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Research article

An optimization approach to prescribed burning for mitigating $PM_{2.5}$ emissions in wildfire management

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ABSTRACT

Prescribed burning effectively reduces wildfire hazards through its use in managing forest fuel loads. However, its broad application often overlooks the health and environmental impacts of $PM_{2.5}$ emissions, which can result in significant costs. While it mitigates wildfire emissions, prescribed burning also generates $PM_{2.5}$, particularly during the smoldering phase, with these fine particles posing serious respiratory and cardiovascular health risks. This study aims to analyze the impact of prescribed burning $PM_{2.5}$ emissions, focusing on strategic planning to minimize total net fires $PM_{2.5}$ emission costs. Specifically, we developed an optimization model that quantifies both the implementation costs of prescribed burning and the social costs of $PM_{2.5}$ emissions from prescribed burning and wildfires. Applying this model to Oregon in 2021, we demonstrated that prescribed burning can effectively reduce wildfire emissions and the associated social costs by 65.30%, with an estimated benefit-cost ratio of 4.35. The total net cost can be reduced by 25.68% at the optimal prescribed burning extent, requiring a 15.65% increase in acreage compared to the actual implementation. However, our case study also showed that exceeding this optimal extent significantly raises net costs due to the social costs of elevated $PM_{2.5}$ emissions from prescribed burning. Over-implementation leads to a proportional increase in adverse health outcomes, ultimately outweighing the benefits. Our study underscores the influence of prescribed burning strategies on $PM_{2.5}$ emission, emphasizing the critical need to integrate emission assessments into fire management planning.

1. Introduction

Globally, wildfires burn over 400 million acres annually. Although the total area burned has declined since 2000, largely due to enhanced preventative measures and agricultural expansion. However, regions such as the western United States, southern Australia, the Mediterranean, northern Europe, and Canada have experienced increasing wildfire frequency and intensity (Chapungu et al., 2024). These trends are largely driven by global climate change, which has extended fire weather seasons and increased the overlap of extreme conditions, such as high fire risk combined with prolonged drought (Richardson et al., 2022). As a result, the amount of emissions produced by these fires is still rising (Zheng et al., 2021). In 2023, wildfires generated 2170 megatonnes of emissions worldwide ("CAMS Atmosphere Data Store", 2014). These emissions include greenhouse gases, such as carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O), which contribute to climate change. They also contain particulate matter (PM), which is particularly concerning due to its adverse effects on human health (Matz et al., 2020; Urbanski et al., 2008). These fine particles, with a diameter of less than 2.5 μm, are small enough to bypass the body's natural defenses, such as nasal hairs and mucus. They can penetrate deep into the respiratory system, reaching the lungs' alveoli where they accumulate, causing inflammation and oxidative stress. This can lead to respiratory and cardiovascular issues, making $PM_{2.5}$ a significant public health concern (Thangavel et al., 2022).

Contrary to the global trend of decreasing wildfire areas, the United States, particularly in the Western U.S., has experienced increasing wildfire (Liu et al., 2021). The National Interagency Fire Center (NIFC) and U.S. Forest Service (USDA) provide detailed historical statistics on wildfires, which include frequency, extent, damage, burned areas by state, and yearly variations. Fig. 1a shows that although the annual number of wildfires has remained stable from 2002 to 2022, the total area burned has steadily increased over time. The Environmental Protection Agency (EPA) collects and summarizes emission data from local government agencies, offering comprehensive wildfire emission datasets from 2002 to 2022. Fig. 1b visualizes this data, highlighting significant increases in $PM_{2.5}$ emissions, including elemental (black) carbon (EC), organic carbon (OC), nitrate (NO_3), sulfate (SO_4), and other fine

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particulate matter (PMFINE) components since 2010. Notably, black carbon (BC) and organic carbon (OC) have shown similar upward trends due to their significant impacts on human health and global climate change (Mar et al., 2000; Rao et al., 2005). Overall, wildfires contribute to 25% of the $PM_{2.5}$ emissions across the U.S. and up to 50% in the Western regions (Burke et al., 2021). The health effects are profound, with emissions from these wildfires causing 75% of the mortality and asthma morbidity outside the Western region and even higher rates within it (Jung et al., 2024; Neumann et al., 2021).

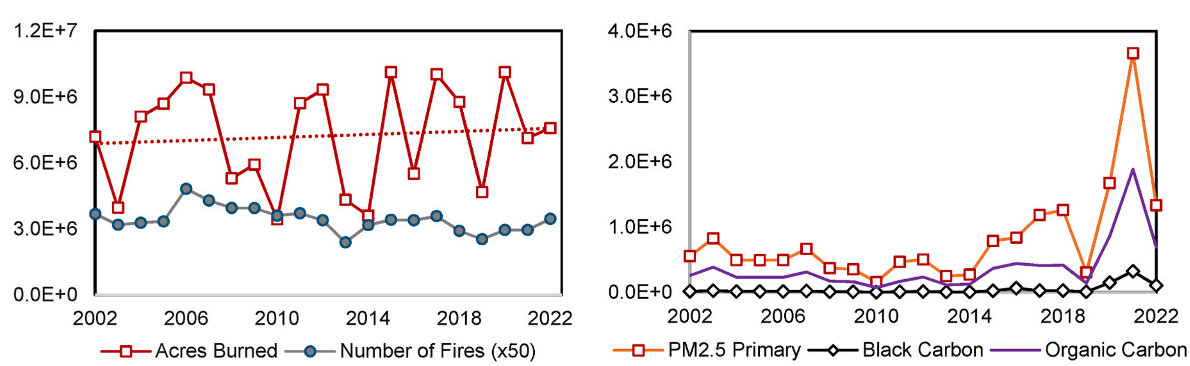
The impact of wildfire extended beyond local emissions, as most U.S. states were also affected by the long-distance transport of wildfire emissions from Canada (Ripple et al., 2023). In 2023, Canada experienced a record-breaking wildfire season, with 6049 incidents recorded by the end of August, burning a total area of 15.6 million hectares (Wang et al., 2024). Throughout the period from April to August, smoke from these Canadian wildfires drifted into large areas of the United States, exposing millions to significant levels of $PM_{2.5}$. This exposure led to an increase of nearly 20% in asthma-related emergency department admissions across the affected U.S. regions (McArdle et al., 2023).

Prescribed burning (Rx, symbolizing a prescribed treatment for land management) is a primary method for managing wildfire, primarily aimed at mitigating risk by reducing the severity and likelihood of wildfire spread through the control of excessive forest fuels (Moritz et al., 2014). Regarded as one of the most effective methods for reducing surface and ladder fuels, Rx involves strategic planning regarding location, timing, and conditions, which allows for more effective management of emissions compared to the wildfire (Casals et al., 2016; Garcia-Menendez et al., 2014; Zhao et al., 2019). These controlled conditions lead to lower emission factors in Rx, influenced by the controlled fire behavior, resulting in higher CO_2 emissions but fewer particulate matters (Altshuler et al., 2020; Hyde and Strand, 2019; Schweizer and Cisneros, 2014). Furthermore, Rx consumes less biomass than wildfire due to their lower fire intensity and the controlled environmental conditions, typically burning less than 50% of the available fuel (Carter and Foster, 2004). The type of fuel also plays a crucial role, as Rx produces approximately one-tenth the emissions of wildfire, primarily because they do not consume canopy fuels that are typically involved in wildfire (Burton et al., 2011; Mitchell et al., 2009). Moreover, Rx can reduce the travel distance of wildfire smoke by lowering wildfire temperatures, thereby decreasing the height of the fire plume (Mallia et al., 2018). The height of the fire plume is a key factor in determining the travel distance of smoke; for example, wildfire smoke has been observed traveling thousands of miles, such as from Canada to Europe across the Atlantic Ocean (Forster et al., 2001). While the lower plume height associated with Rx limits long-distance smoke transport, it can result in higher concentrations of emissions near the ground, leading to more significant local air quality impacts (Toledo et al., 2014). Beyond the emissions management focus of this study, Rx also involves trade-offs across multiple dimensions, including environmental, ecological, biological, and economic factors (Granath et al., 2018; Harper et al., 2018; Vogler et al., 2015). Although Rx helps regulate ecosystems and mitigate wildfire hazards, it simultaneously reduces provisioning vegetation (Pereira et al., 2021). Similarly, while it lowers wildfire severity, it may pose risks to endangered species by altering habitats (McDowell et al., 2021). Additionally, despite its role in asset protection, Rx can sometimes conflict with ecosystem conservation objectives (Williams et al., 2017). These trade-offs underscore the importance of strategic Rx planning to maximize benefits while minimizing ecological and environmental consequences.

Overall, the use of Rx in reducing wildfire emissions carries inherent uncertainties and risks (Williamson et al., 2016). Compared to other forest management practices, Rx poses a higher risk (Toledo et al., 2014), especially in WUI (Wildland-Urban Interface) regions with elevated wildfire risk and high social vulnerability (Afrin and Garcia-Menendez, 2021; Schumann et al., 2024). The benefits of Rx can be offset if its emissions are not significantly lower than those prevented by reducing wildfires (Campbell et al., 2012). Increasing the frequency or extent of Rx may result in equal or even greater net fire emissions (Bradstock et al., 2012), as Rx emissions are strongly influenced by the total burned area Pearce et al. (2012). Additionally, conducting Rx under warmer conditions due to global warming could further increase total emissions because of enhanced combustion completeness (Santana et al., 2016). Consequently, there is a pressing need to assess the differences in fire emissions and explore various Rx strategies to minimize the impact of emissions from all fires (Dos Santos et al., 2021; Jaffe et al., 2020).

The top-down and bottom-up methods are the two primary approaches in estimating fire emissions. The top-down approach uses satellite data and radiative power (FRP) to estimate emissions (Ichoku and Ellison, 2014). In contrast, the bottom-up approach calculates total emissions by multiplying the amount of burned fuel by the emission factor for each component species (Werf et al., 2017). Numerous studies have adopted the bottom-up emissions model under various conditions, considering factors including burned area, fuel load, fuel consumption or combustion completeness (CC), and emission factors (Seiler and Crutzen, 1980). The burned area is often determined using high-level datasets like the Global Fire Emissions Database (GFED) (Werf et al., 2017), while fuel load can be estimated using databases such as the one developed for the Fuel Characteristic Classification System (FCCS) by Pettinari and Chuvieco (2016). CC depends on geographic, weather, and environmental conditions (Kaiser et al., 2012), and emission factors are crucial for calculating emissions and vary by vegetation type and burning conditions, covering common pollutants including *PMs*, *CO*, CO_2, and CH_4 (Prichard et al., 2020).

Utilizing the bottom-up approach, Urbanski et al. (2011) estimated the *CO* and $PM_{2.5}$ emissions from wildfire in the Western United States



(a) Annual trends of wildfire (b) Annual wildfire emission (tons)

Fig. 1. Trend and emission of wildfire in the U.S. (NIFC, 2024; U.S. EPA, 2023).

using the Wildland Fire Emission Inventory (WFEI). The estimation incorporated the burned area (Urbanski et al., 2009), fuel load (Lutes et al., 2009; Ottmar et al., 2007), fuel conditions (Cohen, 1985), fuel consumption (Reinhardt, 2003), and emission factors (Urbanski, 2014). On a boarded scale, Wiedinmyer et al. (2006) developed a model to estimate emissions for all types of fires in the north and central regions of the U.S., utilizing both satellite and ground-based data. Building on the previous model, Wiedinmyer and Hurteau (2010) analyzed the impact of Rx on wildfire emissions, finding an 18–25% reduction in CO_2 emissions in the western U.S. This reduction was attributed to lower biomass consumption and reduced fire severity associated with Rx. By assuming that Rx could completely replace all wildfire in simulations, their analysis provided an upper bound for the potential emission reductions achievable through Rx practices. However, it is important to note that while Rx significantly correlates with reduced emissions and lower wildfire risk (Narayan et al., 2007), they are not likely to eliminate all occurrences of wildfire.

Moisture level, among all burning conditions, significantly influences fire emissions. May et al. (2014) and Hayashi et al. (2014) found that high moisture during burning decreases elemental carbon emissions, which may be hazardous as $PM_{2.5}$. This form of particulate matter is considered toxic due to its associations with respiratory diseases, cardiovascular effects, cancer, inflammatory responses, and its contribution to climate change (Hang et al., 2023). However, Chen et al. (2010) found that high moisture reduces the combustion efficiency of Rx, shortens the flaming phase, and prolongs the smoldering phase, which increases the emission factors for incompletely oxidized carbon and nitrogen species. This leads to substantial emissions of CO and NH_3, both considered hazards of fire (Goldstein, 2008; Lindaas et al., 2021).

Recognizing the coexistence of costs and benefits associated with Rx, studies have explored effective strategies to balance these aspects. Gharun et al. (2017) proposed a framework to consider fire emissions within the broader trade-offs in environmental objectives for Rx planning, relying on a multi-attribute optimization model. Krofcheck et al. (2019) utilized process-based simulation (Hoffman et al., 2018) to spatially prioritize and optimize Rx for the net ecosystem carbon balance (NECB) (Chapin et al., 2006). Recently, Elder et al. (2022) examined the trade-offs between the implementation costs of Rx and the Social Costs (SC) of carbon emissions within an optimization model aimed at minimizing the total cost. They discovered that the SC, which is significantly more expensive than the costs associated with implementing Rx, has a large impact on the overall cost. Their study indicates that the investment in Rx needs to be increased by 5–10 times to achieve the optimal outcome.

In this study, we aim to address the research gap by considering the $PM_{2.5}$ emission as a cost of utilizing Rx to treat wildfire. We use implementation costs to quantify the extent of Rx and SC to measure the emissions from fires. With this framework, we developed an optimization approach aimed at identifying the optimal extent of Rx that minimizes the net cost of mitigating $PM_{2.5}$ emissions. We hypothesized that applying insufficient Rx may fail to adequately mitigate wildfire hazards, leading to increased emissions, while excessive implementation could result in similarly elevated emissions. Therefore, determining the optimal area is crucial for effectively balancing the goals of reducing emissions and managing wildfire through Rx.

The rest of this paper is organized as follows: Section 2 presents the proposed optimization model for Rx, along with the analytical solution, and provides an overview of the data and parameters used and estimated in the case study. Section 3 presents the results of the case study, including the optimal solution, impact analysis of emission from Rx, and sensitivity analysis. Section 4 summarizes this study, discusses its limitations, and suggests future research directions. Finally, Section 5 provides the proof for the optimization model and solution proposed in this study.

2. Method

2.1. Optimization model

Table 1 provides a list of the notations and descriptions for the variables, parameters, and functions employed in this paper. The decision variable x represents the extent of Rx, defined as the total area burned, measured in acres. Parameter A defines the baseline wildfire area susceptible to wildfires; Parameter B represents the fuel load per acre, indicating the amount of combustible material available per acre; Parameter F_p represents the fraction of available fuel burned by Rx, and F_w represents the fraction of available fuel burned by wildfires. Parameter e_p^i and e_w^i are the emission factors for Rx and wildfires in region i, based on the spatial resolution of the data. The parameter α measures the baseline impact of Rx on reducing wildfire emissions, representing the rate at which wildfire emissions decrease per acre of Rx implemented. Cost parameters include c_p, which represents the cost to implement an acre of Rx, and c_s, the social cost of one ton of $PM_{2.5}$ emissions, representing the economic impact of these emissions on society, including health and environmental costs. Finally, the function $E(x)$ represents the net expected cost, encompassing both the costs of implementing Rx and the social costs associated with emissions from Rx and wildfires.

Fire emissions primarily depend on the amount of fuel burned during a wildfire (Jaffe et al., 2020), and Rx effectively reduces wildfire fuel loads, thereby lowering emissions (Wiedinmyer and Hurteau, 2010). Loureiro et al. (2002) applied a time-dependent exponential function to model fuel load accumulation following Rx implementation. Boer et al. (2009) found that Rx can exponentially reduce the annual wildfire burned area. Behrendt et al. (2019) and Jose et al. (2023) used an exponential function to model the relationship between wildfire vulnerability, measured by the wildfire-affected area, and Rx treatment investment. Consistently, Bradstock et al. (2012) observed an exponential decay function between net emissions (Rx and wildfire) and Rx extent, as Rx influences wildfire acreage, interval, and intensity, leading to reduced fire emissions. Based on the previous works, we hypothesize that the correlation between wildfire emissions and the extent of Rx can be modeled by an exponential decay function. We assume that the exponential decay of wildfire emissions accounts for changes in wildfire area, fuel load, fraction of fuel burned, and fire intensity following Rx treatment.

The parameter α indicates the impact of Rx on wildfire emission per unit acreage of Rx, and $e^{-\alpha x}$ is the coefficient for the reduced net wildfire emission by implementing x acreage of Rx. Specifically, the term $e^{-\alpha x}A\beta_w$ quantifies the reduction in wildfire emissions by incorporating the reduced wildfire-affected area (A), available fuel load (B), fraction of fuel consumed during a wildfire (F_w), and emission factor of wildfire

Table 1
Notations used throughout the paper.

Decision Variable	
$x \geq 0$	Burned area of Rx
Parameters	
$A > 0$	Baseline wildfire area
$B > 0$	Fuel load per one acre
$F_p > 0$	Fraction of fuel burned by Rx
$F_w > 0$	Fraction of fuel burned by wildfire
$e_p^i > 0$	Emission factor of Rx in region i
$e_w^i > 0$	Emission factor of wildfire region i
$\alpha > 0$	Baseline Rx impact of wildfire emission reduction
$\beta_p > 0$	$PM_{2.5}$ emission of one-acre Rx
$\beta_w > 0$	$PM_{2.5}$ emission of one-acre wildfire
$c_p > 0$	Cost to Implementing an acre of Rx
$c_s > 0$	Social Cost of one ton of $PM_{2.5}$ emission
Function	
$E(x)$	Total expected cost

(e_w^i). The emission factors e_p^i and e_w^i from the U.S. EPA AP-42 were used in this study to account for the dynamic nature of fire emissions by incorporating key variables such as vegetation type, fuel composition, combustion phases, regional climate conditions, and burn characteristics (U.S. EPA, 2011). These emission factors are developed using a combination of source test data, material balance studies, and engineering estimates to provide standardized estimates across different fire conditions. Collectively, these parameters offer a comprehensive representation of the influence of Rx in reducing wildfire-affected areas and fuel loads, thereby mitigating wildfire intensity and subsequent emissions. Our emission model aims to optimize the net cost of using Rx to mitigate $PM_{2.5}$ emissions by identifying the optimal extent of Rx. The objective function minimizes the total cost, which is the sum of the cost of Rx implementation and the SC of $PM_{2.5}$ emissions from both Rx and wildfires. Our model does not explicitly account for the frequency or number of Rx treatments over time but instead focuses on determining the total Rx burned acreage within a short timeframe (e.g., a single season) in a given region. This approach allows us to assess the immediate trade-offs between Rx and wildfire emissions without incorporating long-term treatment cycles. For simplicity, we define $\beta_p = BF_pe_p^i$ and $\beta_w = BF_we_w^i$ as the $PM_{2.5}$ emission from burning one acre of landscape.

$$\min_{x\geq 0} \quad E(x) = \underbrace{c_px}_{\text{Cost of Rx implement}} + \underbrace{c_sx\beta_p}_{\text{SC of Rx emission}} + \underbrace{c_se^{-\alpha x}A\beta_w}_{\text{SC of wildfire emission}}$$

Where c_p is the unit cost of Rx, and c_s is the unit social cost (SC) of $PM_{2.5}$ emission.

The analytical solutions for the optimal extent of Rx (x^*) and the optimal net cost (E^*) were solved as follows:

$$x^* = \begin{cases} \frac{1}{\alpha}\ln\left(\frac{c_s\alpha ABF_we_w^i}{c_p + c_sBF_pe_p^i}\right), \mathit{if}\ c_p < c_s\left(\alpha ABF_we_w^i - BF_pe_p^i\right) \\ 0, \mathit{otherwise} \end{cases}$$

$$EC^* = \begin{cases} \frac{1}{\alpha}\left(\ln\left(\frac{c_s\alpha ABF_we_w^i}{c_p + c_sBF_pe_p^i}\right) + 1\right)\left(c_p + c_sBF_pe_p^i\right), \mathit{if}\ c_p < c_s\left(\alpha ABF_we_w^i - BF_pe_p^i\right) \\ c_sABF_we_w^i, \mathit{otherwise} \end{cases}$$

The proposition describes the functions for the optimal solutions x^* and E^*, which depend on the relationship between c_p and $c_s\left(\alpha ABF_we_w^i - BF_pe_p^i\right)$. It is economically beneficial to implement $x > 0$ acres of Rx when c_p is less then $c_s\left(\alpha ABF_we_w^i - BF_pe_p^i\right)$; otherwise, implementing Rx provides no benefit for emission management.

2.2. Data and parameter estimation

The wildfire emission data were extracted from the EPA in Air Emissions Inventories (U.S. EPA, 2023), and the state-level $PM_{2.5}$ emissions from wildfire were available from 2002 to 2023. But the acreage of Rx and wildfire in the NEI data was not available until 2014 and is updated triennially. As an alternative, we utilized the data provided by the National Interagency Coordination Center (NICC) and the National Interagency Fire Center (NIFC) for the acreage of Rx (NIFC, 2024).

Table 2
Parameters for the case study in Oregon in 2022.

Parameters	Value	Reference
A	280,000 acres	ODF (2024)
B	60 ton/acre	U.S. EPA (2011)
F_p	0.5	Wiedinmyer and Hurteau (2010)
F_w	1	U.S. EPA (2011)
e_p	0.01304 ton/ton	Urbanski (2014)
e_w	0.02235 ton/ton	Urbanski (2014)
α	0.0000257/acre	Bradstock et al. (2012)
c_p	\$583/acre	Bennett et al. (2018)
c_s	\$128,746/ton	Heo (2018)

We evaluate the influence of Rx on wildfire emissions by considering the year of Rx implementation for several reasons. Firstly, Rx is typically carried out before the wildfire season in the spring, while the highest wildfire risk occurs during the summer and fall seasons (Dong et al., 2021; Knapp et al., 2006). Secondly, the impact of Rx diminishes over time as fuel accumulates after treatment (Hanula et al., 2012). Therefore, the Rx has the greatest influence on wildfire emissions during the year it is put into effect. In our evaluation, Oregon was the only state to show statistically significant impacts of Rx on wildfire emission reduction, with an α value of 2.570×10^{-5} acre^{-1} and a P-value less than 0.05. Note that, in the last 20 years, Oregon has maintained an annual Rx area of 159,532 acres, constituting 7.29% of the national Rx acreage. Despite the efforts to implement Rx, the number of wildfires is still rising, and the area they affect has grown significantly over time.

Table 2 presents the values of the parameters used in the Oregon case study for 2022. The baseline of wildfire area, A, was estimated as the 15-years average of the wildfire acreage in Oregon from 2008 to 2022. The fuel loading (B) and fraction of fuel burned (F_w) were acquired from the EPA document AP-42 (U.S. EPA, 2011). The fraction of fuel burned by Rx (F_p) was estimated by Wiedinmyer and Hurteau (2010), we used the upper bound (50%) for this case study. The emission factors, simplified as e_p and e_w for Region 6 in AP-42, were obtained from Urbanski (2014) and represent averaged values in the Pacific Northwest. The cost of a Rx, c_p, was estimated based on a case study in Southern Oregon (Bennett et al., 2018) by averaging the costs of implementation under different burn conditions and adjusting for inflation to 2022. The SC of $PM_{2.5}$ emission, c_s, was estimated using EASIUR, which evaluates the public health cost of emissions based on air quality simulations in regional conditions (Heo, 2018). We averaged the SC of $PM_{2.5}$ emissions across 377 cities and areas, considering most regions in Oregon are vulnerable to wildfire (OSU Libraries & for Natural Resources, 2021). The actual values of Rx and $PM_{2.5}$ emissions were obtained from the Oregon Smoke Management Annual Report presented by the Oregon Department of Forestry (ODF, 2022).

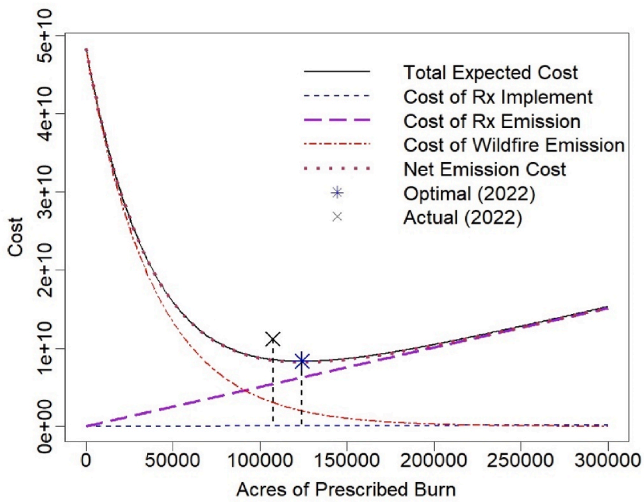


Fig. 2. Costs of emission and implement of Rx in Oregon (2022).

3. Result

3.1. Optimal solution

We applied the optimization model proposed in Section 2 to Oregon, using the baseline value estimated in Table 2.

Fig. 2 visualizes the optimal results for implementing 0 to 300,000 acres of Rx. The net expected cost was the sum of the costs of Rx implementation and the SC of $PM_{2.5}$ emissions from Rx and wildfire. Our optimization model identified the optimal extent of Rx was 124,279 acres with a net expected cost of $8,314,246,087. The analysis shows that increasing extent of Rx can exponentially decrease the SC of wildfire, attributed to the overall impact of Rx on wildfire emission reduction. The SC of emission for Rx was linearly increased while the extent was increased, based on the assumption that the Rx was implemented in the region that has not been treated in recent years to inherit the reduction on emission. The implantation cost of Rx linearly increased with the increasing burn extent, but its impact on the net cost was relatively low due to the significant lower value than the SC. Overall, We observed the net expected cost was significantly influenced by the variation of Rx burned area, showing an exponential decreasing trend before the optimal point and then increase with a near-linear trend beyond the optimal. The deceasing in the net cost was caused by the higher changing rate on the SC of wildfire compared to Rx. Beyond the optimal, the changing rate of the sum of implementation cost and SC of Rx was greater, lead to the near-linear increment in the net cost.

3.2. Sensitivity analysis

To assess the sensitivity of the Rx strategy to various parameters, we conducted one- and two-way sensitivity analyses. The analysis focused on the parameters $A, B, F_p, F_w, e_p, e_w, \alpha, c_p$ and c_s. By varying one parameter at a time while maintaining baseline values for the others (provided in Table 2, we were able to observe the impact of individual parameter changes on the optimal Rx extent (x^*) and the expected net

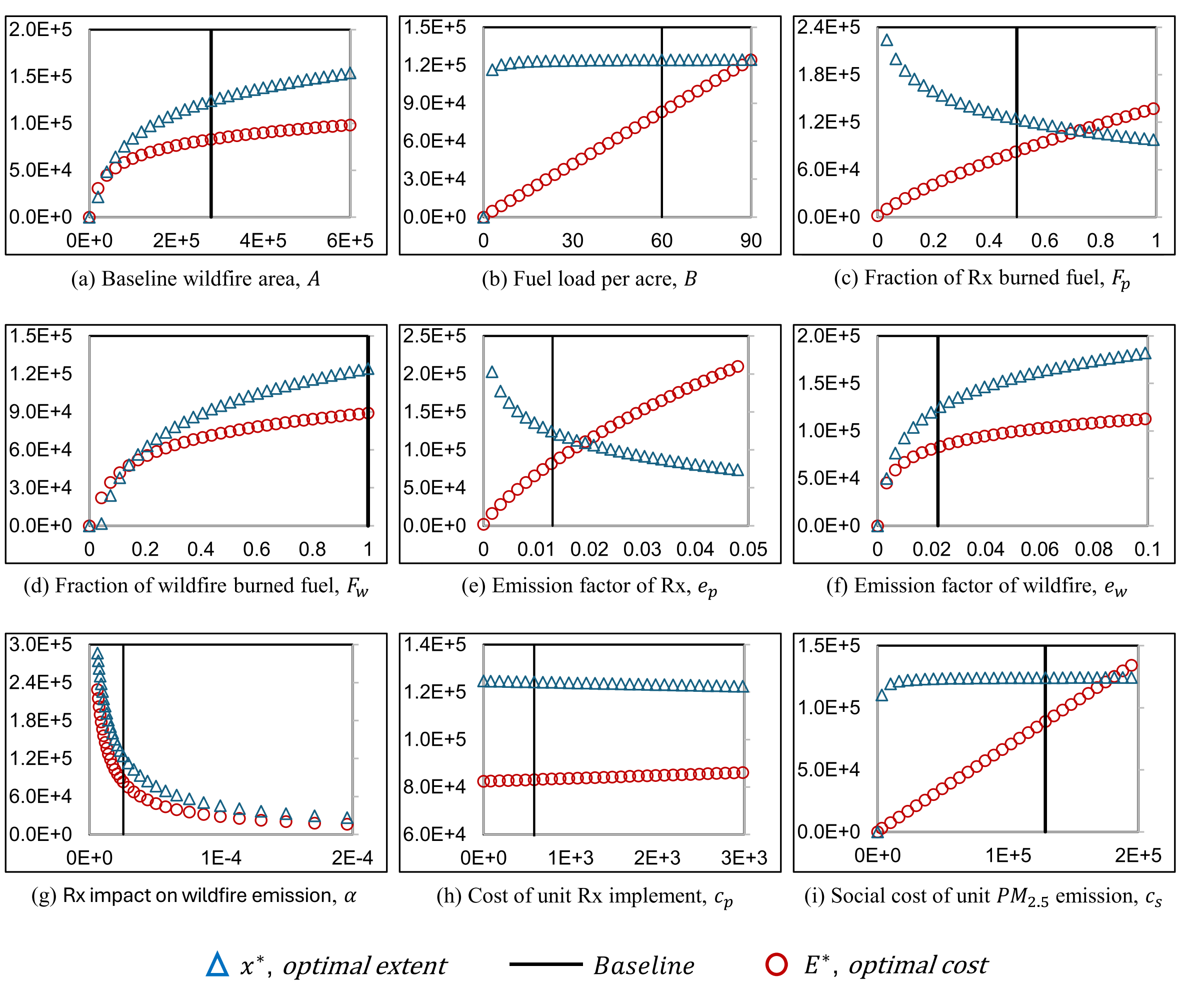


Fig. 3. Sensitivity analysis of parameters $A, B, F_p, F_w, e_p, e_w, \alpha, c_p$ and c_s on the optimal results.

costs (E^*). Although our study considered the overall impact of Rx on wildfire emission in an exponential relation described by $e^{-\alpha x}$, it is practical to study how individual parameters influence the optimal results in order to implicate adjustments in Rx.

Fig. 3a presents the sensitivity analysis of the baseline wildfire area (A), which is positively correlated with both x^* and E^*. As A increases, indicating more land affected by wildfires, the required extent of Rx and associated costs also rise. Conversely, a decrease in A reduces the need for Rx and lowers associated costs. This underscores the importance of managing baseline wildfire areas to optimize fire emission management effectively.

Fig. 3b shows the sensitivity analysis of fuel load per acre (B), which is positively correlated with both x^* and E^*. As B increases, the required extent of Rx, x^*, rises moderately, while E^* escalates significantly, indicating that greater fuel loads lead to higher management costs. This underscores the importance of maintaining lower fuel loads to improve fire emission mitigation.

Fig. 3c illustrates the sensitivity analysis of fraction of fuel burned by Rx (F_p), which is positively correlated with E^* and negatively correlated with x^*. As F_p increases, indicating a higher fraction of fuel consumed during Rx, net expected costs also rise due to increased emissions, while the optimal Rx extent decreases. This reduction occurs because higher fuel consumption during Rx reduces its effectiveness in mitigating wildfire emissions. We assume that F_p does not independently alter F_w but contributes to the overall fire dynamics. This assumption is based on Rx primarily targeting fuels between the ground and canopy, such as leaf litter, grasses, shrubs, and small trees, while avoiding significant impacts on mature trees and overstory vegetation (Burton et al., 2011). This assumption helps isolate the impact of F_p on Rx outcomes without interference from changes in wildfire behavior.

Fig. 3d presents the sensitivity analysis of the wildfire fuel fraction (F_w), which is positively correlated with both x^* and E^*. As F_w increases, indicating more intensive burning during wildfires, both the necessary extent of Rx and the associated costs rise correspondingly. The baseline value of F_w is set to one, based on EPA standards that assume complete fuel combustion in wildfires. This highlights the potential benefits of reducing the fraction of fuel consumed by wildfires to minimize overall management costs.

Fig. 3e examines the sensitivity analysis of the emission factor of Rx (e_p). The analysis reveals a negative correlation between e_p and x^* and a positive correlation with E^*. As e_p increases, indicating higher emissions per unit of fuel burned during Rx, the associated SC rises, leading to a decrease in x^* and an increase in E^*. This outcome suggests that higher emissions from Rx reduce its operational effectiveness and increase overall costs. To mitigate these negative impacts, reducing the emission factor of Rx through improved prediction and management of burn conditions is an effective strategy for enhancing the cost-effectiveness and environmental benefits of Rx strategies.

Fig. 3f presents the sensitivity analysis of the emission factor of wildfire (e_w), showing that e_w positively influences both x^* and E^*. As e_w increases, signaling higher emissions per unit of fuel burned by wildfire, there is a corresponding rise in both the required extent of Rx and the associated costs due to the need to mitigate these additional emissions. This underscores the significance of wildfire emission factors in determining Rx extent and financial implications. A direct approach involves using Rx to reduce wildfire intensity, thereby lowering wildfire emission factors. An indirect but equally important strategy addresses broader environmental conditions contributing to wildfire severity, such as anthropogenic climate change. Changes in temperature and moisture levels significantly influence wildfire behavior and emission factors (He et al., 2019).

Fig. 3g illustrates the sensitivity analysis of the impact of Rx on wildfire emissions (α). Physically, α represents how efficiently Rx reduces wildfire emissions by altering fire behavior and fuel consumption. A higher α means each acre of Rx more effectively limits wildfire spread, decreases fire intensity, and lowers emissions by removing forest fuels that contribute to high-intensity burns. The analysis shows that α is negatively correlated with both x^* and E^*, meaning that as Rx becomes more effective, fewer acres are required to achieve the optimal outcome, reducing both implementation expenses and social costs. The strong sensitivity of α highlights its critical role in wildfire emissions management. Enhancing Rx efficiency through improved planning, targeted treatments, and optimized burn conditions can significantly reduce the need for extensive Rx applications and lower associated costs.

Fig. 3h visualizes the sensitivity analysis of the cost per unit of Rx (c_p) on the optimal results. The analysis indicates a negative correlation between c_p and x^*, where higher unit costs lead to a decrease in x^* due to diminished cost-effectiveness. Conversely, there is a positive correlation with E^*, as increased costs per unit raise the overall expense of Rx operations. Since these changes occur gradually, the implementation cost of Rx does not trigger dramatic shifts in Rx strategy. This suggests that the influence of cp on Rx strategies is moderate, likely due to the significant difference between Rx implementation costs and the SC.

Fig. 3i presents the sensitivity analysis of the societal costs of emissions (c_s), showing a positive correlation with the optimal results. As cs increases, x^* rises gradually, while E^* experiences a more significant escalation. This difference in how x^* and E^* respond can be attributed to the substantial difference in magnitude between c_p and c_s. The sharp increase in E^* with rising cs highlights that the financial burden of managing emissions becomes considerably higher, directly impacting the overall cost of wildfire emission management.

Fig. 4 presented a two-way sensitivity analysis that examines how variations in the baseline impact of Rx on wildfire emissions (α) and the SC of emissions (c_s) affect the optimal Rx extent (x^*) and net expected costs (E^*). Fig. 4a reveals a positive correlation between c_s and x^*. The increasing SC of emissions increase the extent of Rx, primarily due to Rx's comparative efficiency in producing less $PM_{2.5}$ emissions than wildfire. In contrast, a negative correlation is observed between α and x^*; as α increases, signifying enhanced effectiveness of Rx in mitigating wildfire emissions, the required extent of Rx decreases.

This implies that more efficacious Rx can achieve desired outcomes with less extensive burning. The contour lines within the analysis illustrate that α has influence on x^* than c_s, with the contour lines remaining predominantly horizontal across the domains of both α and c_s. Additionally, Fig. 4b shows that c_s is positively correlated with E^*, indicating that rising SC increase the net costs associated with emissions. Conversely, an enhancement in α correlates with a reduction in E^*, affirming that improved Rx efficacy not only reduces the scope of burning required but also diminishes associated costs. The contour lines additionally emphasize the pronounced impact of α on E^* compared to c_s, highlighting its critical role in fire emission management.

Since α was found to has significant impacts on optimal results, and this study has considered the impact of Rx on wildfire emission reduction was aggregate on all the parameters in wildfire emission function. Thus, it is practical to identify the most impacting parameter. Observed on Fig. 3, we noticed parameter A and e_w both have substantial influence on x^* and E^*. Fig. 5a shows that, parameter e_w and A have positive correlation with optimal Rx extent. x^* increases when these two parameters were increasing. More wildfire vulnerable area, indicate by A, requires more Rx implementation to treat with the emission of wildfire. Similar for e_w, a higher emission factor of wildfire needs more Rx treatment to reduce the intensity of wildfire. The contour pattern indicates the wildfire vulnerable area, A, has a greater impact on x^*. Observed from Fig. 5b, these two factors were also positively correlate with the optimal net expected cost. E^* increases as e_w and A were increasing, and A consists of the higher influence on E^* over e_w. Overall, this analysis provides insight for improving the impact of Rx on wildfire emission mitigation. While all the parameters in emission function need mitigation to reduce for emission management, prioritizing in reducing

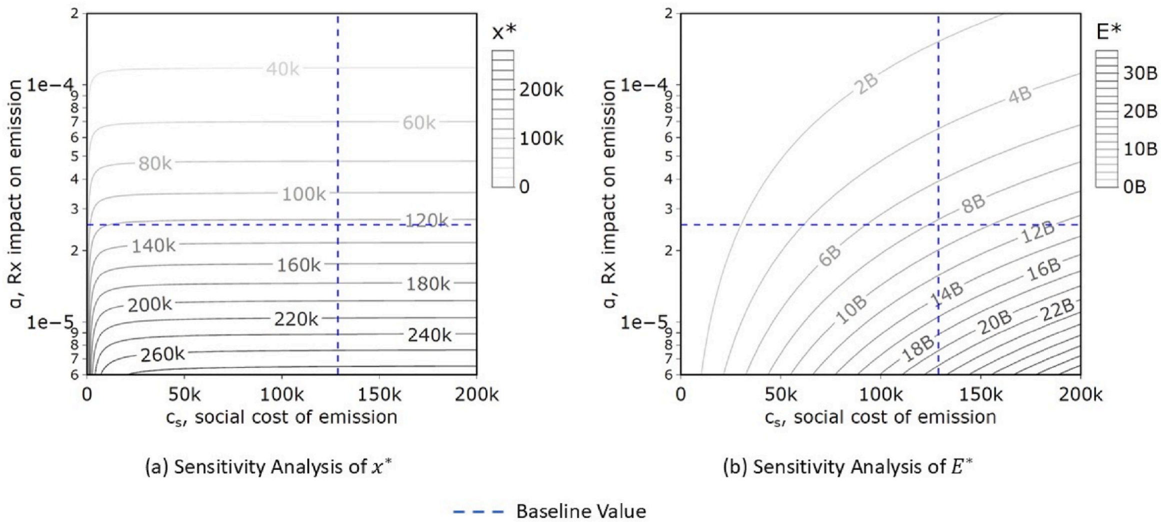


Fig. 4. 2-way sensitivity analysis of x^* and E^* with respected to parameters α and c_s

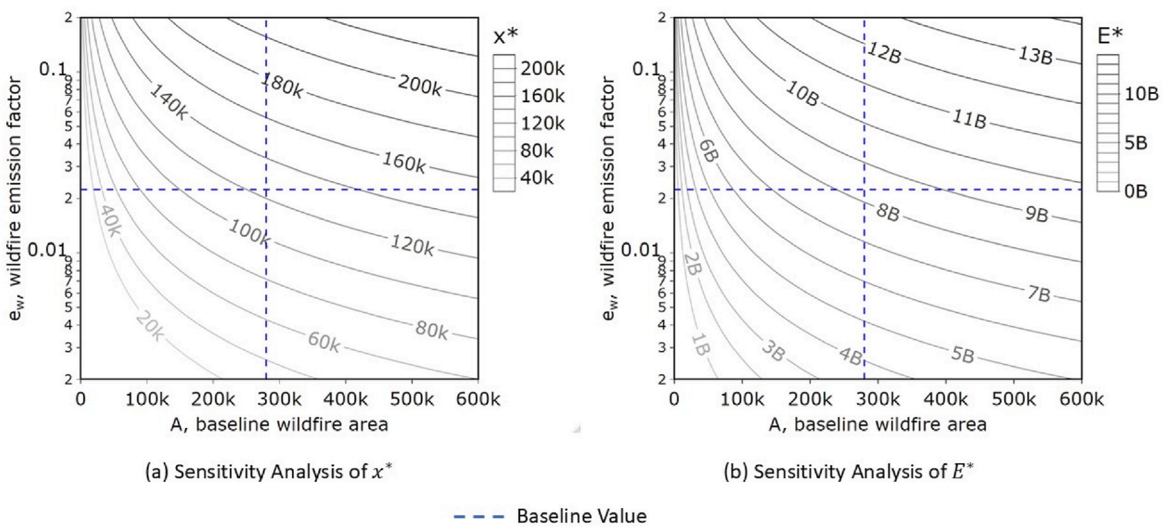


Fig. 5. 2-way sensitivity analysis of x^* and E^* with respected to parameters A and e_w

Table 3
Comparison of optimal, actual, and model from Jose et al. (2023).

Model	Optimal	Actual	Jose et al. (2023)	Optimal vs Actual	Optimal vs Jose et al. (2023)
Rx extent	124,279 acres	107,463 acres	183,488 acres	16,816 acres (15.65%)	−59,209 acres (−47.64%)
Burn cost	$72,454,657	$62,650,929	$106,973,504	$9,803,728 (15.65%)	$-34,518,847 (−47.64%)
Rx $PM_{2.5}$	48,618 tons	42,040 tons	71,781 tons	6578 tons (15.65%)	−23,163 tons (−47.64%)
Rx SC	$6,259,365,921	$5,412,420,763	$9,241,452,974	$846,945,158 (15.65%)	$-2,982,087,053 (−47.64%)
Wildfire $PM_{2.5}$	15,398 tons	44,370 tons	3362 tons	−28,972 tons (−65.30%)	12,036 tons (78.17%)
Wildfire SC	$1,982,429,337	$5,712,521,097	$432,855,987	$-3,730,091,760 (−65.30%)	$1,549,573,350 (78.17%)
Net $PM_{2.5}$	64,016 tons	86,410 tons	75,143 tons	−22,394 tons (−25.92%)	11,127 tons (17.38%)
Net cost	$8,314,249,915	$11,187,592,789	$9,781,282,465	$-2,873,342,874 (−25.68%)	$-1,467,032,550 (−17.64%)
Treatment cost	$186,802,118	$252,626,962	$126,113,656	$-65,824,844 (−35.24%)	$60,688,462 (32.49%)
Total cost	$8,428,597,376	$11,377,568,822	$9,800,422,617	$-2,948,971,446 (−34.99%)	$-1,371,825,241 (−16.28%)

the wildfire vulnerable area may provide higher effectiveness.

4. Discussion

To examine the impact of $PM_{2.5}$ emissions from Rx, we conducted a comparative analysis involving the actual scenario, this study, and a previous study by (Jose et al., 2023).

Table 3 visualizes the Rx extent, emissions, and costs, encompassing both the implementation and societal costs associated with Rx and wildfire. Data for the actual burning extent and emission of Rx were extracted from the ODF annual report (ODF, 2022), while the actual costs were estimated using the same parameters as those applied in the case study. The least-cost optimization model proposed by Jose et al. (2023) aimed to minimize the total costs of treatment and suppression through strategic Rx application. The principal trade-off in their study was between the costs of implementing Rx and the expenses associated with wildfire suppression. However, a critical limitation of their model was the omission of potential hazards associated with Rx, such as emissions. This oversight provided an opportunity for our study to further examine the optimization results, particularly assessing the impact of emissions as a significant side effect of utilizing Rx. To ensure consistency in the parameters used across the two optimization models, we updated the parameters used in Jose et al. (2023) to account for the inflation rate from 2017 to 2022. To understand the influence of considering emissions in Rx-extent optimization models, we estimated the total treatment costs in three scenarios without factoring in the social cost of emissions. Lastly, we examined the performance of the models by comparing the total expected cost, which includes the sum of treatment costs and emission costs.

Our study identified the optimal extent for Rx in Oregon to be 124,279 acres, which exceeds the actual implementation by 16,816 acres (15.65%). Consequently, the implementation cost for Rx in the optimal scenario is $9,803,728 higher than the actual costs, attributed to the increased area burned. The SC of $PM_{2.5}$ emissions from Rx in the optimal scenario was 15.65% higher than the actual value. We estimated the actual $PM_{2.5}$ emissions based on the extent of the actual Rx because the actual number reported by ODF was substantially lower than expected. This discrepancy suggests the potential residual effects of previous Rx influencing the emission. The societal cost of wildfire emissions in the optimal scenario amounted to $1,982,429,337, marking a significant decrease of $3,730,091,760 (65.30%) from the actual costs of $5,712,521,097. The overall actual net cost stood at $11,187,592,789, whereas the optimal net expected cost was $8,314,249,915, reflecting a substantial reduction of $2,873,342,874 (25.68%) by increasing the Rx area by 15.65%. The results indicate that the benefit-cost ratio (BCR) for Rx to wildfire is 4.35, meaning that for every additional dollar invested in Rx, the social cost of wildfire emissions is reduced by $4.35. In contrast, the model proposed by Jose et al. (2023) suggested that the optimal acreage of Rx to minimize the total expected cost was 183,488 acres, which is 59,209 acres (48%) more than our results. The increased Rx reduced the SC of wildfire emissions by approximately $1,549,573,350 (78.17%), while simultaneously increasing the SC of Rx emissions by $2,982,087,053 (47.64%) to $9,241,452,974. Consequently, the total expected cost increased by $1,467,032,550 to $9,781,282,465, marking an 18% increase compared to our findings. When emissions were excluded and the optimization only consider the expected cost of treatments, the model proposed by Jose et al. (2023) identified the optimal Rx extent that provides the lowest expected cost at $126,113,656. The model in this study results in a moderate cost of $186,802,118, while the actual burning extent yields the highest treatment cost at $252,626,962. However, if comprehensively considering the total expected cost as the sum of the cost of Rx implementation, wildfire suppression, and social cost of emissions, our proposed model provides the best outcome at $8,428,597,376, which is $2,948,971,446 (34.99%) less than the actual scenario and $1,371,825,241 (16.28%) lower than the model by Jose et al. (2023).

The analysis underscores the effectiveness of Rx in managing wildfire $PM_{2.5}$ emissions, highlighting the significant influence of the extent of Rx. When the Rx extent is less than optimal, wildfire emissions are not effectively mitigated, leading to higher net costs. Increasing the Rx extent can reduce wildfire emissions and the associated social costs but exceeding the optimal extent causes Rx emissions to outweigh the reduced wildfire emissions, ultimately increasing total emissions and social costs. Therefore, Rx is only effective in fire emission management when the trade-off between its benefits and costs is carefully balanced. Notably, while the social cost of emissions is quantified in monetary terms, it primarily depends on health and environmental impacts. These impacts include exacerbation of respiratory and cardiovascular conditions, long-term diseases, and increased mortality rates (Matz et al., 2020). Therefore, it is essential to factor emissions into Rx optimization due to its potential risks to the population.

5. Conclusion and future research

The increasing frequency and severity of wildfire globally necessitate effective management strategies to mitigate their environmental and health impacts. This study is motivated by the trade-offs involved in utilizing prescribed burning (Rx) as a method for wildfire emission management. While Rx is recognized for its potential to reduce wildfire risks through fuel load management, its implementation is associated with considerable challenges, including the direct costs of implementation and the emissions from Rx that could adversely affect air quality. Our research aims to dissect these trade-offs, exploring how Rx can be optimized to balance the benefits of reducing wildfire emissions against the costs and potential negative impacts of Rx practices. This balance is critical for developing sustainable wildfire management practices that protect ecosystems and human health without imposing undue economic or environmental costs.

Despite extensive research on fire emissions and the utilization of Rx, a clear understanding of how to optimize Rx to maximize the benefits while minimizing the costs remains elusive. Specifically, there is a gap in quantifying the optimal extent of Rx needed to effectively reduce wildfire emissions and in evaluating how this optimization changes with varying environmental and managerial conditions. The nuanced impact of Rx on wildfire emission dynamics, considering different parameters such as fuel load, emission factors, and implementation costs, has not been fully explored. Addressing this gap is essential for refining Rx practices and policies to ensure they are both effective and efficient.

Our study employed a net cost objective to assess the trade-offs in $PM_{2.5}$ emission from Rx and wildfire, including the implementation cost of Rx. The findings reveal a nuanced understanding of the factors influencing fire emission estimation and the strategic role of Rx. Through an optimization model, we demonstrated an exponential relationship between the extent of Rx and the reduction in wildfire emissions, highlighting the potential of Rx to significantly lower $PM_{2.5}$ emissions when optimally implemented. The proposed optimization model identified a Benefit-Cost Ratio of 4.35, suggesting that the wildfire emission cost can be reduced by 65.30% with a 15.65% increase in Rx extent in Oregon. Notably, in the optimal scenario, about 75.28% of the net expected cost was attributed to the SC of $PM_{2.5}$ emissions from Rx, while the actual SC of Rx was 48.38% of the actual net cost. This implies that the reduction in net cost must be traded with an increase in Rx-related costs. Furthermore, we found that the net cost would increase by 17.64% if Rx was over-implemented by 47.64%, based on the previous study that aimed to minimize the total cost of fire treatments (Jose et al., 2023). While our findings highlight the potential of optimized Rx to significantly reduce $PM_{2.5}$ emissions and wildfire risks, the implementation of such strategies faces practical challenges. Expanding the extent of Rx is increasingly difficult due to the narrowing burn windows caused by global warming (Swain et al., 2023). Climate change has reduced the periods of favorable weather conditions necessary for safe Rx, constraining opportunities for application. Furthermore, warmer and drier conditions may heighten the risk of escaped prescribed fires, particularly as the frequency and extent of Rx increase (Tian et al., 2023; Varner et al., 2021). These factors underscore the importance of integrating climate-adaptive strategies into Rx plans to ensure their feasibility and effectiveness.

The sensitivity analysis further illuminated how variables influence the Rx treatment level and outcomes. Notably, the impact of Rx on wildfire emissions exerts a more significant influence than the cost parameters, serving as a pivotal determinant in achieving cost-effective wildfire emission management. Specifically, the analysis highlights the importance of prioritizing the reduction of areas vulnerable to wildfire, along with other variables, within the emission model. By focusing on these key areas, policymakers and land managers can significantly enhance the effectiveness of Rx, ultimately contributing to more sustainable and cost-effective approaches to wildfire emission management. Overall, our research contributes valuable insights into optimizing Rx as a vital tool for wildfire emission management. By addressing the identified research gap, we offer a foundation for future studies and practical recommendations for leveraging Rx more effectively in combating the escalating challenge of wildfire.

One limitation of this study is the assumption that the implementation cost of Rx remains constant. In practice, these costs can vary widely depending on factors such as the scale of burning, regional influences Cleaves et al. (1999), and the proximity of burns to populated areas (Berry and Hesseln, 2004). Although this assumption facilitates macroscale analysis, applying our optimization model to specific regions with unique characteristics necessitates a detailed calibration to accurately reflect the varying costs. While our study utilized the emission factors provided by AP-42, which were estimated based on variables such as vegetation type, composition, burn phases, and conditions to help capture the dynamics of fire emissions, these factors are averaged over large regions and may not be suitable for studies focused on smaller areas (Liu et al., 2013). AP-42 emission factors are widely used for large-scale studies because they provide standardized estimates applicable to broader geographic regions, even though they may not explicitly account for fine-scale spatial variability. A more detailed representation of spatial heterogeneity in emissions could be integrated into future studies that focus on site-specific decision-making. Moreover, the integrated nature of the AP-42 emission factors does not allow for the independent modeling of individual factors influencing fire emissions. For studies requiring a more detailed and factor-specific approach, the Fuel Characteristic Classification System (FCCS) provides a more precise alternative, offering spatially explicit data at a 30 m resolution on fuel characteristics. This finer-scale data allows for a localized assessment of fire behavior and emissions, offering greater flexibility in capturing spatial heterogeneity (Pettinari and Chuvieco, 2016). Future research could explore integrating FCCS data with dynamic emission models to account for variations in fire frequency and fuel consumption at a finer resolution. Additionally, we assumed that Rx has a uniform impact on the emission function when mitigating wildfire emissions, following existing research by Bradstock et al. (2012). However, the actual impact of Rx may vary across different emission model parameters, necessitating further research to explore how Rx influences these parameters individually to reduce emissions. Notably, the correlation between Rx and the emission factor of wildfire is acknowledged but not quantified. While it is recognized that reducing fire intensity through Rx can decrease wildfire emissions, this relationship has yet to be defined quantitatively. Lastly, this study focused exclusively on $PM_{2.5}$ emissions to evaluate the cost-effectiveness of Rx compared to wildfire. However, there are numerous other impacts that warrant consideration in strategic planning. While Rx generally has a more positive impact than wildfire, it also carries certain negative effects, including fire emissions, which need to be thoroughly assessed to optimize treatment outcomes (Pereira et al., 2021). Both the positive and negative impacts across environmental, ecological, economic, and biological dimensions must be carefully evaluated to develop comprehensive wildfire risk mitigation strategies (Qi and Zhuang, 2024), especially considering the U.S. Forest Service's call to expand the use of Rx as a means to reduce fuel loads and mitigate wildfire risk.

In future Rx models, we suggest incorporating the spatial and temporal dynamics of fire emissions to better capture the differences between Rx and wildfires. Wildfire $PM_{2.5}$ emissions often travel longer distances and are emitted at higher altitudes due to the intense heat and stronger convection associated with wildfires, allowing the smoke to disperse broadly and remain aloft for extended periods. In contrast, $PM_{2.5}$ emissions are more localized, with lower plume heights and ground-level impacts, as Rx produces less intense heat and weaker convection (Paugam et al., 2016). These differences in smoke transport and dispersion significantly influence the environmental and health impacts of fire emissions (Jaffe et al., 2020). Current models focus on the total amount of $PM_{2.5}$ emissions without considering these spatial and temporal variations. Future studies could address this limitation by integrating meteorological and dispersion models to capture the movement, concentration, and altitude-dependent effects of $PM_{2.5}$ emissions, providing a more comprehensive evaluation of the trade-offs between Rx and wildfire emissions. Future Rx modeling should expand its scope to include a broader range of costs and benefits, ensuring a more comprehensive evaluation of fire management strategies. While this study primarily focused on emissions from Rx as a significant cost in balancing wildfire emission mitigation, other critical factors such as water quality, biodiversity, habitat structure, and local vegetation, also warrant detailed consideration. These factors are essential for evaluating the overall effectiveness and desirability of Rx practices. Understanding this full spectrum of impacts is crucial for optimizing fire management strategies and achieving a balanced approach to wildfire risk reduction. To address these complexities, Multi-Criteria Decision-Making (MCDM) paradigms offer a promising solution in forest management planning, providing a structured framework for developing optimization and decision models that account for multiple, often conflicting objectives (Cegan et al., 2017; Kiker et al., 2005; Sadeghi Ravesh, 2020). These methods enable stakeholders to balance social, economic, and environmental factors in decision-making. By integrating MCDM into Rx planning and optimization, future models can better align with societal values and address the inherent challenges of wildfire management. This integrated approach holds the potential to significantly improve the effectiveness and sustainability of wildfire management strategies in forest ecosystems.

CRediT authorship contribution statement

Jianzhou Qi: Writing – review & editing, Writing – original draft, Visualization, Methodology, Formal analysis, Conceptualization. **Jun Zhuang:** Writing – review & editing, Validation, Supervision, Funding acquisition.

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Declaration of competing interest

There is no conflict of interest between the authors.

Appendix

Before solving the objective function, we analyzed the second derivative of the objective function $E(x)$ to verify the existence of a minimum optimal solution for our optimization model:

$$\frac{d^2E}{dx^2} = a^2 c_s ABF_w e_w e^{-ax}$$

Given that the parameters $\alpha, cs, A, B, F_w, e_w > 0$ and x are positive, the second derivative $\frac{d^2E}{dx^2} > 0$. This confirms the convexity of the objective function across its domain, thereby ensuring a minimum optimal solution exists.

To identify the analytical form of optimal extent of prescribed burning, denoted as x^*, we derived the first derivative of the objective function and equated it to zero:

$$\frac{dE}{dx} = c_s BF_p e_p - e^{-\alpha x} c_s \alpha ABF_w e_w + c_p = 0$$

Solving this equation for x yields the optimal prescribed burning:

$$x^* = \begin{cases} \frac{1}{\alpha} \ln\left(\frac{c_s \alpha ABF_w e_w}{c_p + c_s BF_p e_p}\right), \mathit{if}\ c_p < c_s(\alpha ABF_w e_w - BF_p e_p) \\ 0, \mathit{otherwise} \end{cases}$$

Upon finding the x^*, we proceed to compute the optimal net cost E^* by substituting x^* back into the objective function:

$$EC^* = \begin{cases} \frac{1}{\alpha}\left(\ln\left(\frac{c_s \alpha ABF_w e_w}{c_p + c_s BF_p e_p}\right) + 1\right)(c_p + c_s BF_p e_p), \mathit{if}\ c_p < c_s(\alpha ABF_w e_w - BF_p e_p) \\ c_s ABF_w e_w, \mathit{otherwise} \end{cases}$$

This mathematical exposition substantiates the existence of a minimum optimal solution for the optimization model and delineates the methodology for determining the optimal extent of prescribed burning and calculating the corresponding optimal net cost.

Data availability

Data will be made available on request.

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