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Wildfire, Suppression, and Federal Spending, 2020–2100

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Key Points:

- The United States federal government spends billions of dollars annually to respond to wildfires on federal lands
- A changing climate and society will affect wildfire activity, motivating management responses to reduce societal burden
- Federal median area burned is projected to triple and real suppression spending nearly double by late-century compared to recent history

Supporting Information:

Supporting Information may be found in the online version of this article.

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Abstract

Wildfire extent is growing in the United States (US), a fact attributable to increasingly favorable weather and climatic conditions and the net result of human interventions. US federal land management agencies act upon the wildfire threat by managing hazardous fuels, discouraging human-caused ignitions, and suppressing active fires. Costs of these actions are rising, so policy makers and wildland managers seek information that can help them understand the trade-offs of resource allocations. This study generates new information about potential future wildfire and suppression demands by uncovering statistical relationships between observed wildfire and its hypothesized drivers, including socioeconomic, fuels, and climate variables, and by capturing the endogenous relationship between suppression spending and wildfire activity on lands managed by the USDA Forest Service (USFS) and the four key bureaus of the US Department of the Interior (DOI). Climate uncertainty is addressed by modeling wildfire and suppression spending under ten scenarios of potential future climates. Projected wildfire and spending trends to 2100 vary widely across scenarios but are universally upward. When summarized across all ten climate scenarios, real dollar suppression spending rises by a median rate of about 0.87% per year for the USFS and 0.65% per year for the DOI. The highest rates of wildfire and spending growth are projected for the northwestern US.

Plain Language Summary

Changes in climate and populated areas are connected to changes in the amount of wildfire experienced and managed by people in the US. The two main US land management agencies, the US Department of Agriculture's Forest Service and the Department of the Interior (DOI), are responding to these changes by spending more to respond to wildfires when they occur. We develop statistical models that link driving factors of wildfire and spending and then apply scenario-based projections of future changes in those factors to anticipate changes in wildfire on federal lands and associated suppression spending. Although spending trends by agency vary markedly across possible future climates, overall trends in inflation-adjusted spending are positive, with a multiple-scenario median rate of rise of 0.87% per year from 2020 through 2100 on Forest Service lands and 0.65% per year on DOI lands.

1. Introduction

In the United States and around the world, governments are increasingly pressed to take actions to mitigate rising rates of damaging wildfires (Abatzoglou & Williams, 2016; Abatzoglou et al., 2025; Burke et al., 2021; Williams et al., 2019). Fire management agencies across all levels of government in the US, for example, have experienced 131% higher area burned and spent 268% greater real dollar spending on wildfire response in 2014–2023 compared to 1985–1994 on US federal lands (Figure S1 in Supporting Information S1) (National Interagency Fire Center, 2025). With area burned and fire frequency still well below pre-European colonization rates, increases in area burned may translate to positive effects in some ecosystems and desired planned outcomes for land management agencies (O'Connor & Calkin, 2019). However, increases in fire severity and impacts to valued resources in some areas can have negative consequences (Iglesias et al., 2021; O'Connor & Calkin, 2019; Parks & Abatzoglou, 2020). Two decades ago, the trends in expenditures led the US General Accounting Office (2004) to express concerns that the elevated suppression spending had resulted in undesirable distortions in agency budgets, internal funds transfers, and repeated requests to approve emergency allocations in years with unexpectedly high firefighting needs. In response, agencies have adopted new strategies, such as the Wildfire Crisis Strategy of the US Department of Agriculture (USDA) Forest Service (2022), to reduce hazardous fuels and restore landscapes to more fire-adapted conditions. Congress has also recently implemented a new approach to manage suppression spending interannual volatility by creating a multibillion dollar funding stream, available to both the USDA

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Forest Service (USFS) and the Department of the Interior (DOI), to cover suppression expenditures during its most severe wildfire seasons, when annual wildfire appropriations are insufficient. The 2018 legislation, commonly referred to as the "Fire Funding Fix" (contained in Public Law 115–141, 115th Congress of the US. https://www.govinfo.gov/content/pkg/PLAW-115publ141/pdf/PLAW-115publ141.pdf), established additional new budget authority of up to $2.25 billion for wildfire suppression operations of the Forest Service and the DOI in fiscal year 2020, rising to $2.95 billion by 2027. Such agency and legislative actions are predicated on expectations, based in part on research (Burke et al., 2021; Flannigan et al., 2009; McKenzie & Littell, 2016; Riley et al., 2019), that the US will likely experience more wildfire in the future as society and climate evolve. Given the rising rates of wildfire-related property losses (Domke et al., 2023) and projected increases in population (US Census Bureau, 2025) and housing in wildfire-prone parts of the country (Hauer, 2019; Radeloff et al., 2023), it is logical to conclude that resources demanded for wildfire management, including the suppression expenditures incurred, will continue to rise in the coming years.

Wildfire managers in the US, including those involved in responding to wildfires, are grappling with the consequences of increasing hazardous wildfire fuels and sources of wildfire ignitions. Rises in such fuels can be attributed to multiple factors related to climate and land use but also can be linked to a legacy of wildfire suppression (Marlon et al., 2012), which can limit the beneficial fuel-reduction effects of current period wildfires (Donovan & Brown, 2005; Parks et al., 2015). In other words, successful fire suppression in the current period affects wildfire hazard over the long run, with impacts on firefighting expenditures (Belval et al., 2019; Bustic et al., 2015; Donovan et al., 2020; Mercer et al., 2007; Thompson et al., 2017). In any effort to better understand how a changing climate and society may lead to changes in the demand for wildfire response resources, it is critical to account for how changes in wildfire-driving factors, human and biophysical, will contribute to that rising budgetary burden.

Wildfires occurring on most federally managed land are under the jurisdiction of the USFS or the several bureaus of the DOI. Wildfires igniting on national forests and national grasslands are under the budgetary responsibility of the USFS. Likewise, on bureau lands of the DOI, the DOI is responsible for covering the firefighting costs of wildfires ignited on their lands. Although fire suppression resource sharing occurs between the USFS and DOI, related expenditures remain with the federal government. Likewise, both the USFS and DOI devote resources to managing wildfires that are State responsibility, with eventual reimbursement from the State to the assisting federal agency.

Wildfire suppression policy on federal lands has evolved over time, with an emphasis since the mid-1900s on full suppression (Dale, 2006) and then more recently implementing approaches that do not apply full suppression but instead comprehend the ecological and fuel reduction potential of wildfires (Franz et al., 2024; Huffman et al., 2017; Young et al., 2020). Some less than full suppression strategies are applied to limit firefighter exposure to dangerous conditions (e.g., Thompson et al., 2016). Widespread application of such strategies is inherently constrained by terrain, fuel conditions, consideration of adjacent values at risk, and weather.

In both the USFS and DOI, wildland fire managers are tasked with using limited budget allocations such that people, property, and natural resources (in that order of priority) are protected, while also recognizing the need to ensure that public lands continue to produce their multiple benefits. Economists have summarized and simplified these wildfire management goals as stating that managers seek to balance wildfire management resource use (spending) against the damages that wildfires may generate (Rideout & Omi, 1990). Expenditures to achieve such a balance must be made in the context of uncertainty and involve decisions about how much wildfire management investment to commit to a given landscape (Donovan & Brown, 2005; Donovan et al., 2011; Donovan & Rideout, 2003; Rideout & Omi, 1990). This uncertainty includes how factors not under their management purview affect when and where wildfires occur (e.g., Romps et al., 2014; Thompson & Calkin, 2011; Williams et al., 2019) and the existence and susceptibility of values at risk (Radeloff et al., 2023).

The objective of this study is to quantify the plausible range of mid-to late-century wildfire suppression spending by the USFS and DOI. To meet our objective, we specify models that relate wildfire area burned to climate and hypothesized drivers related to biophysical and socioeconomic variables and then connect those models that relate wildfire to suppression spending. Model estimates are based on historical values of wildfire and spending drivers and projections of those drivers to early fiscal year 2100. Extensive model testing using out-of-sample goodness-of-fit measures provide empirical support for the model specifications selected and applied in the projections. We make our projections of wildfire and suppression across ten scenarios of the future, based on two warming scenarios (Representative Concentration Pathway (RCP) 4.5 and 8.5) combined with five global climate models (GCMs), for a total of ten future projections.

2. Methods and Data

2.1. Theoretical Background

Our approach to understanding how wildfire generates suppression spending is based on an economic model of wildfire management. Since the dawn of wildfire economics in 1916 (Headley, 1916), research on optimal wildfire management has framed optimal decision making comparing the marginal costs of management and the marginal losses from wildfire. As first formalized by Sparhawk (1925): management inputs are increasingly applied to an active wildfire until the last management dollar spent equals the expected marginal value of damages averted. This is the classical cost plus loss model. As elaborated by Rideout and Omi (1990), in recognition that wildfires can often provide benefits, optimization was restated as the cost-plus-net-value-change model. Donovan and Rideout (2003) clarified the overall wildfire management problem as an effort to balance the management inputs to fire across spatial and temporal scales, including consideration of spending on wildfire suppression, fuels management, and other actions (ignition prevention, ignition detection, hazardous fuels management, and post-fire mitigation) that are taken to reduce overall expected damages. Nevertheless, wildfire managers understand that achieving the best wildfire outcomes requires building in consideration of the values at risk that are not easily quantified (e.g., Venn & Calkin, 2011) and a recognition of the complex set of constraints and uncertainty about feedbacks that can lead to divergence from what a formal mathematical model might prescribe (Bayham et al., 2022; Calkin et al., 2015).

2.2. Empirical Models

We based our model development on theories of both wildfire production and an economic approach to predicting wildfire suppression spending. Statistical models were built for wildfire production and suppression spending in response to that production. Then these models were applied in forecast mode to make projections to the end of the century on both wildfire and suppression spending for the USFS and the DOI. A detailed description of how we specified our empirical models of both wildfire area burned and wildfire suppression spending is provided in the online supplemental material. The empirical models of area burned and the sum of the square roots of area burned are of reduced form, although they have features that recognize nonlinearities and temporal dynamics. The models account for the nonlinearity of wildfire production by expressing them as exponentials, that is, Poisson Pseudo-Maximum Likelihood specifications, relating area burned or the sum of the square roots of area burned to at most two climate variables (vapor pressure deficit (VPD) and maximum daily temperature for each month). For the conterminous U.S., these models also include lags of previous years' area burned, implying that the models are dynamic—current wildfire is affected by previous years' wildfire. Nevertheless, we acknowledge that finer spatial scale and longer time-scale dynamics of wildfire and wildfire management are not included in the final specifications, potentially leading to biased or more uncertain projected suppression expenditures and wildfire activity.

Spatial units of inference for our statistical models of wildfire were based on national forest boundaries for the USFS (Figure S2A in Supporting Information S1) and on the DOI-administered lands (Figure S2B in Supporting Information S1) contained within the geographical boundaries of the USFS regions that are managed by each of the four main bureaus of the DOI. We estimated models predicting the area burned and, based on initial tests of suppression spending models, the sum of the square roots of area burned for fires occurring in each of the modeled spatio-temporal units. These models were expressed as functions of measures of values at risk (housing, population, personal income, and combinations of those variables), hazardous fuels, historical wildfire area burned, and climate (Figure 1). As Figures S3 and S4 in Supporting Information S1 show, many of these variables have been trending at the national scale when aggregated across all jurisdictions containing the federal lands in our study, raising the possibility that their trends, beyond simply those of the climate variables, could be explaining trends in wildfire and suppression expenditures. We addressed this possibility through extensive model testing, separately including and excluding individual variables or sets of variables and evaluating out-of-sample prediction.

For wildfire suppression expenditures, Durbin-Wu-Hausman (Durbin & Watson, 1951; Hausman, 1978; Wu, 1973) tests confirmed that the sum of square roots of areas burned by wildfire in a spatio-temporal unit was endogenously related to (jointly determined with) suppression expenditures for that unit (see the Results section),

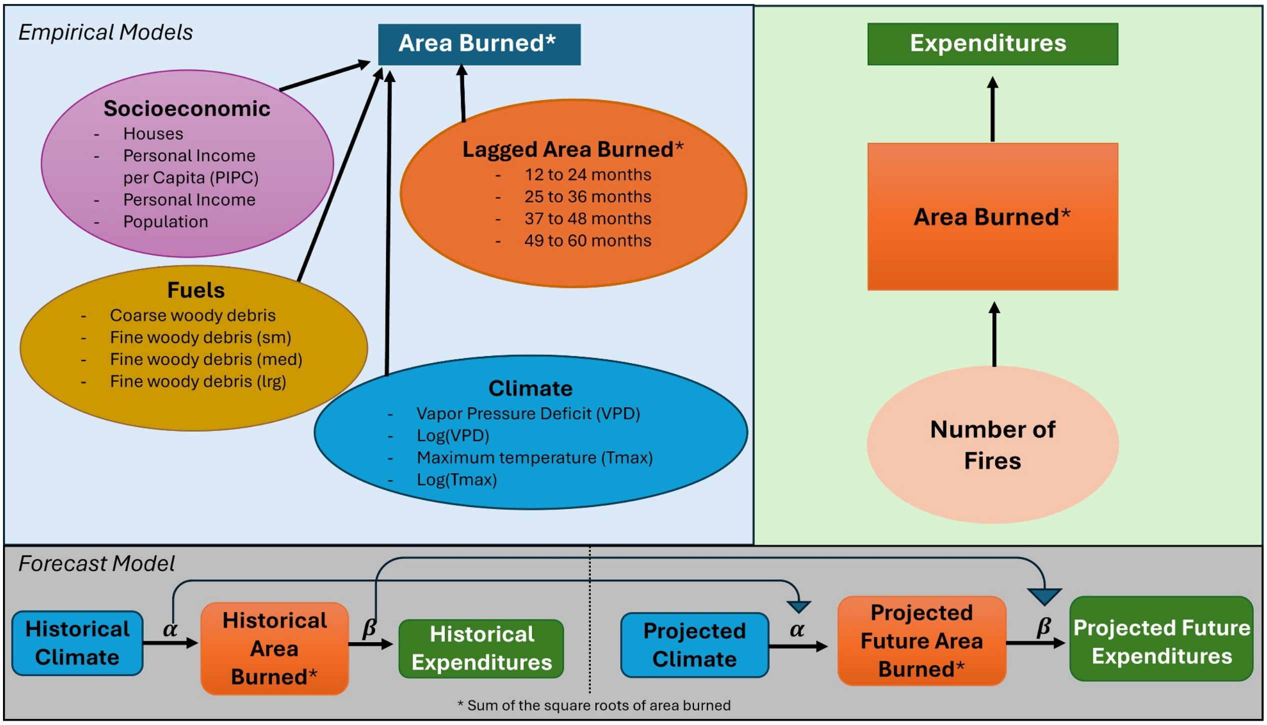

Figure 1. Structure of wildfire and suppression spending models for this study.

implying the need to instrument for the square root measure in estimation. To statistically control for endogeneity, we used two-stage least squares, with the count of reported wildfire ignitions of all types specified as the exogenous instrument. The count of such fires is considered exogenous to suppression spending decisions because the count is predetermined in time, occurring before wildfire response.

Figure 1 illustrates the overall structure of the modeling system. USFS models were estimated as time series-cross sectional panels of observations by month by national forest, with panel models estimated separately for each USFS Region, excluding Region 10 (Alaska, which had 186 acres per year of wildfire reported for the two national forests, 1992–2020). For the DOI, we estimated models of wildfire by month for the lands protected by each of the four largest bureaus (Bureau of Indian Affairs (BIA), Bureau of Land Management (BLM), Fish and Wildlife Service (FWS), National Park Service (NPS)—the Bureau of Reclamation has little land and historically no significant wildfire) across each physical region defined by USFS boundaries. Exceptions to the wildfire modeling were for DOI lands in Alaska (with 1.19 million acres per year, 1992–2020) and Hawaii (part of the Pacific Southwest Region (Region 5), with 1,658 acres per year, 1992–2020), neither of which were modeled directly. This study also ignores wildfires for Puerto Rico (460 acres per year, 1992–2020), the US Virgin Islands, and all US-affiliated Pacific Islands, even though a small share of Office of Wildland Fire (OWF) expenditures could be attributed to the wildfire occurring in those jurisdictions. Variables tested, their sources, units of measure, temporal range, frequencies, and transformations applied are described in Table S1 in Supporting Information S1. Goodness of fit statistics are shown in Tables S2 and S3 in Supporting Information S1.

Models of suppression spending were identified with a similar process as for area burned but specified at the USFS Region level for the USFS and at the Bureau level for the DOI. It was in the model fitting process, recognizing that spending on any particular fire contains a fixed cost component and a variable cost component, meaning that suppression expenditures per acre decline as the area burned by the fire increases (e.g., Donovan et al., 2011). With that in mind, we discovered that suppression spending models performed better (lower bias, lower uncertainty) when current and lagged values of the sum of the square roots of area burned were used as the main predictors. The lagged values would be expected to explain the current month's spending because of delays in spending charges appearing in the suppression expenditure databases of both the USFS and the DOI. The suppression spending equations recognized potential endogeneity of the current period sum of the square roots of

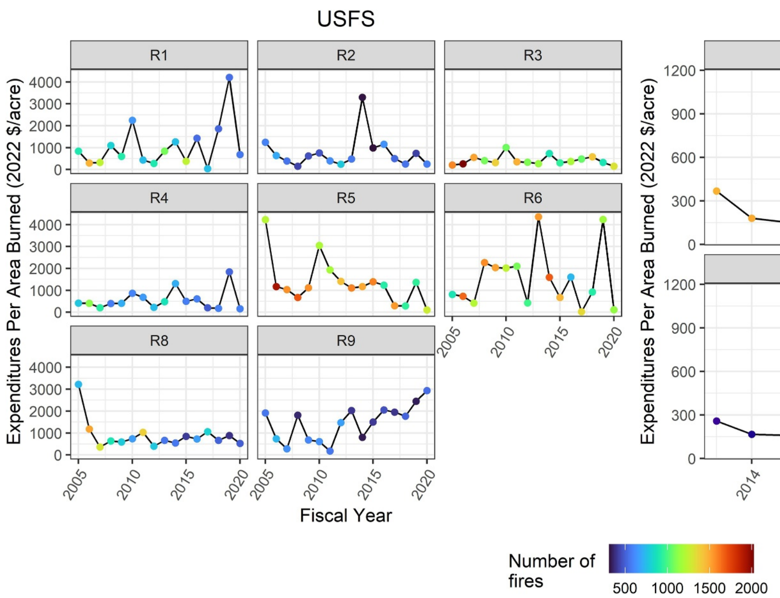

Figure 2. Real dollar, deflated with the United States (US) GDP deflator (US Bureau of Economic Analysis, 2024b), suppression expenditures per unit area burned for regions of the USDA Forest Service (2005–2020) and bureaus of the Department of the Interior (2013–2020).

area burned by applying an instrumental variables method. Recognizing that per-unit-area expenditures vary widely by USFS region and DOI bureau (Figure 2), expenditure models were specified at the USFS Region level for the USFS observations and at the bureau level for DOI. Not all spending by the USFS or the DOI is directly attributable to spatial land units. For the USFS, there is a separate category of spending in its suppression accounts that covers the national office of Fire and Aviation Management, expenditures on suppression connected to research stations, and the USFS share of the cost of administering the National Interagency Fire Center, which we label "Rest of Forest Service" (RFS) (Prestemon et al., 2008). RFS expenditures were modeled as a function of the Region 1–9 (i.e., excluding Alaska, Region 10) total of the sums of the square roots of area burned. For DOI, the OWF has a small level of spending that is modeled as a function of the aggregate, across all four main bureaus, of the sum of the square roots of area burned on all land administered by these bureaus, excluding the area burned in Hawaii and Alaska (and US territories). The suppression expenditures in Alaska by the USFS were added to the RFS totals. For DOI, the suppression expenditures in Alaska and Hawaii in each bureau were added to each of the four main bureau's national total spending.

A lack of climate projection data for all scenarios for the states of Hawaii and Alaska prevented a globally consistent analysis that included direct modeling of wildfire and suppression expenditures for those states. However, for four of the climate scenarios, we did possess such data for Alaska. Therefore, to provide insights on how Alaska wildfire suppression spending affected our projections, we carried out a separate analysis for a subset of the four scenarios for which we had corresponding climate projections. That analysis is reported in the Results section and in the online supplement.

2.3. Data

All historical suppression expenditure data were modeled in constant 2022 dollars (obtained from the President's Budget, "Table 10.1—Gross Domestic Product and Deflators Used in the Historical Tables: 1940–2026," at https://www.whitehouse.gov/omb/historical-tables/). Regional expenditure and RFS expenditure data for the USFS were monthly, 2005–2020. For the DOI, data were also monthly, 2013–2020. We divided the US into regions that coincide with the USFS regions and roughly with the Geographic Area Coordination Centers of the National Interagency Fire Center. Agency spending by USFS region and DOI bureau were obtained by special requests from USFS Fire and Aviation Management and the DOI, Office of Wildland Fire. Monthly expenditure data for DOI were available separately for each of the main DOI bureaus and the OWF for fiscal years 2013–2020, while consistent monthly data for the USFS were available for fiscal years 2005–2020 by USFS Region and the RFS.

Table 1
General Circulation Models/Global Climate Models Used in This Study (Source: Joyce & Coulson, 2020)

Model name	Representative climate	RCP scenarios	Climate model institution
MRI-CGCM3	Least Warm	4.5, 8.5	Meteorological Research Institute, Japan
HadGEM2-ES	Hot	4.5, 8.5	Met Office Hadley Centre, United Kingdom
IPSL-CM5A-MR	Dry	4.5, 8.5	Institut Pierre Simon Laplace, France
CNRM-CM5	Wet	4.5, 8.5	National Centre of Meteorological Research, France
NorESM1-M	Middle	4.5, 8.5	Norwegian Climate Center, Norway

Wildfire data, also summarized monthly (fiscal years 1992–2020, with the omission of the first three months of fiscal year 1992 because October-December of calendar year 1991 were not available), were based on actual fire ignition locations from the Fire Program Analysis fire-occurrence database (FPA FOD) (Short, 2022). Data included spatial unit monthly sum total of wildfire area burned (in acres), the sum total of the square roots of area burned (i.e., the square root of the size of each wildfire was calculated and then summed across all wildfires in the spatial unit for the month), and the count of recorded wildfires. The database included point locations, discovery dates, and final area burned estimates from individual jurisdictional reporting units for the USFS and each of the DOI bureaus, summed to the month and spanning FY1992 to 2020. Wildfires assigned to the NWCG (National Wildfire Coordinating Group) Reporting Agency of "Tribe" were added to the wildfires assigned to NWCG Reporting Agency of "BIA".

2.4. Historical and Projected Climate Data

We used gridded historical maximum daily temperature (Tmax) and VPD data for the period 1979–2020 from GRIDMET (Abatzoglou, 2013). We used modeled historical and future projections of those variables from MACAv2-METDATA (Abatzoglou, 2013; Abatzoglou & Brown, 2012). For the modeled data, we used scenarios from the USFS's 2020 Resources Planning Act Assessment (RPA), which comprise five climate models under each of two RCPs: RCP 4.5 and RCP 8.5 (Langner et al., 2020; see Table 1). The RCP 4.5 and RCP 8.5 scenarios were chosen for the RPA assessment as these scenarios frame the range of future greenhouse gas emissions. Global climate historical modeled projections (1950–2005) and future projections (2006–2099) from the Coupled Model Inter-Comparison Project 5 (CMIP5) were downscaled to the 4-km grid size using the Multivariate Adaptive Constructed Analogs (MACA) method for the continental US. The MACA method is a statistical downscaling method that uses historical observations to remove historical biases and match spatial patterns in climate model output (Abatzoglou, 2013; Abatzoglou & Brown, 2012). The available climate model projections were screened based on their historical model performance (Rupp, 2016; Rupp et al., 2013). Priority was also placed on selecting only one model from a modeling institution and the same model for RCP 4.5 and RCP 8.5 to reduce model variability across the RCPs (Joyce & Coulson, 2020; Langner et al., 2020).

For each RCP, five climate models were selected, four of which captured the national range of temperature and precipitation at mid-century: the hottest projection (HadGEM2-ES365, hereafter "Hot"), the least warm projection (MRI-CGCM3, "Least Warm"), the wettest projection (CNRM-CM5, "Wet"), the driest projection (IPSL-CM5A-MR, "Dry"). Rather than use an ensemble, a fifth model that projected future change near the means of all 20 projections was selected (NorESM1-M, "Middle").

We obtained the historical monthly aggregates of daily maximum temperature data for the period 1979–2016 and the projected temperature data for the entire projected (2021–2099) period from https://www.fs.usda.gov/rds/archive/catalog/RDS-2017-0070-2. We added historical observed maximum temperature data for 2016–2020 by aggregating daily data from GRIDMET to monthly for that period (Abatzoglou, 2013). For monthly VPD, we calculated monthly averages of the daily data from GRIDMET (https://www.climatologylab.org/gridmet.html) and MACAv2METDATA (https://www.climatologylab.org/maca.html).

We generated regional and national averages, monthly and annual, for historical observed and modeled maximum daily temperature and average VPD. We created regional monthly averages by first converting all monthly spatial data to Albers Equal Area Conic to ensure spatial alignment of grid cells from differing data sets, then included only grid cells corresponding to Federal lands (USFS or DOI, Figure S2 in Supporting Information S1) (Snyder, 1987).

Figure S5 in Supporting Information S1 summarizes historical and projected VPD and Tmax for the combined USFS and the DOI lands in this study, showing a general rise into the future, continuing the recent historical trends. Regional details of these same trends document the same pattern across each of the eight CONUS regions for the USFS (Figure S6 in Supporting Information S1) and DOI bureaus (Figure S7 in Supporting Information S1), showing a consistent historical regional pattern across all, consistent with the increased synchronicity of climatic conditions found throughout the western US (Abatzoglou et al., 2021).

2.5. Climate Projections

We used the projected climate data in our selected models to generate monthly estimates of area burned and the sum of square roots of area burned for all spatial and temporal units, fiscal year 2021 through fiscal year 2099 (only three months of fiscal year 2100 are included in the downscaled data set of the GCMs) and then used the sum (i.e., summed across all reported wildfires) of the square roots of area burned in the expenditure projections. Monte Carlo simulations were used to provide a sense of the uncertainty contained in the statistical equation parameters relating climate to area burned, and area burned to expenditures. Climate uncertainty is contained in the climate projections, so the Monte Carlo simulations were conducted independently for each climate scenario. The Monte Carlo simulations involved (a) randomly sampling with replacement from monthly observations of area burned and backcast historical climate over fiscal years 1999–2020, monthly observations of USFS suppression expenditures over fiscal years 2005–2020, and monthly observations of DOI suppression expenditures over fiscal years 2013–2020; (b) estimating statistical relationships for area burned and suppression spending with the randomly sampled data; (c) projecting area burned and spending through 2099 with the estimated parameters; and (d) repeating steps (a)–(c) 200 times for each of the climate projections (each of the 10 GCM × RCP combinations).

Monte Carlo projection results were summarized for mid-century (2041–2059) and late-century (2081–2099) in terms of medians of area burned and expenditures, 80% and 90% upper and lower bounds of area burned and expenditures, and then medians across each of the ten climate projections. To provide context for the projections, we generated predictions of area burned, the sum of the square roots of area burned, and suppression expenditures for the historical period spanning fiscal years 1999 through 2020. The two area burned variables were predicted with the Monte Carlo-generated parameter estimates and the historical observed wildfire data and the historical back-casts of climate data from each of the five GCMs defining our climate scenarios. Historical suppression expenditures were predicted with the Monte Carlo-generated parameter estimates and the predicted sum of the square roots of area burned. In evaluating changes in projected future wildfire and spending, we restricted the recent historical period to fiscal years starting in 2013 because historical monthly observations on expenditures by DOI bureau were only available from fiscal year 2013.

3. Results

3.1. Equation Estimates

Testing of model goodness-of-fit out-of-sample identified models that had the best fit, and results showed that the best-fitting models for wildfire area burned and the sum of the square roots of area burned included at most two measures of climate, historical wildfire area burned up to 5 years, but no measures of values at risk or proxies for fuels. For the USFS region panel models, results of model estimates of area burned and the sum of the square roots of area burned showed that VPD was statistically significant, as were most model estimates that included lagged wildfire variables and national forest indicator variables. Lagged historical wildfire was usually negatively or unrelated statistically to area burned and the sum of the square roots of area burned. These findings are consistent with other literature (e.g., Parks et al., 2015) and support research describing the role of recent historical fires at reducing spending for future suppression (Belval et al., 2019). Model fit was generally high, with pseudo-R^2's ranging from approximately 0.2 to 0.8, with a median of 0.45 (Tables S4–S11 in Supporting Information S1). Wald tests, as conducted with chi-square tests, showed that models with included variables are statistically significantly different from intercept-only models. For the DOI, BIA models for all regions and most other regions for other bureaus showed that VPD significantly explained the monthly sum of the square roots of area burned (Tables S8 and S9 in Supporting Information S1) and area burned (Tables S10 and S11 in Supporting Information S1). For the BLM, the US Fish and Wildlife Service (FWS), and the National Park Service (NPS) lands in regions 4 (lands contained with the boundaries of the USFS Intermountain Region), 5 (within the boundaries of the USFS Pacific Southwest Region), and 6 (within the boundaries of the USFS Pacific Northwest Region) (Figure S2 in Supporting Information S1), initial estimates showed that Tmax was significant but that VPD was not, so the latter was dropped in their specifications. All models except for BIA wildfires in Region 8 (within the boundaries of the USFS Southern Region) and FWS and NPS wildfires in Region 9 (within the boundaries of the USFS Eastern region) were found to be statistically different from intercept-only models. Results on the positive relationship between area burned and the sum of the square roots of area burned and VPD and maximum temperature support other research on wildfire (e.g., Parks & Abatzoglou, 2020; Riley et al., 2013). In summary, VPD and in some cases Tmax were effective at explaining observed historical wildfire on federal lands.

For two-stage least squares (2SLS) estimates of suppression expenditures as a function of current month and one- and two-month lags of the sum of the square roots of area burned (Tables S12-S14 in Supporting Information S1), models were all statistically significantly different than intercept-only models for all USFS regions for the USFS, the expenditure category of the Rest of the Forest Service, all DOI bureaus, and the DOI expenditure category of the Office of Wildland Fire. Durbin-Wu-Hausman tests for endogeneity of the current period sum of the square roots of area burned rejected a null of no endogeneity for USFS regions 1 (Northern Region), 2 (Rocky Mountain Region), 4 (Intermountain Region), 5 (Pacific Southwest Region), 6 (Pacific Northwest Region), and 8 (Southern Region) but could not reject it for Region 9 (Eastern Region) or RFS. For these regions where the null was rejected, application of instrumental variables methods was necessary to avoid biased parameter estimates, and failure to do so would have led to biases in our expenditure projections. In nearly all USFS regions and DOI bureaus, one-month and two-month lags of the sum of the square roots of area burned significantly explained suppression expenditures, positively. Instrumented current period sum of the square roots of area burned was not as commonly significantly different from zero. The instrument applied in these expenditure models was the current count of the numbers of reported wildfires in each region. Such instrumenting identified significant and positive effects of current period sum of the square roots of area burned for regions 1 through 8; it was not significant for Region 9 (Eastern Region). In Region 8 (Southern Region), the coefficient was negative (although half the magnitude of the included one-month lag of that variable, preserving an overall positive effect of wildfire on suppression spending in that region). For DOI bureaus, Durbin-Wu-Hausman tests of endogeneity rejected the null of no endogeneity for BLM only. For these bureaus, lagged sums of square roots of area burned were all positive, and they were statistically different from zero for BLM, NPS, and OWF for lag 1, for BLM, FWS, NPS, and OWF for lag 2. Instrumented current period sum of the square roots of area burned were not significant for any bureau or the OWF.

3.2. Projection Results

Results from the projection of annual expenditures (Table S15 in Supporting Information S1) show that, compared to the medians of expenditures projected for a historical period (2013–2019) (noting that our historical data extended to 2020 for model fitting), expenditures are projected to rise by a median of 41% for the USFS and 29% for DOI by mid-century (2041–2059) and by 89% and 61% by late-century (2081–2099), respectively, with USFS + DOI increasing by 39% and 84%, respectively. Projections of expenditure increases vary widely across climate scenarios and RCPs (Figures 3a, 4a and 4b, Table S15 in Supporting Information S1), with late-century rises in scenario medians for the USFS ranging from 27% for the least-warm model under RCP 4.5 to 335% for the hot model under RCP 8.5; for DOI, the range is 24% (least-warm, RCP 4.5) to 195% (hot model, RCP 8.5). Analogous results for the sum of the square roots of area burned and area burned are shown in Figures 3b and 3c, 4b–4f, and Tables S16 and S17 in Supporting Information S1.

Expenditure distributions across all models considered together (Figure 4a and Table S15 in Supporting Information S1) for the USFS show increasingly dispersed projected spending, depending on the scenario, and that, by late-century, 90% of projections fall between \$2.74 and \$13.16 billion, compared to the multi-model projected historical median (2013–2019) of \$2.60 billion. For DOI (Figure 4b, Table S15 in Supporting Information S1), 90% of projections by late-century are between \$0.67 to \$2.03 billion, compared to a projected historical median (2013–2019) of \$0.62 billion. For both the USFS and DOI combined (Figure 3a, Table S15 in Supporting Information S1), in late-century, 90% of total expenditures are found between \$3.43 billion and \$15.10 billion, compared to the multi-model median over the historical comparison period of \$3.23 billion. These represent rises of 39% by mid-century and 84% by late-century (Figure 5). For the USFS, the multi-model median rises by 89%

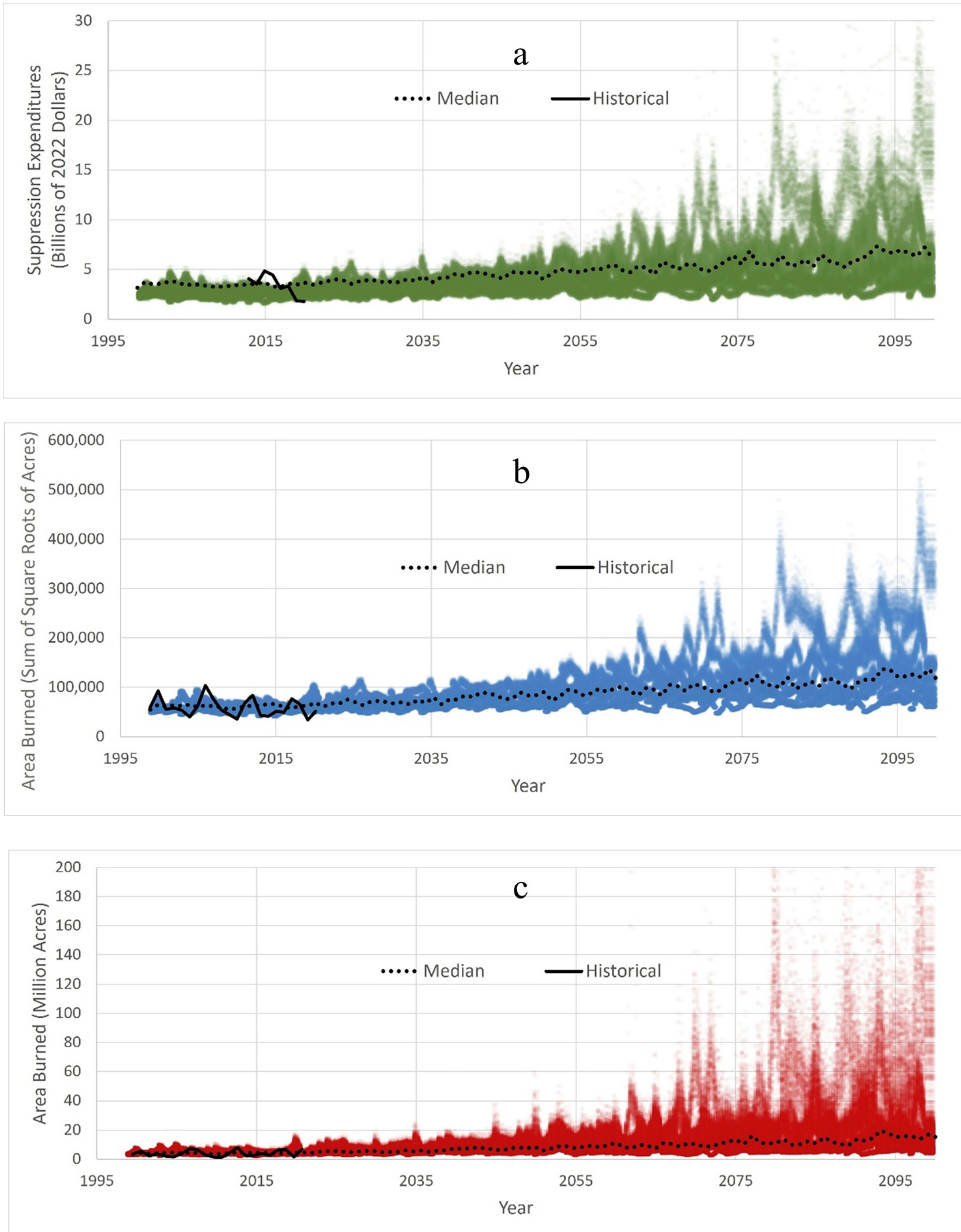

Figure 3. Historical and projected (a) suppression expenditures, in billions of constant 2022 dollars, (b) sum of the square roots of area burned, and (c) area burned for the USDA Forest Service and the Department of the Interior, combined. Colored points depict the projected Monte Carlo outcome density across all ten climate scenarios. Median projections (dotted lines) in the historical era, 1999–2020, are based on modeled historical climate and wildfire observations, while the projected span 2021–2099; observed values (solid lines) span 2013–2020 (suppression expenditures, (a)) and 1999–2020 (area burned measures, (b) and (c)).

by late-century, which represents a compound annual real dollar growth rate of 0.87% per year. For DOI, the median rise is 61%, a compound annual growth rate of 0.65% per year. Combining USFS and DOI, the total compound annual growth rate to late-century is 0.83%.

The widening of the spending distributions from the historical projected values to late-century values (Figures 3a, 4a, 4b, 5) highlights two features: First, all projections show rising real dollar expenditures. Second, uncertainties

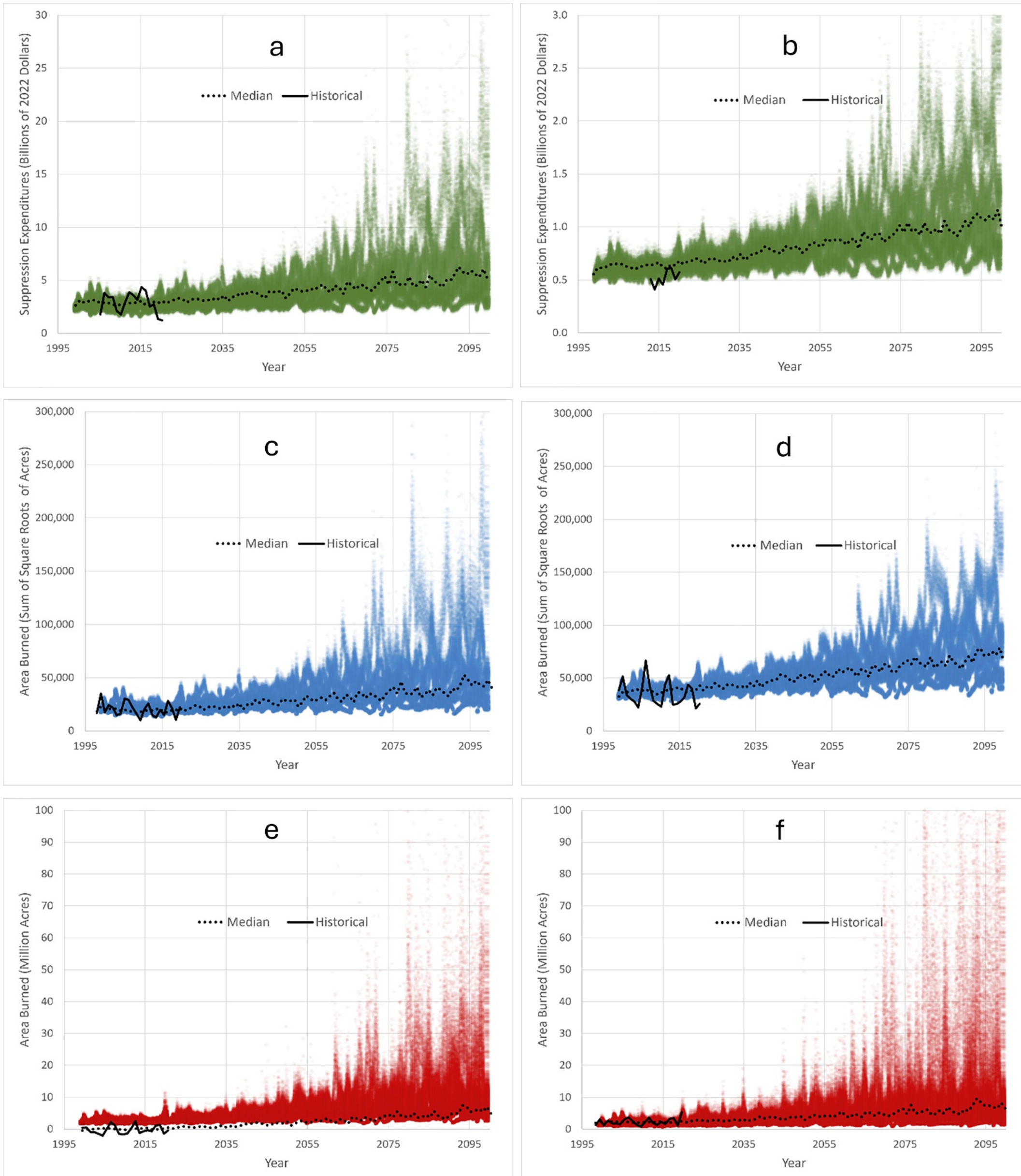

Figure 4. Historical and projected suppression expenditures, in billions of constant 2022 dollars, for (a) the USDA Forest Service (USFS) and (b) the Department of the Interior (DOI); sum of the square roots of area burned, for (c) the USFS and (d) DOI; and area burned for (e) the USFS and (f) DOI. Colored points depict the projected Monte Carlo outcome density across all ten climate scenarios. Median projections (dotted lines) in the historical era, 1999–2020, are based on modeled historical climate and wildfire observations, while the projected span 2021–2099; observed values (solid lines) span 2013–2020 (expenditures—(a) and (b) and 1999–2020 (area burned measures, (c)–(f)).

about the future, as measured by both parametric uncertainty captured in the Monte Carlo process and climate uncertainty comprised in the ten scenarios of GCM × RCP combinations, rise over time. The rising uncertainty is expected, as parametric uncertainty causes diverging projected values of spending as it plays out to the end of the century in each iteration. The climate scenarios were chosen (Joyce & Coulson, 2020) to bracket uncertainties in temperature and precipitation futures, which explains the remaining portion of the rise in spending distributions.

The sum of the square roots of area burned and area burned projected medians and densities (Figure 3b, 3c, 4c–4f) document substantial rises in both measures of wildfire activity and their rising uncertainty due to divergent climate projections across scenarios and the natural rise in variance of an exponential process. Tables S16 and S17

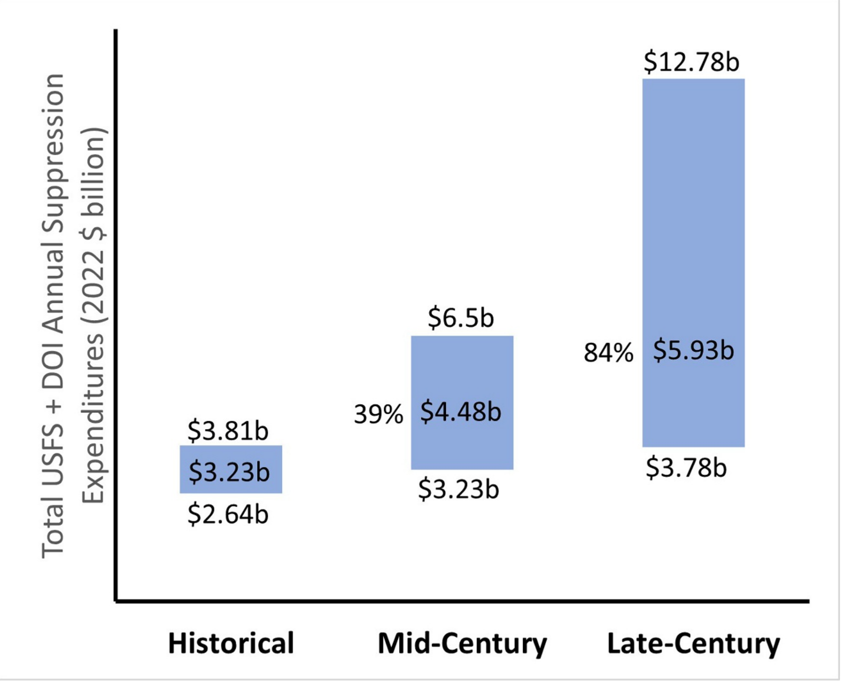

Figure 5. Projected real median annual expenditures, USDA Forest Service + the Department of the Interior, projected historical (2013–2019), projected Mid-Century (2041–2059), and projected Late Century (2081–2099), and 80% upper and lower bounds, in billions of constant FY 2022 dollars, and percentage increases by Mid-Century and Late-Century relative to the historical median annual expenditures. The Historical average shown are model-based predictions.

in Supporting Information S1 report the projections of the sum of the square roots of area burned and area burned, respectively, for both agencies. Given the linear structure of suppression expenditure models, it is not a surprise that projected changes in the sum of the square roots of area burned are of a similar magnitude as the projected rises in expenditures. For both the USFS and DOI combined (Figure S8 in Supporting Information S1), with multi-scenario medians rises are by 40% and 85% by mid- and late-century, respectively. For the USFS (Figure 4c), multi-scenario medians rise by 45% and 98% by mid- and late-century, respectively, compared to 2013–2019; for DOI (Figure 4d), rises are by 37% and 78% by mid- and late-century, respectively, compared to 2013–2019 (Table S16 in Supporting Information S1). Area burned (Figures 4e and 4f, Table S17 in Supporting Information S1) is projected to rise much more, given its greater historical sensitivity to VPD and Tmax. For the USFS and DOI combined, rises are by 80% and 208%, by mid- and late-century, respectively (Figure S12 in Supporting Information S1). For the national forests and national grasslands of CONUS, multi-scenario median rises are by 91% and 237% by mid- and late-century, respectively (Figures S13 and S14 in Supporting Information S1). For the DOI lands modeled in this study, rises are 73% and 181% by mid- and late-century, respectively (Figure S15 in Supporting Information S1). The area burned projections for the USFS and the DOI vary widely in their amounts of projected increases (Table S17 in Supporting Information S1). For the USFS, median rises by late-century range from 50% under the Least Warm model (MRI-GCM3) and lower emissions to 1,528% under the Hot model (HadGEM2-ES365) and high emissions. For DOI, median rises by late-century range from 67% under the Least Warm model and lower emissions to 758% under the Hot model and higher emissions (Table S17 in Supporting Information S1).

Evaluation of climate models has been an increasing endeavor, particularly as model development continues. These model projections are from the CMIP5 collection (Joyce & Coulson, 2020). Using criteria to evaluate the temperature projections from each model, all models used in this analysis meet the criteria for an analysis of the transient climate response and all models, except HadGEM2-ES, meet the criteria for equilibrium climate sensitivity (Nijsse et al., 2020). This result for the HadGEM2-ES model suggests that it is hotter than models that met that criteria, so not as likely as other models but still an important component of an analysis of potential future climate. The RCP 8.5 scenario was developed for the CMIP5 data set and coupled with the SSP5 in the CMIP6 data set. The RCP 8.5 scenario is a high fossil-fuel-dependent and development intensive scenario and results in large temperature increases in all projections. However, it is difficult to preclude warming of 4°C or more if positive emissions continue (Hausfather, 2025). Figures 3 and 4 and Tables S15, S16, and S17 in Supporting Information S1 show how influential the divergent projections are across scenarios, meaning that expectations about the future depend on which forcing level will be realized. Our results support the findings of Riley and Loehman (2016) and Riley et al. (2019), positing higher levels of area burned later this century.

Results showing that the projected changes in wildfire area burned summarized for CONUS (Table S17, Figures 3c, 4e, 4f) and then in regional detail (Figures S12, S13 in Supporting Information S1) vary widely across space and are connected to the differences in changes in fire-prone conditions. Area burned projected increases are smallest for regions 3 (Southwest Region), 5 (Pacific Southwest Region), 8 (Southern Region), and 9 (Eastern Region), showing a multi-model median rise by late-century compared to recent historical wildfire of less than 111%. Each of regions 1 (Northern Region), 2 (Rocky Mountain Region), 4 (Intermountain Region), and 6 (Pacific Northwest Region) have analogous projected rises exceeding 179%, the highest for Region 1, at 418%, implying that the more northern and western USFS regions would shoulder a progressively higher share of wildfire for the agency as the century progresses. Likewise, the most northwesterly regions (regions 1 and 6) would demand a progressively higher share of suppression resources and associated spending. Region 1 would experience a 189% rise in spending, Region 2 113%, Region 4 146%, and Region 6 117% compared to their 2013–2019 historical medians. Other USFS regions would experience real dollar rises of less than 103%.

Projections for the DOI bureaus show increasingly divergent rates of rise in both wildfire area burned (Table S17 in Supporting Information S1, Figure 4f) and spending (Table S15 in Supporting Information S1, Figure 4b), but increases are smaller in magnitude compared to those of the USFS. The largest multi-scenario median projected percentage rises in area burned are for lands administered by the BLM, at 220% by late-century, and the lowest for those of the FWS, at 63% by late-century. The BLM in recent years has had the highest spending of all DOI bureaus, and this reality is projected to remain the case by late-century. Lands administered by BIA and NPS represent similar annual expenditures historically, but suppression expenditures on wildfires on lands managed by the NPS are projected to surpass those of the BIA by late-century, making NPS the second-costliest bureau in terms of suppression expenditures.

3.3. Special Analysis of Alaska

Although wildfire area burned and suppression expenditures on the two national forests in Alaska have comprised a small share of total agency area burned and expenditures, wildfire area burned on DOI bureau-protected lands in Alaska has comprised a significant share of all wildfire reported for the four main bureaus over the past two decades. Wildfire represents a large proportion of the four-bureau national total reported area burned in many years (averaging 38%, 1992–2020, ranging from 3% to 93% of the four-bureau total), but a much smaller expenditure share (averaging 8%, ranging from 4% to 13% of the national four-bureau total, FY 2013–2020). Recent history and studies indicate that wildfire will be more widespread in the state, adding uncertainty to our projections of suppression expenditures, in which the Alaska share of total spending is presumed to be unchanged compared to the historical era. Northern boreal regions worldwide have been and are projected to continue to rapidly warm (Stocks et al., 1998; Venäläinen et al., 2020), leading to expected potential increases in wildfire activity (de Groot et al., 2013; Flannigan et al., 1998; Girardin & Mudelsee, 2008; Wang et al., 2015).

To evaluate the potential importance of a changing climate on federal wildfire suppression expenditures in Alaska and how direct accounting of wildfire in Alaska would affect our projection results, we undertook a special modeling effort. We augmented our projections to directly include the changes in climate and wildfire in Alaska for four scenarios (Hot and Least Warm, for each of RCP 4.5 and 8.5) for which we had available climate data for the spatial and temporal scales of our analysis and corresponding to the same global climate models used for our scenarios. We found through testing that zero-inflated Poisson specifications of both area burned and the sum of the square roots of area burned fit the historical with the least root mean squared error out-of-sample and the least bias, compared to PPML models. We separately projected area burned and the sum of the square roots of area burned for the two national forests of Alaska (Chugach, Tongass) and the lands administered by the four main bureaus of the DOI. For model parameterization of the area burned and the sum of the square roots of area burned models, we obtained historical data on monthly average daily maximum temperature, monthly average daily minimum temperature, precipitation, daily average total evaporation, and monthly wet-day fraction; VPD observations were not available (Mizukami et al., 2021; https://gdex.ucar.edu/datasets/d010111/citation/). Models were specified as zero-inflated Poisson with a heteroscedastic error distribution assumed. Models fit best with only daily average maximum temperature and average daily precipitation. Full-sample estimation results are shown in Tables S18-S19 in Supporting Information S1. For expenditures, we modeled DOI bureau expenditures and the Office of Wildland Fire as containing the current and two lagged months of the sum of the square roots of area burned and the same variables but only for Alaska (Table S20 in Supporting Information S1). For the USFS, we modeled the Region 10 expenditures as a function of current and two lags of the sum of the square roots of area burned, and for the rest-of-Forest Service spending, we included separately current and one lag of the total USFS Alaska sum of the square roots of area burned. Because wildfire in Alaska was included in the expenditure equations for the four DOI bureaus, equations were reestimated (Table S21 in Supporting Information S1). Compared to the main modeling (Table S14 in Supporting Information S1), specifications shown in Table S21 in Supporting Information S1 include up to three lags of the sum of the square roots of area burned for Alaska as additional regressors in the bureau equations. The added Alaska-only lags allow for the potentially lower overall unit expenditures needed for the wildfire responses on DOI lands in that state.

Results of this separate exercise to explicitly account for how climate may affect expenditures (Table S22 in Supporting Information S1) and wildfire area burned in Alaska (Tables S23-S24 in Supporting Information S1) showed modest effects for both the USFS and DOI. For the Hot model under low emissions (RCP 4.5), real dollar expenditures for the USFS by late-century were nearly identical, 107% higher in this Alaska-focused analysis (Table S22 in Supporting Information S1) and 106% higher as originally modeled, compared to recent historical median levels (Table S15 in Supporting Information S1). In the higher emissions case for the Hot model, these were 345% higher rather than the 335% higher as originally modeled. Under the least-warm model, the addition of Alaska had essentially no effect on projected expenditures under both lower and higher (RCP 8.5) emissions projections. For the DOI, expenditures by late-century under the Hot model under low emissions were 60% higher compared to recent history, less than the 65% projected under our original modeling framework (Table S15 in Supporting Information S1). Under the hot model with high emissions, expenditures were 179% higher instead of the 195% higher found in our original modeling. For the Least Warm scenario, changes were not substantially different compared to the original modeling framework, rising by 20% with the addition of Alaska and 24% without it under the least-warm low emissions, and by 55% rather than 65% by late-century under higher emissions. For the USFS and DOI combined, impacts were intermediate, with the Hot model projections 98% and 314% higher and the Least Warm model projections 26% and 71% higher under low and high emissions, respectively, while the original modeling produced rises of 98%, 311%, 27%, and 76%, respectively. In summary, directly accounting for climate change in Alaska in the modeling had no substantial effect on projected expenditures for USFS or DOI. Directly accounting for Alaska in our models did reveal the additional wildfire area burned associated with Alaska (Table S24 compared to Table S17 in Supporting Information S1), although with wide variation across climate model and emissions scenarios, rising in median levels by 24%–783% across the combined lands of the USFS and DOI by late-century.

4. Discussion

Given the long-expressed concerns about the growing burden of wildfire suppression spending on agency budgets (e.g., US General Accounting Office, 2004), it makes sense to compare how projected changes in only federal wildfire suppression expenditures (i.e., excluding the costs of all other forms of wildfire management related spending) would compare with the size of the US economy and overall federal net outlays. First, we compare our study results (for the USFS and DOI, respectively, a compound real dollar growth rate of 0.87% and 0.65% per year by late-century in median projected suppression spending, and combined at 0.83% per year) with those of US economy-wide growth, such as those of the Intergovernmental Panel on Climate Change-inspired Shared Socioeconomic Pathways (O'Neill et al., 2014) and those available from IIASA (2024). The real dollar compound annual growth rate of US gross domestic product over the same years for SSP's 1 through 5 range from 0.86% to 1.51%. Federal net outlays as a percent of GDP have been static to rising over the past 35 years (Federal Reserve Bank of St. Louis, 2025), ranging from 18% to 30% of GDP. Our projections imply that, if federal net outlays relative to GDP remain constant, median projected suppression spending would represent a smaller share of the federal budget in the future. Nevertheless, projected rises in median real dollar federal suppression spending across climate scenarios and both the USFS and DOI combined range from a compound annual growth rate of 0.32%–1.93%, implying substantial uncertainty in the changes in its component of future federal budgets and its size relative to future GDP. We emphasize, however, because we did not project the future trends in the economic value of damages created by wildfire or the costs associated with other forms of wildfire management, our study cannot quantify the overall economic burden of wildfire in the US. Furthermore, given that our models are parameterized on historical data, an underlying assumption is that suppression spending relationships to wildfire are stationary; that is, they represent a business-as-usual case of our wildfire future.

With regard to our special analysis of Alaska wildfire, the relatively small differences in projected expenditures across the four climate scenarios with Alaska directly modeled revealed that the original approach of our modeling framework, subsuming Alaska spending within overall agency or bureau spending, might have adequately accounted for that state's role in future federal suppression spending. The Monte Carlo medians were slightly lower in late-century when directly modeling wildfire in Alaska, a fact meriting further study. In particular, we did not have available the same variables for Alaska for modeling in the historical period and available in the projected period as we did for the rest of the US for the two climate models and each of the two emissions levels, perhaps weakening our ability to compare between the main model results and the Alaska-inclusive results. Our modeling also revealed high uncertainty in future area burned nationwide across federal lands, even after accounting for Alaska, which highlights the need for further development of climate models, including those that can accurately predict and then project future wildfire prone conditions in the nation's boreal region.

Although our analysis addressed multiple sources of uncertainty, there are notable shortcomings in our approach. Wildfire activity, though highly variable, has been shown to be responsive to recent changes in climate (Abatzoglou et al., 2025; Abatzoglou & Williams, 2016). Consistent with our results, burned area in U.S. forests is projected to increase under multiple future scenarios, generally showing greater increases in the West and smaller increases in the East (Anderegg et al., 2022; Costanza et al., 2023). However, multiple factors influence our projections. Future changes may be affected by regional climate patterns such as the El Niño Southern Oscillation and the 1-year lagged Tropical North Atlantic Index (TNA+1) that influence the variability of wildfire activity across the US (Keeping et al., 2026). Most of those regional climate factors are not explicitly accounted for in the climate projections we used. In addition, the climate scenarios underpinning the wildfire area burned were selected to span a range of temperature and precipitation by 2070 across the conterminous US. Yet temperature or precipitation may change more within some regions of the country in other general circulation models (GCMs) not used in this study; such alternate GCMs could have generated area burned projections at a regional level that would have been outside the envelope that we projected.

Furthermore, our analysis does not distinguish between wildland landscapes and wildland-urban interface landscapes, and Cunningham et al. (2025) has shown that wildfires may intensify in the wildland-urban interface under climate change. While we tested fuels-related variables across aggregate management units as predictors in our Forest Service models, our analysis does not incorporate the potential for variation in area burned in response to fine-scale variation in fuels and other landscape features including topography and vegetation type. Spatially explicit fine-scale variation in those factors as predictors of fire probabilities or area burned has been incorporated for individual landscapes using landscape simulation models (e.g., Ott et al., 2023; Robbins et al., 2024), but such models for all FS and DOI lands would be computationally challenging and beyond the scope of this study because suppression expenditure data are only available at aggregate scales. While our models included lagged historical wildfire for national forests, significances were not typically high, perhaps revealing the empirical effects of attempting to connect current period wildfire in one subunit of a national forest to historical wildfire occurring in different subunits of a national forest. Likewise, assuming similarities in wildfire behavior and therefore wildfire suppression responses and unit costs across subunits within a larger geographical unit could be interpreted as what Banzhaf et al. (2019) refer to as the Ecological Fallacy.

In addition, although our Monte Carlo methods characterized the parametric uncertainties of our selected models, this uncertainty measurement was limited to a relatively short time series of observations—particularly for suppression spending—and the models were parsimonious and aggregated to large spatial land units, even though they underwent a thorough process of model out-of-sample testing. Detection of the effects of finer scale influences on both wildfire and suppression, including how housing affects suppression and how hazardous fuels affect both fire and suppression, was shown to not be possible at our modeled spatial scale. This fact compels future research that effectively captures such complexity and allows for more insights into the effectiveness of efforts to reduce overall costs and losses from wildfire in the US, a goal of federal policy (USDA Forest Service, 2022). Furthermore, the modeling of suppression spending as a function of only the sum of the square roots of area burned, while fitting the data effectively, could be overly simplified because of its inattention to unobserved or unmodeled factors affecting that spending that could themselves be trending into the future, leading to projection biases. Finally, the estimated suppression expenditure models, based on historical data, presume stable relationships between input resources (labor, capital, materials) and wildfire that could change in the future, not least because of changes in technology and relative prices of these inputs not captured by our projections.

5. Conclusions

Suppression spending by the USFS and the DOI has been rising in inflation-adjusted terms over the past three decades. Much of this rise can be traced to increasingly fire-prone weather and climate conditions becoming more common and widespread over time. We sought to understand how changes in the rates of such conditions, as projected by multiple global climate models, would translate into wildfire suppression spending implications for both agencies. Part of our modeling effort also sought to account for the fuels changes caused by recent wildfires on current wildfires as well as other hypothesized drivers of wildfire and suppression expenditures, including direct fuels measures and socioeconomic conditions.

By specifying our models at the level of the national forest and for regional aggregations of lands administered by each of the four main bureaus of the DOI, we showed how future wildfire can be parsimoniously expressed as a function of VPD or maximum daily temperature. Research has established that higher fuel loads lead to more intense wildfires when they burn, but at least at the spatial scale of national forests, the relationships of direct fuels measures to observed wildfire area burned and hence suppression spending was not supported by data. Fuels variables included only surface fuel variables summarized from sparse FIA plots at National Forest scales, and this resolution was not sufficient to capture the effect of fuels on fire spread. In contrast, inclusion of short lags of recent wildfire area burned were statistically significant and negative in model estimation for several regions of the USFS, indicating at least the short-run suppressive nature of wildfire (Parks et al., 2015). However, improvements in goodness-of-fit out-of-sample over the historical period were not as supportive, particularly for DOI lands. The absence of statistically significant negative relationships between current and historical wildfire area burned could be attributed to the more dominant rangeland fuel types found on DOI lands as compared to USFS lands. Rangeland fuels can rebound or exceed pre-fire levels within weeks of burning, whereas forest fuels take longer to recover. For USFS lands, despite slight erosion in fit out-of-sample over the historical data, compared to models that excluded the lagged wildfire, we found that, in projection mode, models including the lagged wildfire tended to attenuate some implausible, extreme wildfire area burned predictions under some climate futures for some USFS regions, hinting that controlling statistically for fuels, whether with direct measures that are projected, or indirect measures such as lagged wildfire, reduces some extreme uncertainty about future fire and suppression.

Next, although many studies have documented the relationship between socioeconomic factors and observed wildfire activity (e.g., numbers of fires ignited) and the proximity of built up areas to the rate of suppression spending to protect these areas, statistical tests at the level of national forests and collections of lands managed by DOI bureaus failed to show that changes in such variables were connected to changes in wildfire and its associated suppression spending. While the failure to reject null hypotheses that such fuels and socioeconomic factors do not affect observed wildfire could be attributed to simple Type II error brought about by too-spatially coarse resolution of our wildfire models or poor choices on the specific measures for these factors, for purposes of projections, their abandonment from empirical specifications greatly simplified the projection modeling. The implication of these statistical findings is that wildfire area burned and suppression spending at the monthly time scale for national forests and DOI bureaus can be explained, albeit with substantial residual uncertainty, with parsimonious models involving one or two climate variables and, for the USFS, lagged wildfire in recent years. Research by some authors have documented much longer lasting relationships to historical area burned when modeled at the annual time step—e.g., Prestemon et al. (2002) for the case of Florida counties, up to 12 years for lightning-caused wildfire—implying that more elaborate specifications or refinement in spatial resolutions could identify the expected statistical relationships between wildfire and wildfire-fuels and hence fuels-suppression spending relationships. Nonetheless, the cited study did not test model goodness-of-fit out-of-sample to evaluate whether inclusions of long lags of historical wildfire would result in better fits.

This study was among the first to thoroughly explore how climate may be linked to spending on wildfire management, in this case suppression resource demands as measured by overall spending. It is also the first to estimate how prospective changes in wildfire-prone conditions in the coming decades may lead to greater demands for suppression resources, including those directed at potentially rapidly increasing wildfire-prone conditions in Alaska. To the extent that the inflation-adjusted unit prices of such resources do not rise over time and the resources demanded per unit of wildfire are not altered over time, across the range of our ten scenarios, projected changes in spending would be generally within the economic capacity of the US economy and the federal government to absorb. However, per-unit prices are not likely to be constant in real terms and technology will change. Greater wildfire extent and rising values at risk imply increasing complexity in firefighting, with economic consequences beyond those quantified in this study.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Availability Statement

Historical wildfire data are available from Short (2022). Historical information on population and housing are available from the US Census Bureau (2024). Personal income information can be obtained from the US Bureau of Economic Analysis (2024a), which were deflated to real dollars with the GDP deflator (US Bureau of Economic Analysis, 2024b). Historical gridded climate data are available from the USDA Forest Service (2024) by starting at https://research.fs.usda.gov/inventory/rpaa/2020. Historical data used for model testing and parameterization, projected climate and socioeconomic variables, and all Stata program code used to make the projections are currently available at https://doi.org/10.2737/RDS-2026-0017. These data and all outputs of suppression expenditure projections, wildfire sum of square roots of area burned projections, and wildfire area burned projections by USFS Region, DOI bureau, and in total, and the Stata Version 17 (StataCorp, 2021) model code used for the projections are accessible from Prestemon et al. (2026).

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