011) did a descriptive study of the constraints and priorities of stakeholders in planning and carrying out prescribed burning. The study found significant differences in priorities among stakeholders, particularly concerning nonecological impacts. Sturtevant et al. (2009) used multivariate variance analysis (MANOVA) to optimize fire and fuel mitigation strategies, including Rx, to balance wildfire risk reduction and ecological goals in multiowner landscapes. This provided insights on aligning diverse human values and objectives during fire mitigation in landscapes with mixed ownership (Keselman et al., 1998). Hiers et al. (2003) proposed a multicriteria approach for prioritizing prescribed burning on a broader scale, taking into account biological impacts. This approach was developed by stakeholders, including managers and biologists, with the goal of identifying essential criteria and management objectives connected to prescribed burning, which were then weighted and graded based on their relation to Rx priority and necessity. The model was based on two workshops for producing desired conditions for all species and a consensus-based scoring approach, which allowed participants to understand how it worked and make any necessary changes.

In contrast to call-and-response engagement, Cullen et al. (2023) proposed a framework based on the National Science Foundation's convergence research principles to actively involve stakeholders in wildfire management decision-making. This approach integrates expertise from multiple disciplines and partners with stakeholders, including governmental, tribal, and local decision-makers, to coproduce information that directly informs decision-making. By holistically addressing wildfire management, the framework ensures that strategies are regionally tailored and directly applicable to operational and policy decisions, enhancing their relevance and overall effectiveness. Shared decision-making (SDM) is another collaborative approach for organizing stakeholder preferences in environmental management decisions (Bunnefeld et al., 2017; Failing et al., 2007; Garrard et al., 2017), was effectively applied by Gazzard et al. (2019) in a multiobjective optimization model for Rx. Their approach aimed to optimize social, economic, and environmental outcomes, encapsulating both monetary and nonmonetary objectives. The study also examines the ethical challenge of placing a monetary value on human life, a sensitive issue often avoided due to its complexity (Chorus et al., 2018; Daw et al., 2015; Fiske & Tetlock, 1997). It estimates the value of a human life at AU$3.7 million using a sensitivity analysis based on stakeholder scores, aligning with previous research suggesting human life values range from $3 to $9 million (Kip Viscusi, 2000). The study approached the delicate issue by comparing monetary loss ranges to loss of life ranges across different scenarios, carefully weighing both life and monetary values.

Understanding the interactions among stakeholders' needs is another challenging task in planning fuel treatments, given the conflicting and diverse priorities that must be balanced across multiple perspectives. Alcasena et al. (2018) introduced a multiobjective optimization approach to evaluate trade-offs based on decision-makers' priorities for Rx treatment. This study utilized spatial optimization analysis and the Landscape Treatment Designer to identify the optimal Rx locations, aiming to align with decision-makers' priorities while also considering cost efficiency. The study factored in multiple local managers as decision-makers, assigning objective weights to their treatment outcome priorities on a scale from 0 to 5. The decision variable was binary, indicating the choice to implement Rx in a treatment unit within the study area, with the aggregate value representing the sum of decisions across all units. While past research on Rx modeling has typically employed one, two, or three-stage approaches, Chen et al. (2022) introduced a more elaborate four-stage spatial multiobjective model for Rx planning. This model encompasses candidate selection, fire simulation, objective function development, and optimization, leading to enhanced results in minimizing wildfire risks across landscapes. By integrating fire simulation and equity considerations, the authors assessed the effectiveness of Rx plans, ensuring a fair distribution of benefits and costs. This advanced approach facilitates more precise, effective, and equitable Rx planning at the landscape level for wildfire risk mitigation. The geographic information system (GIS) can enhance the candidate selection process by enabling users to superimpose the weighted criteria onto geographic conditions. Mollasalehi (2015) employed this methodology in a GIS-based multicriteria analysis to spatially optimize the placement of Rx. This model incorporates diverse elements needed for prioritizing Rx, such as weighted criteria derived from environmental and fire risk variables, as well as vital planning information. As a result, it offers a comprehensive framework for allocating Rx. In addition, Phelps (2021) introduced an ecological decision tool designed to prioritize stands and burn units for Rx based on the GIS criteria. This tool aims to assist in the strategic planning of Rx by enabling the selection of areas that align with ecological, safety, and management objectives. The integration of these diverse criteria ensures that Rx planning is both ecologically sound and effective in mitigating wildfire risks.

3.1.4 | Trade-offs

Aligning Rx outcomes with stakeholder expectations involves addressing trade-offs in prescribed burning planning, including the impacts of Rx and its integration with other management methods like fire suppression. Researchers utilize a variety of tools, such as visualization, multicriteria modeling, and variance analysis, to explore these aspects, aiming to find a balance between Rx benefits, its risks, and how it fits with other fire management strategies. This approach underscores the importance of considering a broad spectrum of environmental, economic, social, and biological factors in fire management planning.

In examining the trade-offs in the benefits and costs of implementing Rx, Thompson et al. (2017) investigated the cost-effectiveness of prescribed burning at multiple investment scales. They used integer programming models to maximize fire risk reduction and volume harvested in two objective functions, with a binary decision variable determining the Rx for the selected cell. The study simulated fire behavior, spreading, and ignition using the Large Fire Simulator (FSim, Finney et al., 2011), while wildfire suppression costs were estimated using a regression model of suppression cost developed by the Forest Service (Gebert et al., 2007). The case study demonstrated that the optimization model reduces both wildfire probability and flame length, further indicating that burn probability can be reduced by 3% for every $10 million investment based on the proposed strategy. Skinner et al. (2024) found that there was more than a 90% chance of reducing wildfire flame length when prescribed fire is combined with mechanical thinning. Their study proposed a decision analytic framework for forest fuel treatments that balances conflicting objectives related to fire behavior and other considerations. The decision tree methodology was employed to evaluate the probabilistic outcomes of various treatment alternatives, including mechanical thinning and prescribed fire. The study offered a practical approach to addressing the trade-offs in forest management by engaging with expert stakeholders, while also emphasizing the importance of addressing the challenges associated with assigning numerical values to the objectives.

More studies are increasingly recognizing the complex relationship between prescribed burning and wildfire suppression, emphasizing their interconnected roles in wildfire risk management. These interventions are closely interrelated in terms of budget allocation as they are both funded from the same source. An increase in funding for one typically results in decreased funding for the other (Minas et al., 2015). Besides, the performance of fire suppression resources, similar to Rx, proved to have an efficiency curve in which the net value is only maximized when the level of suppression resources is optimized (Silva and González-Cabán, 2016). Thus, it is necessary to balance different interventions in order to achieve optimal outcomes. To fill this research gap, Minas et al. (2015) used budget as a constraint in their proposed integer programming model, which optimized the allocation of resources for prescribed burning and suppression. They assumed that the suppression resource and Rx conduction were available at all cells. Two objective functions were formulated: the first aims to maximize the number of high-risk cells covered by Rx conduction, and the second seeks to minimize the resources needed to cover all high-risk cells. The total budget constraint is applied to both objective functions, with each cell weighted based on ignition probability and values threatened. The test results showed that budget flexibility improves the performance of fuel treatments, with the pooled budget providing the most coverage across the tested cells. With a similar research focus, Heines et al. (2018) explored the trade-offs between Rx and fire suppression costs using Reed's method in an optimal control model. Moreover, Rx and fire suppression can work simultaneously to mitigate wildfire risks. Rx can enhance the effectiveness of wildfire suppression, and integrating Rx programs with fire suppression efforts can provide better cost-effectiveness ratios for mitigating wildfire risks (Schaaf et al., 2008). In the case study of the Las Conchas Fire in New Mexico, the model reduced fire suppression costs from $46.5 million to $29 million by allocating $1.5 million to fire prevention. A 50-year fire simulation in the Santa Fe National Forest further indicated that fire suppression costs could be reduced by $194 million with an investment of $65 million in fire prevention. The overall cost reduction was primarily driven by the significant decrease in fire suppression expenses, which resulted from a lower number of wildfires due to the increased investment in fire prevention. Considering wildfire prevention education (WPE) as another wildfire intervention to reduce human-caused wildfire, Butry et al. (2010) proposed a long-term model focusing on the balance between Rx and WPE to minimize costs and societal losses. They found the Rx performed better in the long term but was less flexible in the short term on wildfire mitigation, while the WPE performed conversely. Despite the differences, both interventions are encouraged to increase their optimal solution.

To enhance the accuracy of net value assessments in fire management, a comprehensive approach should include both the direct costs associated with fire management and the financial implications of wildfire-related losses. By integrating these diverse cost factors into the analysis, a more holistic and effective financial evaluation of fire management strategies can be achieved. Florec et al. (2019) employed three models to explore the optimal spatial Rx location: minimum cost plus net value change (C+NVC) model, equal asset value and modified cost model, and minimum house loss model. The objective of the minimum C+NVC model is to minimize the sum of Rx cost, wildfire suppression cost, and loss. The model uses continuous decision variables to determine the extent of the Rx, its distance to the WUI region, and its associated cost. The equal asset value and modified cost model shares the same objective as the previous model but varies in its approach to valuing assets. The cost of Rx is calculated only based on the extent of conduction. The value-at-risk is assumed to be uniformly distributed in the WUI

TABLE 2 Factors considered in spatial-extent models.

Focus	Factors/Attributes				References
Economic impacts	Climate condition, Fire stochastic				Mercer et al. (2008)
		Rx impact	Vegetation		Prestemon et al. (2001)
				Regional factors	Pais et al. (2023)
					Mercer et al. (2007)
			Fire intensity		Florec et al. (2013)
					Jose et al. (2023)
		Fire emissions			Elder et al. (2022)
MCDM	MOP, GP, CP, MAUT, FMCP, etc.				Diaz-Balteiro and Romero (2008)
	Ecological impact	Wildfire hazard, Existing fuel treatments, WUI			Addington et al. (2020)
		Economic impact, Social impact			MacGregor (2005)
Simulation-based	Fire behavior, Carbon dynamics, Weather condition				Dicus and Osborne (2015)
	House protection, Water quality, Emissions, Species conservation				Driscoll et al. (2016)
	Ecological impact	Management effort	Timber, Property, Air quality		Ohlson et al. (2006)
					Hmielowski et al. (2016)

Abbreviations: CP, compromise programming; FMCP, fuzzy multicriteria programming; GP, goal programming; MAUT, multiattribute utility theory; MOP, multiobjective programming; WUI, wildland-urban interface.

region (Mercer et al., 2007). The aim of the minimum house loss model is to minimize the loss of houses due to wildfire. This model accounts for the probability of wildfire reaching houses without considering fire severity. A generalized linear model is used to calculate the Rx conduction cost based on the extent and location (Penman et al., 2014). All three optimization models operate under the assumption that the desired amount of Rx can be conducted within the estimated budget. To reflect real-world problems, this assumption may need to be relaxed with setting up a budge limit (Burrows & McCaw, 2013; Radford et al., 2020). The case results indicated that the optimal burning extent depends on the objectives considered in different models, and selecting the model based on the region type can maximize treatment benefits.

3.2 | Spatial-extent models

Wildfire risk mitigation is significantly influenced by the prescribed burning extent in the current and previous years, as numerous studies have shown (Addington et al., 2015; Kolden, 2019; North et al., 2012; Vaillant & Reinhardt, 2017; Walker et al., 2018). Unfortunately, many of these studies have found that the current level of Rx implementation is insufficient to achieve desired outcomes, indicating a need to increase the total acreage of Rx being used. As summarized in Table 2, various factors have been considered in the spatial-extent models for optimizing prescribed burning, including fire behavior, environmental conditions, ecological aspects, and economic considerations. By examining these factors and enhancing the use of prescribed burning, researchers can develop more effective and comprehensive strategies for implementing prescribed burning to better manage wildfire risk and mitigate its impact.

3.2.1 | Economic impact

The net values have been considered in several studies as objective values in the spatial-extent optimization model of Rx, which considers cost of implementation, fire suppression, loss due to fire, and value-at-risk. Prestemon et al. (2001) and Mercer et al. (2007) utilized the stochastic dynamic optimization model of Rx to maximize the expected net present value of welfare in Volusia, Florida. The former study identified the optimal Rx percentage as 3% of the total forest area, while the latter study found that burning 13% of forest lands was most beneficial to net welfare. Prestemon et al. (2001) found 1% increment in prescribed fire area can reduce the wildfire area by 0.07% and 1.4% when considering the lagged wildfire risk in 7 years. In contrast, Mercer et al. (2007) found 1% increment in prescribed fire area can reduce the wildfire risk by 0.27% and 0.65% over 3 years and within 1 year. The differences in the optimal results between two studies were driven by considering both wildfire size and intensity in the wildfire production function in the second study, which was supported by their simulation result in the later study (Mercer et al., 2008). They found that the elasticity of the intensity-weighted area burned with respect to Rx was less than that of the wildfire area, emphasizing the importance of considering the wildfire intensity in assessing the fire risk in the optimization modeling. By incorporating the intensity-weighted risk measure into the model, the study conducted Monte Carlo simulations to estimate the welfare changes resulting from different prescribed burning policies. In order to directly assess the impact of Rx on mitigating wildfires, they employed an exponential function that is reliant on Rx efforts to quantify the correlation between Rx efforts and the cost of suppressing wildfires. This study considered a C+NVC model optimization model applied in Western Australia. The results indicated that the optimal cost-effective Rx strategy was about 5% of the landscape, and the patch size of the Rx had no significant effect on the results. However, their conclusion on the patch size may change if they consider the risk of escaping fire, which was not specifically mentioned in the study. This was further expanded in a later work by Addington et al. (2020), which they found the most suitable patches were in smaller sizes. This study integrates a comprehensive range of elements that influence the decision-making process for Rx. These factors include wildfire threats, vegetation types, current fuel treatments, the WUI, and Rx behavior. The objective is to determine an appropriate region for Rx treatments using a multicriteria suitability analysis. The result from their case study in the Southern Rocky Mountain area indicates approximately 13.4% of the landscape is highly suitable for Rx, and moderate-high and moderately suitable areas are about the same percentage.

Besides the direct costs of fire treatments, several indirect costs related to forest fires also significantly influence fire management outcomes. The social cost of emissions is recognized as one primary indirect contributor to the economic outcomes of fire management (Mills et al., 2015), encompassing health and climate-related consequences of emissions (Zelasky & Buonocore, 2021). Both wildfires and prescribed burns are major sources of particulate matter (PM) emissions (Cascio, 2018), with $PM_{2.5}$ from fire emissions accounting for over 90% of the social (health) costs associated with mortality and morbidity (Lueken et al., 2016). Considering both prescribed burns and wildfires generate emissions with associated social costs, understanding the differences is essential. Kiely et al. (2024) found that prescribed burns can reduce $PM_{2.5}$ emissions by nearly 50% compared to wildfires in California. A comparative analysis by the US Environmental Protection Agency (EPA) showed that prescribed burns have significantly lower health and environmental impacts than wildfires (EPA, 2021), and can substantially reduce the overall health impacts and associated costs of fire emissions. In a related study, Elder et al. (2022) explored the trade-offs between prescribed burn implementation costs and the social cost of carbon (SCC) in an optimization model aimed at minimizing total costs. Their findings revealed that total costs are primarily driven by the SCC, which is far higher than the costs of implementing prescribed burns. They also found that prescribed burn costs would need to increase 5–10 times to achieve the lowest total cost by reducing the SCC from wildfires. Overall, the planning of prescribed fire needs to calibrate the burning extent and frequency to ensure public health while achieving forest management goals (Rosenberg et al., 2024).

Considering the significant changes in global climate conditions (Abbass et al., 2022), it is crucial to assess the effectiveness of prescribed fire as its performance is highly influenced by these shifts. To evaluate its role in wildfire mitigation, Pais et al. (2023) conducted a simulation study using the REMANS model, which dynamically integrates wildfire and vegetation factors. The study assessed effectiveness based on three treatment levels, allocation strategies, and land-use scenarios. The case study focused on the 276,000-ha Transboundary Biosphere Reserve, which features varied topography and climate conditions. Results indicated that prescribed fire could reduce potential wildfire area by 36% in the best-case scenario, with a leverage ratio of 0.18. The study also found that increasing the annual prescribed fire treatment level led to better wildfire mitigation results, though the effectiveness was influenced by location and the integration with land-use scenarios. Extending the assessment to a broader scale, Jose et al. (2023) proposed an economic optimization model aimed at minimizing the total expected costs of prescribed fire treatments, wildfire suppression, and associated losses. The model uses an exponential decay function to quantify wildfire risk reduction as prescribed burning extents increase (Behrendt et al., 2019a; Price, 2012). Case study validation suggested that increasing prescribed fire extents by 143% in Oregon could reduce total expected costs by an average of 24% over the study period. The study emphasized that the effectiveness of prescribed burns depends on the treatment scale and the specific wildfire risks of the landscape and treatment patterns. High-risk areas require more deliberate planning to mitigate potential negative effects. While the study provides valuable insights into balancing pre- and post-wildfire efforts, incorporating more direct economic impacts could enhance its practical application.

3.2.2 | Multicriteria decision-making (MCDM)

The variations in these optimal solutions point out the need for tailored Rx strategies that consider specific regional conditions, methodological approaches, and the unique objectives of each study. This diversity in findings reinforces the value of considering a broad spectrum of factors and uncertainties in determining the most effective Rx strategies for different regions and landscapes. The multicriteria analysis used by Addington et al. (2020) within the MCDM framework can address challenges outlined by the Federal Wildland Fire Management Policy (Calkin et al., 2011), focusing on the valuation of nonmarket assets and stakeholder cognitive limitations (Altangerel & Kull, 2013; Halliday et al., 2012; Venn & Calkin, 2011; Winter & Fried, 2000). Diaz-Balteiro and Romero (2008) reviews MCDM methods such as multiobjective programming (MOP), goal programming (GP), compromise programming (CP), multiattribute utility theory (MAUT), fuzzy multicriteria programming (FMCP), and other discrete methods (ODM). These methods balance interests across social, economic, and environmental aspects, enhancing wildfire management strategies to align with societal preferences and addressing Rx implementation challenges (Cegan et al., 2017; Kiker et al., 2005; Sadeghi Ravesh, 2020). By using the multiattribute-based approach, MacGregor (2005) established a foundation for examining the trade-offs across various aspects, including ecological, economic, social, and Rx primary effects. Their study facilitates comprehensive objective evaluation in Rx decision-making using visual tools to illustrate and clarify the trade-offs between different management objectives.

3.2.3 | Simulation-based model

Dicus and Osborne (2015) conducted a study to investigate the effects of fuel treatment location and quantity on fire behavior and carbon dynamics, using the Forest Vegetation Simulator (FVS) with Fire and Fuels Extension (FFE) and FlamMap, alongside GIS technology. They analyzed 13 fuel treatment scenarios, finding that spatial allocation and treatment quantity significantly influence fire behavior and carbon emissions. The results indicated that the optimal treatment intensity depends on the type of treatment and the associated carbon loss in the short or long term. However, since prescribed fires produce 50% fewer emissions than wildfires for the same burned area (Kiely et al., 2024), strategically balancing the use of prescribed fires alongside wildfire management can significantly reduce overall emissions. The discrete decision variables for treatment intensities (10%, 20%, and 30% of the landscape) may hinder the model from identifying the global optimal (Klemmt et al., 2009). This limitation is common when using simulation-based optimization models to handle decision-making in uncertain environments, such as wildfire management. For instance, Ohlson et al. (2006) considered three treatment alternatives in the multiattribute trade-off analysis (MATA) for fuel management. They focused on identifying management objectives like minimizing costs, maximizing timber resources, minimizing property damage, and enhancing ecological values. Similarly, Driscoll et al. (2016) considered five levels of burning among the 22 alternatives in their MCDM optimization model. They considered objectives such as protecting houses from wildfires, maintaining water quality, minimizing carbon emissions and health impacts, and conserving species. Their model identified two optimal strategies, both achieving 60% total utility but differing in objectives, highlighting the trade-offs between competing priorities. The limitation of using discrete decision variable in simulation was relaxed by Hmielowski et al. (2016) using an index termed management effort, which was estimated by the number of treated management units. The index is utilized in a cost–benefit analysis model to prioritize the Rx area in Wisconsin, aiming to maximize ecological benefits while reducing treatment effort. The stakeholders were highly involved in the modeling process, such as estimation of the management effort and valuation, to improve the quality and utility of this tool for stakeholders.

3.3 | Temporal-only models

Planning the timing of prescribed burning adds complexity to wildfire risk management, as it requires a balance between allowing sufficient time for vegetation regrowth (White et al., 1990) and not exceeding a specific time frame, given that the effectiveness of Rx in mitigating wildfire risk diminishes over time (Ager et al., 2007). Numerous studies have focused on scheduling forest fuel treatments to reduce wildfire risk. These temporal-only models incorporate a variety of factors, enabling researchers to develop dynamic strategies that account for the ever-changing nature of wildfire risk. By considering fire behavior, environmental conditions, ecological aspects, and economic impacts, the temporal optimization models presented in Table 3 underscore the significance of these factors in formulating adaptive and effective wildfire risk management strategies.

The scheduling of prescribed burning treatments significantly influences their optimization and the mitigation of wildfire risk. This fact is supported by multiple studies that have included fuel accumulation as a critical factor in their optimization models. Yoder (2004) used a dynamic economic model to optimize the timing and precaution of Rx, aiming to maximize net value by determining the optimal interval between treatments and considering the precautionary efforts in Rx conduction. This model accounted for fuel accumulation over time and was the first to incorporate the probability of escaped fire, using a function that considers the time elapsed since the last Rx conduction and the level of precautionary effort to estimate this probability. The decision variable in this model is continuous, representing the timing of the Rx conduction. The expected damage of escaped prescribed fire is considered in the objective function, which the probability of escaping is a function of precautionary effort for prescribed burning. The study found that the effectiveness of prescribed fire depends on both wildfire risk and the potential damage caused by prescribed burns. Higher wildfire risks necessitate more frequent and precautionary prescribed burns, while liability concerns related to prescribed fire damage can discourage their use, despite their effectiveness in reducing overall wildfire damage. With the same focus on reducing fuel load, Minas et al. (2014) proposed a decision model to identify the optimal time for fuel treatment, considering fuel age as a central element. They employed an MIP model with binary decision variables to establish Rx conduction within a cell, dividing the study area into several cells. The objective was to minimize wildfire risk concerning forest fuel age in the area while adhering to a major constraint on the total treatment budget. This study offers a decision model for optimizing the timing of Rx use, further highlighting the importance of fuel management. Note that the researchers assumed a constant suppressive effect of Rx on wildfire risks within a cell for a set period. Although this assumption simplifies the model, incorporating a decay function that reduces the Rx effect over time could better reflect reality, acknowledging that the potency of Rx treatments diminishes as time progresses. This decay is not uniform and can be influenced by various factors, such as fuel regrowth and changes in environmental conditions (Valkó & Deák, 2021).

Factoring ecological consideration into planning, León et al. (2023) introduced a multiobjective stochastic programming (MSP) model for scheduling Rx. MSP aims to balance conflicting objectives in models where parameters within the

TABLE 3 Factors considered in temporal-only models.

Focus	Factors/Attributes		References
Fuel reduction	Production value, Escaped fire, Net value		Yoder (2004)
	Rx budget	Animal habitat	León et al. (2023)
		Ecosystem health	Minas et al. (2014)
	Biological diversity, Environmental impacts		Gharun et al. (2017)
Risk reduction	Timber harvest, Timber price, Rx cost		Susaeta and Carney (2023)

objectives or constraints are probabilistic (Abdelaziz, 2012). Their model seeks to reduce high-fuel load connections and total high-fuel load areas while enhancing habitat quality for two species. It accounts for uncertainty and multiple criteria, with binary decision variables dictating whether Rx is conducted in a burn unit at a given time. Furthermore, the model takes into consideration an age threshold for defining a unit as high-fuel load, which varies based on vegetation type, and incorporates the habitat needs of fauna, reflecting both the age and type of vegetation present. The researchers set limitations on the total Rx area and budget, modeling the allowance of Rx in a burn unit as a discrete probability distribution. In addition, the model accommodates the necessity for risk-averse strategies, recognizing the significant implications that the burning of vegetation has on human safety and the environment. In sum, this MSP model offers a comprehensive method for addressing the challenges associated with prescribed burns, integrating multiple objectives and the inherent uncertainties of such interventions. To improve the accuracy of mapping the fuel load for Rx treatment, Gharun et al. (2017) suggested the use of remote sensing combined with ground surveys. Their study developed a framework that integrated ecological objectives into the traditional Rx temporal optimization model, focusing on the examination of major effects and their interactions leading to changes in secondary effects, such as water, carbon, ecosystem resilience, and recovery. Further evaluating both primary and secondary effects, Susaeta and Carney (2023) proposed a temporal optimization model to determine the optimal burning frequency that maximizes net value. Wildfire risk is estimated using a Poisson model, where the probability of a wildfire occurring is constant over time, and the likelihood of destruction is calculated based on the stand's age relative to the wildfire rotation age. Case study results showed that the greatest benefit from prescribed burns was in mitigating wildfire risk, with only a minor improvement in harvest volume.

3.4 | Spatial–temporal models

Spatial–temporal optimization models improve the analysis of prescribed burning management by incorporating both spatial and temporal dimensions. This integrated approach enables the development of precise and effective strategies, accounting for the varied landscapes and changing patterns of fuel accumulation. Table 4 provides a summary of the factors included in various spatial–temporal models examined in this review.

3.4.1 | Surface fuel

Surface fuel significantly influences fire behavior. Effective management of fuel continuity, type, and load is vital for reducing wildfire risk and promoting healthy ecosystems. Fuel continuity determines how a fire spreads through an area, while fuel load affects the fire's intensity and duration. High fuel loads can lead to more intense fires that burn for extended periods, whereas low fuel loads may result in less intense fires that extinguish more quickly (Sah et al., 2006). By managing fuel continuity and load, managers can effectively mitigate catastrophic wildfire risks and support the development of diverse and resilient plant communities.

Loureiro et al. (2002) developed an optimization model that integrated spatial and temporal objectives for managing fuel continuity and load. The spatial objective aimed to minimize fuel continuity, while the temporal objective established thresholds related to the effectiveness of prescribed burning in reducing fuel hazards. The model predicted fuel load accumulation over 25 years using exponential and time-dependent models, constrained by a plateau representing the "steady-state" fuel load (Burgan, 1984). The authors also considered the effect of climate conditions on prescribed burning, as these conditions influence fuel dynamics and prescribed burning effectiveness. To evaluate the impact of prescribed burning on fuel continuity, they used FRAGSTATS, a software tool that measures changes in landscape-level fuel patch structure and continuity. The best scenario in their case study suggested an optimal burning cycle of 5 years, with 45% of the landscape treated using prescribed fire. The results indicated that the Largest Patch Size of fuel was reduced and maintained below 50%, while the Mean Patch Size was slightly higher but remained under 70%. The fireline intensity of wildfires was also mitigated to below 500 kW/m in most years by the proposed strategy, compared to the general fireline intensity, which typically ranges from 700 to 10,000 kW/m (Volkova et al., 2019).

Recognizing the importance of different fuel types in optimizing prescribed burning strategies, Rachmawati et al. (2015) proposed an MIP model to optimize Rx use by minimizing the weighted total fuel load while accounting for multiple ages and vegetation types. The MIP model featured

TABLE 4 Factors considered in spatial–temporal models.

Focus	Factors/Attributes			References
Fuel reduction	Fire spreading	Climate condition		Loureiro et al. (2002)
	Ecosystem health			Rachmawati et al. (2015)
		Loss of fire		Rachmawati et al. (2016)
			Habitat, Vegetation, Rx cost	Williams et al. (2017)
				Matsypura et al. (2018)
Fire behavior	Rx Cost	Computational effort		Arca et al. (2013, 2015)
		Harvest		Kim and Bettinger (2005)
			Climate condition	Kim et al. (2009)
				Nguyen and Wei (2022)
				Alexandridis et al. (2011)
				Quartieri et al. (2010)
	Loss of fire	Fire protection cost		Payyappalli (2019)
	Surface fuel			Sun et al. (2012)
		Ecosystem health	Value-at-risk	Chung et al. (2013)
				Anstedt (2011)

two binary decision variables to determine Rx conduction, vegetation type, and age in the treated cell. However, the study adopted two simplifying assumptions: all vegetation within the same type in the treatment cell had the same age, and each treatment cell had only one dominant vegetation type. Addressing these assumptions would substantially increase the computational effort required for the model. Considering a 6- or 10-year planning horizon in the case study, the total fuel load can be reduced by 50% with the optimal burning level. Expanding on the last work, Rachmawati et al. (2016) used an MIP model to optimize the spatial and temporal location of prescribed burning treatments for fuel hazard reduction. The objectives aimed to minimize the spatial connectivity of fuel hazards and maximize the area treated by prescribed burning, complying with fuel treatment requirements. The same region from previous work was used for the case study, where the two-phase model identified 7% as the optimal burning level for achieving about 30% reduction in the integrated objective value. The study assumed that all vegetation in a treatment unit was of the same age and that the ecosystem was healthy if prescribed burning occurred between the minimum and maximum fire events. Although no explicit decision-maker or stakeholder was specified, the implied beneficiary was the ecosystem, with the hypothetical decision-maker being the authority planning the prescribed burning. The study stressed the importance of balancing prescribed burning utilization for asset protection with ecosystem health. However, the balance between objectives can lead to prioritization challenges. Integrating a weight variable could improve the model by allowing decision-makers to assign different priority levels to the objectives.

Considering the importance of addressing both ecological and economic factors in fuel management, Matsypura et al. (2018) introduced a multiperiod optimization model for wildfire fuel management. The model aims to minimize surface fuel load while considering species regeneration and survival in the Rx treatment area. It utilizes a binary decision variable to select whether Rx is conducted for each treatment cell, and surface fuel accumulation over time is computed using Olson's equation, which employs a negative exponential function (Watson, 2011). This research makes a significant contribution to the field of wildfire fuel management by presenting an effective approach that addresses both ecological and economic factors. With a similar focus on balancing ecological and economic impacts, Williams et al. (2017) enhanced the approach in their Rx optimization model. The study used integer linear programming to optimize Rx spatially, with asset protection representing the economic impact and several conservation objectives reflecting the ecological impact. The optimization aimed to maximize the total expected value while balancing asset protection and conservation objectives. Rx conduction was strategically planned to safeguard assets, and conservation values were determined by attributing weight factors to each objective from the perspective of the ecosystem. A binary decision variable indicated whether Rx was conducted in selected cells, while an annual budget constraint restricted the number of Rx that could be carried out. The protection benefit of Rx was calculated based on population density and proximity to residential areas, adopting methodologies from Gibbons et al. (2012) and Penman et al. (2014). The proposed model achieved 6% asset protection and 23% conservation benefits in the case study, effectively balancing the conflicting objectives over a 10-year period. Yet, the assumption in the study of a fixed budget and universal Rx permission may not align with actual conditions, where financial constraints are variable and Rx application is often limited by regional regulations and accessibility challenges, emphasizing the necessity for models that account for these real-world complexities.

3.4.2 | Fire behavior

Incorporating fire behavior into prescribed burning optimization models is necessary for understanding the complex dynamics of wildfires and developing effective strategies to reduce their potential impacts. By considering fire intensity, spread, and other fire behavior parameters, these models can provide more accurate and relevant information to support decision-making. To study the fire ignition and severity, Payyappalli (2019) provides a machine learning model to predict the spatial–temporal fire risk based on the value-at-risk, vulnerability, and suppression resources. The assessed fire risk can be utilized in the optimization models, such as the resource allocation model they proposed in the previous section that minimizes the sum of wildfire loss and investment in fire protection. The model considers various factors, such as the probability of a wildfire occurring, the expected loss due to a wildfire, and the cost of implementing fire protection measures. The objective is to find an optimal allocation of resources that minimizes the total expected loss while staying within budget constraints.

Chung et al. (2013) investigated the optimization of prescribed burning treatments by minimizing total expected loss over time and space using a simulated annealing algorithm. The prescribed burning effect was evaluated using FlamMap-MTT (Minimum Travel Time) in terms of wildfire intensity and spreading. These two continuous variables served as decision variables in the objective formula. The study assumed constant fire conditions when estimating spreading through MTT (Finney, 2002). The model was later incorporated into a decision support tool for prescribed burning planning (Anstedt, 2011), which integrated multiple prescribed burning decision support systems, including land management optimization functionality (MAGIS), vegetation capabilities (FVS0FFE) (Reinhardt, 2003), and fire behavior modeling functionality (FlamMap) (Finney, 2006). In the studied region, the optimized solution with 60% treatment intensity reduced the total expected loss by 76% compared to the no-action scenario and by 41% compared to random solutions. However, the large computational time required to solve the optimal solution may limit the number of fire scenarios considered in the simulation.

Given the importance of spatial patterns in fuel treatment optimization and forest management, as highlighted in previous studies, researchers have continued to explore innovative approaches to address this aspect. Arca et al. (2013) presented an approach for the automatic design of fuel treatments to mitigate wildfire hazards, formulating the problem as an optimization of a subset of treatment units taken from a predefined spatial pattern. They proposed a GPU-accelerated optimization model to maximize the treatment effect of Rx within a limited budget, using a Tabu Search procedure coupled with a wildfire simulator. Depending on the spatial characteristics, the high-risk area can be reduced to less than one-quarter of its initial value. The use of GPUs significantly lowers computation time, averaging less than 20 min for the optimal solution. In a follow-up study, Arca et al. (2015) applied the GPGPU (General-Purpose Computing on Graphics Processing Units) approach for biobjective optimization, aiming to minimize both wildfire hazards and fuel treatment costs. The experiment result showed that the reduction effect on the high risk area was influenced by the Rx treated area, the most efficient tested solution was treating 7.2 ha area with 65% reduction. In a related effort, Kim and Bettinger (2005) and Kim et al. (2009) developed new methods for scheduling forest management activities in a spatial pattern, with the earlier study focusing on a smaller area and the latter study expanding to a larger area. These studies examined both operational and fuel reduction management prescriptions, employing a heuristic to schedule the activities. In the later study, the impact of Rx spatial patterns on simulated wildfire behavior was also investigated. Four spatial patterns were analyzed using a single heuristic modeling approach, the Great Deluge Algorithm. The objective of the optimization model was to minimize the difference between actual harvest and target volumes while managing the total distance among treatment units, all under a limited Rx conduction budget. In the first study, which considered harvest volume as an objective, the dispersed pattern scheduling model provided the highest harvest volume and the greatest number of units scheduled for harvest. In the second study, the regular treatment pattern demonstrated the highest effectiveness ratio of 0.16 in the Oregon case study, based on the treated area, adjacent area, and the number of treated cells.

A recent study by Nguyen and Wei (2022) presents a comprehensive approach to fire management by integrating fire behavior, fuel treatment, and fire suppression into a single optimization model. This model aims to minimize the total costs of prescribed burning, wildfire suppression, and wildfire losses across raster cells. To optimize Rx decisions, the study employed a multistage stochastic MIP using sample average approximation (SAA), a technique that handles stochastic optimization while providing confidence intervals. By approximating the expected values of uncertain variables, the SAA method refines the objective function and enhances the model's capability to solve complex stochastic problems. The model, validated in a synthesized test, demonstrated that optimal first-period prescribed burning could reduce the objective function by 23.8% in low-value forests and 48.4% in high-value forests. To capture the complexity of fire behavior, the study modeled wildfire ignition as a random event, with fire spread influenced by varying wind directions and speeds, simulated using cellular automata (CA) (Sullivan, 2009). CA updates the state of each grid cell based on time and the states of neighboring cells (Zheng et al., 2011), a method applied in various fire modeling studies (Alexandridis et al., 2011; Rienow & Goetzke, 2015; Sun et al., 2012), some of which incorporate fire ignition probability (Quartieri et al., 2010). However, integrating multiple components into a single optimization model increases its complexity, especially when attempting to formulate a unified objective function (Bettinger, 2010; Konoshima et al., 2008).

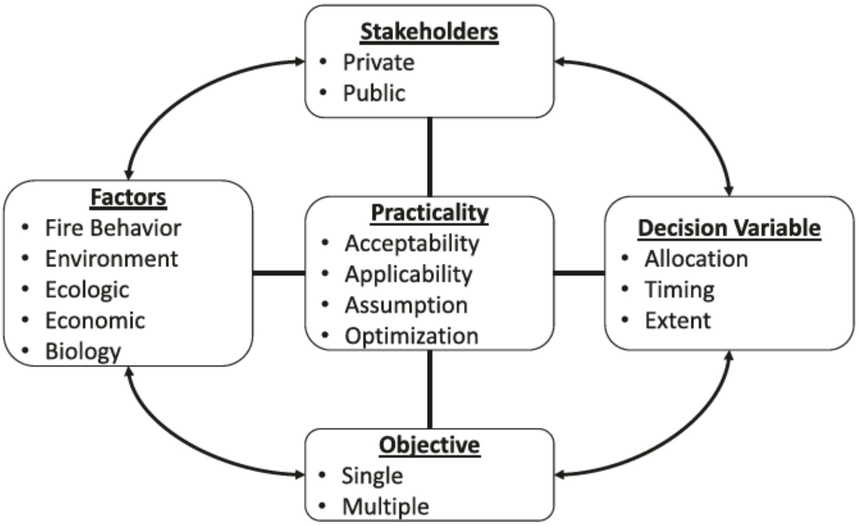

FIGURE 3 Components in the prescribed burning optimization.

4 | CONCLUSIONS

This study provides a systematic review and analysis of the prescribed burning optimization literature by examining 61 papers published over the past 25 years. We identify four major focus areas and criteria in the optimization models, including spatial-allocation, spatial-extent, temporal-only, and spatial–temporal. We also summarize several elements that significantly impact prescribed burning optimization models. Our review presents the major considerations and perspectives of the relevant aspects of prescribed burning optimization. Our analysis revealed that incorporating a broader range of components into model formulation can enhance its realism and applicability to real-world problems. The complexity of these components plays a crucial role in determining a model's realism. Models with fewer components require less computational effort to produce accurate results based on their formulation, but they may represent fewer real-world scenarios, potentially limiting their practical application. In contrast, models that encompass a diverse array of components are likely to provide a more accurate representation of real-world scenarios, but with a higher potential for uncertainty. Given the nature of fire behavior and its impacts, fire models must be sufficiently complex to accurately represent the fire behaviors (McKenzie & Perera, 2015). Although there is no clear standard for complexity (Hantson et al., 2016), it is still necessary to expand the range of factors considered in current fire models (Miller & Aplet, 2016).

We performed a comprehensive assessment and modified the components chart proposed by Chung (2015), tailoring it to meet the unique requirements of prescribed burning planning. Our revised chart, illustrated in Figure 3, replaces the "treatment effect" component with "factors." This change better captures the multifaceted interactions between subcomponents and prescribed burning. It acknowledges that aspects like fire behavior are crucial not only preconduction but also influence outcomes postconduction (Wei et al., 2008).

Recognizing the significant interplay between biology and fire, we incorporated biology as an additional factor. The influence of fire on biological aspects and its consequential secondary effects are critical considerations in Rx planning (Hiers et al., 2003). We also acknowledged the influential role of stakeholders, adding them as a major component to reflect their impact on model variance. Given the varying expectations of different stakeholders for prescribed burning, it is imperative to understand that private parties' priorities can diverge markedly from public organizations' objectives (Costanza & Moody, 2011). Stakeholder preferences not only influence but are crucial in determining the suitability of prescribed burning, underscoring their importance in decision-making (Addington et al., 2020). In our revised chart, we have included the extent of prescribed burning as a decision variable, recognizing its significant impact on wildfire management (Addington et al., 2015). Furthermore, we introduced "acceptability" as a subcomponent under practicality (Ryan et al., 2013). Ensuring that the objectives, effects, and outcomes of prescribed burning are acceptable to both the decision-maker and society is vital for successful implementation (Calkin et al., 2011; Miller et al., 2020; Shindler, 2007). Lastly, while the goal of modeling prescribed burning is to aid decision-makers in strategic decisions based on utility maximization (Herrnstein et al., 1993), this process requires complete information (Aleskerov et al., 2007). Yet, our review found that none of the studies comprehensively considers all the components related to modeling prescribed burning optimization and decision-making, often relying on incomplete information (Yang et al., 2015). Therefore, although existing models have contributed significantly to the field, there is a clear need for more comprehensive approaches. Incorporating diverse stakeholder perspectives and providing a more realistic estimation of costs and risks are essential to enhance the accuracy and applicability of decision-making models in prescribed burning management.

Building on the previous discussion, delving deeper into the specifics of prescribed burning optimization reveals noteworthy trends and gaps. Many studies in this area assume a model formulated and strategic planning executed by a single decision-maker. However, this approach often fails to accommodate the diverse priorities and preferences of various stakeholders, potentially leading to disagreements and complicating the decision-making process. Incorporating the perspectives of stakeholders can significantly enhance the accuracy and comprehensiveness of the decision-making process (Costanza & Moody, 2011). Regarding objective values, the earlier studies focus primarily on a single objective, often optimizing for monetary value. Recent research, however, tends to favor models that maximize the benefits of prescribed burning. Some models diverge from this trend, focusing instead on factors like fuel load within a region or delaying the time of wildfire ignition. MCDM has emerged as a potent tool that amalgamates various objectives into one function, adding complexity to problem formulation but proving beneficial for strategic modeling of prescribed burning (Mardani et al., 2015; Perera et al., 2013; Perez-Gallardo et al., 2018; Yu, 2013). In terms of modeling techniques, studies employing the management cells (MC) method generally aim to identify the ideal allocation and timing for prescribed burning using integer or MIP models. Others use continuous decision variables to optimize the extent of prescribed burning or stakeholder priorities. Popular solution techniques include linear programming and MIP. Stochastic dynamic programming models are utilized when fire randomness is considered, and techniques like MOP and FMCP are applied for multiple objectives or objective functions. As these objectives often conflict, the goal shifts to finding a balance instead of optimizing all objectives. Most decision and optimization models for prescribed burning rarely consider the risk of fire escaping and usually assume a steady unit cost of prescribed burning. They also presuppose a definitive effect of prescribed burning on wildfire mitigation within a certain period, which may not always hold true. Prioritizing prescribed burning under constraints is more effectively guided by identifying the value-at-risk for each cell (Hunter & Robles, 2020; Stevens et al., 1997; Yoder, 2004).

The effectiveness of prescribed fire models was demonstrated through case studies in most of the reviewed works, though some studies placed a strong emphasis on the tradeoffs between costs and benefits. We observed no significant differences in model performance across the four identified modeling types, each of which focuses on strategic planning for prescribed burning by addressing decision-making in three dimensions: location, timing, and the amount of burning. The treatment benefits associated with prescribed fire impacts indicate substantial improvements across various objectives. Strategically implemented prescribed burns have been shown to reduce fuel loads within treated areas by 30–50% (Elia et al., 2014; Rachmawati et al., 2015, 2016; Rytwinski & Crowe, 2010) and to decrease wildfire-affected areas by 36–50%. Depending on the cost parameters included, the optimized burning strategy achieved a reduction in total expected costs ranging from 24% to 76% (Arca et al., 2015; Chung et al., 2013; Jose et al., 2023; Nguyen & Wei, 2022). When multiple objectives were integrated, prescribed fire exhibited differential impacts on treatment outcomes, particularly when more qualitative impacts were considered (Addington et al., 2020; Gharun et al., 2017; León et al., 2023; Ohlson et al., 2006). Notably, while prescribed fire remains effective, its relative impact on improving target outcomes becomes less pronounced as additional aspects are incorporated into the objectives. While no existing studies have developed a fully three-dimensional model for prescribed fire, significant progress has been made in two-dimensional modeling. spatial–temporal models typically consider either the location or the amount of prescribed fire, along with the timing of the burn, using integrated decision variables. In addition, some spatial models have attempted to determine both the location and the amount of prescribed fire using the MC method, where decisions are made based on the sum of treated cells (Matsypura et al., 2018; Nguyen & Wei, 2022; Rachmawati et al., 2015; Williams et al., 2017). Most spatial-allocation and spatial-extent studies suggest that actual burning levels need to be increased to reach optimal levels for the best treatment outcomes. However, models that incorporate more factors and interactions—particularly the potential hazards of prescribed fire—tend to recommend lower optimal burning extents. Deak et al. (2024) assessed the impact of prescribed fire on reducing forest carbon storage and wildfire severity under changing climate conditions. Through simulations in northwest California and southwest Oregon, they confirmed the local effectiveness of prescribed burning but not at the landscape scale. The findings indicate that prescribed burns are only beneficial when strategically allocated to regions with specific climate and geographic conditions, emphasizing the need for three-dimensional models that consider the location, timing, and extent of prescribed fire.

Through an extensive review of the literature on prescribed burning management, we can address our research questions as follows: (i) Optimization and decision models in the field of prescribed burning management encompass a wide range, from qualitative and quantitative optimization methods to multicriteria suitability analyses, GIS-based decision models, and stakeholder preference models. These models are notably applicable to wildfire management, addressing critical factors such as fire behavior, environmental conditions, and ecological and economic considerations. Their broad scope enables a comprehensive approach to wildfire management, considering various aspects of fire control and mitigation strategies. (ii) Models in this area utilize diverse formulation and solution techniques, including multicriteria decision analysis (MCDA), economic optimization, and GIS-based decision models. Objective functions within these models often aim to maximize or minimize the economic, environmental, and societal impacts of prescribed burning. Solution techniques span from mathematical optimization, like integer programming, to simulations and advanced machine learning algorithms, offering robust tools for analyzing and predicting fire management outcomes. (iii) The assumptions inherent in these models, such as uniform fire behavior or consistent weather conditions, present challenges in terms of realism and practical application. Relaxing these assumptions requires incorporating more complex interactions, uncertainties, and dynamic aspects of wildfire behavior. This can be effectively addressed through advanced simulation models, machine learning algorithms, and iterative stakeholder engagement processes, which add depth and adaptability to the models, making them more reflective of real-world conditions.

In conclusion, the primary objective of modeling prescribed burning is to facilitate rational strategic decision-making by decision-makers, based on the principle of utility maximization (Herrnstein et al., 1993). This process necessitates complete information in model formulation (Aleskerov et al., 2007). However, our review reveals that none of the studies comprehensively consider all components crucial for accurately modeling the optimization and decision-making aspects of prescribed burning. Most models are formulated based on incomplete information (Yang et al., 2015), which can lead to gaps in decision-making accuracy and efficacy. Despite their contributions, existing models in the field of prescribed burning optimization require a more comprehensive approach. It is essential to account for the varied perspectives of stakeholders and incorporate more realistic estimations of costs and risks. Such enhancements are necessary to improve the accuracy and practicality of decision-making models in prescribed burning management. Future research should thus focus on developing models that integrate a wider array of data and stakeholder inputs, ensuring that all relevant factors are considered for more informed and effective wildfire management strategies.

5 | FUTURE RESEARCH DIRECTION

Future work on prescribed burning planning should expand the scope of model components and stakeholder viewpoints, integrate risk assessment, investigate long-term impacts, and emphasize collaborative decision-making and shared learning. Expanding the scope of models, as suggested by Costanza & Moody (2011) and Driscoll et al. (2016), could address diverse influencing factors and reconcile trade-offs between conflicting objectives. Respecting the interests and priorities of various stakeholders, from land managers to the general public, is crucial. Similarly, incorporating risk assessment and management into optimization models can help mitigate adverse impacts. Studies such as those by Yoder (2004), Stevens et al. (1997), and Hunter and Robles (2020) highlight the importance of quantifying and managing risks associated with prescribed burning. In addition, understanding long-term impacts on ecosystems, communities, and wildfire risks, as discussed by Alcasena et al. (2018), provides critical insights for future management. Integrating adaptive management approaches can enable decision-makers to adjust strategies in response to changing conditions. Finally, fostering collaboration, communication, and learning among stakeholders, as shown by Failing et al. (2007), Garrard et al. (2017), and Bunnefeld et al. (2017), is essential. Addressing the proposed research directions will lead to more comprehensive and accurate prescribed burning models. These improvements will help decision-makers manage wildfire risks, along with other treatment goals, while considering stakeholders' preferences.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

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