Technical Appendix: Climate Risk Exposure: Federal Wildfire and Suppression Expenditures. Research and Development, USDA Forest Service[50,51]

Executive Summary

Climate change is anticipated to raise land and sea temperatures globally, including in the United States, and this change is likely to lead to shifts in the rate, severity, and extent of wildfire on Federal lands. Relevant to Federal budgets, such changes bring with them the expectation that spending to suppress and manage wildfires would generally change as the climate changes.

This report extends similar work done in 2016. We build on the 2016 analysis by updating information on climate change to comprise a larger number of future climate projections, updating data on wildfire suppression expenditures through 2020, increasing the observation frequency for suppression and wildfire to monthly compared to annual in the previous effort, increasing the time span of historical wildfire to fiscal years 1993 through 2018, and expanding our consideration of the potential drivers of wildfires. Similar to the 2016 report, we evaluate how changes in climate in the United States could lead to changes in annual spending to suppress wildfires on USDA Forest Service (FS) and Department of the Interior (DOI) managed lands by the middle and the end of the current century. As in 2016, we developed statistical models of wildfire at regional spatial scales based on historical data on climate and wildfire. Given the new monthly frequency of our data on both wildfire area burned and wildfire suppression spending for both FS and DOI, we are additionally able to estimate separate models of wildfire suppression spending by region for the Forest Service. Because Interior Department spending detail is not available at regional spatial scales, its suppression spending model was based only on historical *nationwide* monthly expenditures as related to departmental area burned nationwide.

In the current effort, we assembled an expanded set of projections by five global climate models (GCMs) and two alternative projections of radiative forcing levels (representative concentration pathways [RCPs] 4.5 and 8.5 Watts/m^2) to the year 2100. Hence, we show projections for five GCMs x two RCPs, i.e., 10 projections of future climate for the continental United States. Expanding from the previous effort, we tested model uncertainty on multiple measures of historical climate, including maximum daily temperature, vapor pressure deficit, average daily precipitation, potential evapotranspiration, the climate moisture index, and minimum relative humidity. With the exception of relative humidity, observations on all variables were available for both the historical time series and the projected time series to 2100. Area burned models' uncertainty analysis showed that, nationwide, the combination of average daily vapor pressure deficit (VPD) and average daily maximum temperature performed best across nearly all regions

[50] Contributors: Jennifer Costanza and Jeffrey Prestemon, Southern Research Station; Erin Belval, Sarah Brown, Linda Joyce, Shannon Kay, Jeff Morisette, Karen Riley, and Karen Short, Rocky Mountain Research Station; Mark Lichtenstein, USDA Fire and Aviation Management

[51]Acknowledgements: We would like to thank Mark Finney, Frank McCormick, Larry Scott Baggett, and other unlisted agency and Department reviewers for their comments and suggestions in the drafting of this report.

of the continental United States (CONUS). Forest Service suppression monthly expenditures were modeled for each region as a linear function of current area burned and area burned in the previous two months. The remainder of the Forest Service (RFS) expenses, whose spending is not directly associated with particular regions, and the aggregated nationwide suppression expenses for the Department of Interior were similarly modeled but at the national level. Region 10 (Alaska) of the Forest Service was found to not be related to area burned in that region and was specified as a simple constant model. All spending projections were done with constant 2020 dollars. Uncertainty in the area burned and suppression spending for each climate projection was quantified using Monte Carlo simulation, while overall uncertainty about climate was captured by projecting wildfire and spending under the ten projections (5 GCMs x 2 RCP scenarios). The ten projections differed widely in their projected futures by intention, with GCMs selected to capture a range of plausible futures in two climate dimensions: temperature and precipitation (Langner et al. 2020).

This analysis uses two methods to construct a baseline for historical burned areas with which to compare future projections. One is based on *observed* historical area burned. The other is based on *modeled,* or *backcast,* historical area burned, where climate variables were projected by the GCM for fiscal years 2006-2018 and then area burned projected from that climate backcast. Results show that median area burned, across both USDA and Interior lands and across all climate projections, is projected to be 104% higher by mid-century and 237% by late-century, when compared to observed historical (fiscal years 2006-2018) area burned. When compared to modeled historical area burned, these percentages are 106% and 241% higher by mid- and late-century, respectively. Given such changes in area burned, annual spending of both the Forest Service and DOI is projected to rise. Compared to back-cast spending, fiscal years 2006-2018, in real, inflation-adjusted 2020 dollars, expenditures would rise by 83% by mid-century and 186% by late-century. Applying these percentage increases to observed historical spending, we project that total Federal spending for the Forest Service and Department of the Interior would rise from a historical median (fiscal years 2006-2018) of $2.0b per year to a projected $3.66b per year in mid-century and $5.70b per year by late-century. Additional detail of the area burned and spending projections are presented in Figure A-1 and Table A-1 of this Appendix's Executive Summary.

The statistical modeling approach used in this study and the projected results are conditional upon several assumptions, violation of any of which would alter both the projected changes in spending and the ranges of our uncertainty bands. Primary assumptions include aggregation biases, omitted variables biases, and model structures. The details and caveats of these assumptions are treated in detail in the full report. An overarching assumption is that hazardous fuels were not modeled, and so no what-if scenarios were carried out that would evaluate how Federal efforts to accelerate rates of hazardous fuel reduction would affect wildfire and suppression spending. Even with these caveats and assumptions, our models, along with the literature we have cited (and much that we have not), provide evidence that both wildfire extent and suppression expenditures are expected to increase with climate change. Our models, specifically, show that temperature and vapor pressure deficit do a sufficient job of accounting for monthly area burned and associated suppression spending. Our models also show that increases in area burned and inflation-adjusted suppression spending could plausibly double over the next 80 years.

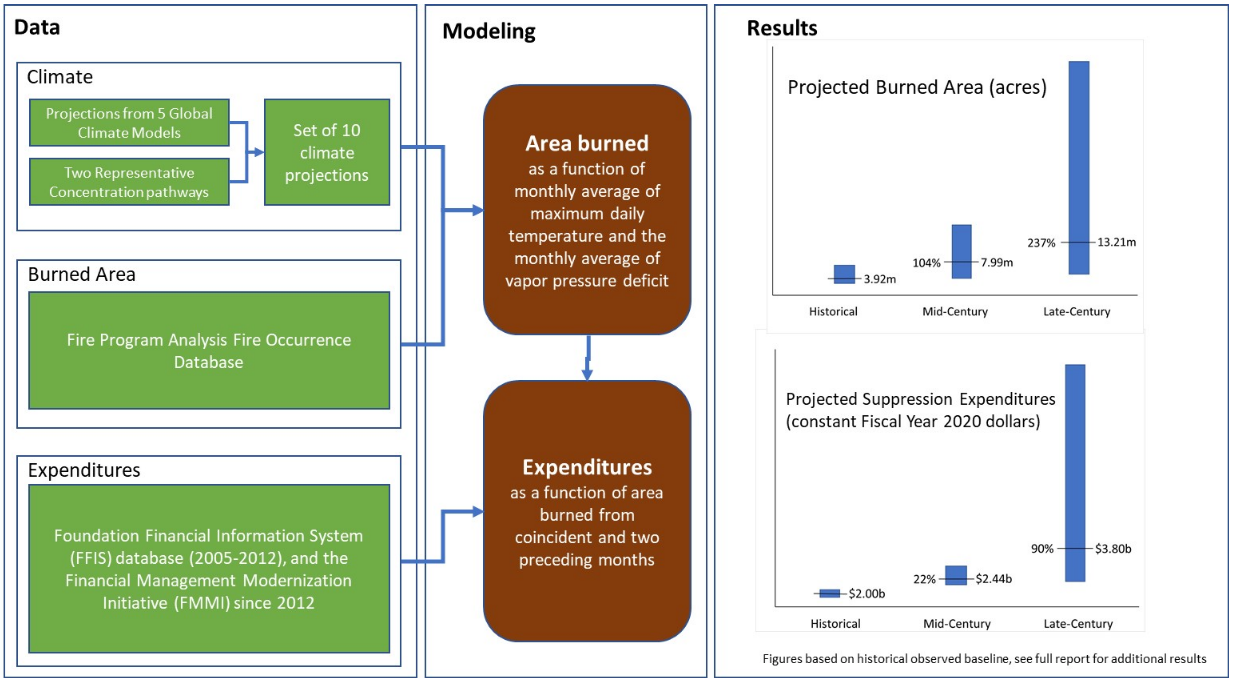


Figure A-1. Summary of area burned and suppression expenditure projections methods and results across FS and DOI lands combined. Note: range and height of area burned and suppression spending bars in the right panel reflect an 80% uncertainty bound.

Table A-1. Detailed projections of area burned and suppression spending, by DOI and FS and combined.

Projected change in area burned by mid-century (fiscal years 2041-2059)

Compared to:	Forest Service (FS)	Dept. of Interior (DOI)	Combined FS & DOI
Observed climate	94%	114%	104%
Modeled, climate back-cast	129%	83%	106%

Projected change in real suppression expenditures by mid-century (fiscal years 2041-2059)

Compared to:	Forest Service (FS)	Dept. of Interior (DOI)	Combined FS & DOI
Observed climate	16%	57%	22%
Modeled, climate back-cast	109%	48%	83%

Projected change in area burned by late-century (fiscal years 2081-2099)

Compared to:	Forest Service (FS)	Dept. of Interior (DOI)	Combined FS & DOI
Observed climate	244%	226%	237%
Modeled, climate back-cast	306%	180%	241%

Projected change in real suppression expenditures by late-century (fiscal years 2081-2099)

Compared to:	Forest Service (FS)	Dept. of Interior (DOI)	Combined FS & DOI
Observed climate	85%	128%	90%
Modeled, climate back-cast	234%	114%	186%

Introduction

There is little doubt that changes in climate will affect wildlands, wildland fire, and suppression of fire (Abatzoglou and Kolden 2013, Abt et al. 2009, Flannigan et al. 2005, Flannigan et al. 2006, Flannigan et al. 2016, Littell et al. 2009, Littell at al. 2016, Liu et al. 2014, McKenzie et al. 2016, Mitchell et al. 2014, Prestemon et al. 2009, Riley et al. 2019, Westerling et al. 2006). Direct increases in area burned and numbers of large fires, resulting from more days with extreme fire weather, longer periods of sequential days with extreme fire weather, and longer fire seasons in many parts of the world are to be expected (Abatzoglou et al. 2021, Gao et al. 2021, Jolly et al. 2015, Lenihan et al. 2003, Riley and Loehman 2016). Natural ignition patterns may change with shifting storm tracks and lightning occurrence (Romps et al. 2014), and there are likely to be changes in human ignition patterns due to land use change. Using an approach similar to that used in Hope et al. (2016), this analysis evaluates an aggregate set of data on US Federal wildfire area burned and Federal suppression expenditures and projects both area burned and expenditures to calculate the effect of climate on Federal area burned and Federal expenditures in mid-century (2041-2059) and late-century (2081-2099). We evaluate area burned and wildfire suppression expenditures for both the USDA Forest Service (FS) and the US Department of the Interior (DOI). The FS and DOI were modeled separately because their management objectives differ, as did data availability.

Methods

Overview

This study extends similar work done in 2016 (Executive Office of the President 2016, USDA Forest Service 2016). In the 2016 study, we used the two-step model approach where area burned was projected and then projected area burned was used in a model of suppression expenditures. We take this two-step approach in the 2021 study also. However, we refined the models in terms of variables and time period and expanded the number of climate projections used. For this analysis, we were able to obtain data and project suppression expenditures for Alaska. For model fitting on wildfire to climate variables for the continental United States (CONUS), we assembled monthly data from fiscal year 1993 to fiscal year 2019 for the Forest Service and fiscal year 1993 to fiscal year 2018 for the Department of the Interior.

In the present study, the final burned area models, specified by region of the continental United States (CONUS), were Poisson pseudo-maximum likelihood (PPML) models with variables of monthly maximum temperature and vapor pressure deficit (e.g., Motta 2019).[52] This combination of variables for projected area burned performed better out of sample (random and

[52] The assumption of a constant mean/variance proportion restriction of the PPML model could have been relaxed with estimation of other functional forms. See the Variable Preselection and Model for Area Burned section for additional explanation of the choice of the PPML model.

end of series hold-out) than alternatives (linear, log-transformed area burned). Log-transformation of maximum temperature (in degrees Kelvin) and VPD in the PPML specifications slightly improved the out-of-sample goodness-of-fit (as measured by root mean squared error and bias) of the area burned projections compared to leaving temperature and VPD untransformed. Each CONUS region of the Forest Service and each corresponding collection of lands managed by the Department of the Interior defined by the boundaries of each CONUS Forest Service region, was allowed to differ in its relationship of area burned to climate variables.

For model fitting on suppression expenditures, we had consistent monthly data for each region of the Forest Service from 2005-2020. For DOI, suppression expenditures were available only in aggregate across the entire agency, 2013-2020. We considered evaluating suppression spending using preparedness levels, but the preparedness level (PL) time series was short, and the use of PL's would have required development of a new method to project them to 2100, which was beyond the scope of this study.

<u>Variable Preselection and Model Formulation for Expenditures</u>

We initially tested linear models of suppression expenditure as a function of area burned to test for model feasibility, and we found that these models performed well, particularly when compared with univariate time series models (i.e., modeling spending as a function of lags of spending and seasonal components). For the Forest Service, we considered fixed-effects three-staged-least squares models of area burned, an approach used in the 2016 effort, but opted to exploit the greater frequency of expenditure data (as monthly) and specify expenditures separately for each of FS regions 1-9 with two-stage least squares (2SLS) methods, with expenditures in the region as a function of instrumented current month area burned in the region and the two most recent months' lags of area burned in the region. Instruments current month area burned were the current number of fires reported and the current month natural log of human population of counties (U.S. Census Bureau 2021) containing national forests in the region. For Forest Service Region 10 (Alaska), expenditures were statistically unrelated to area burned and, given that they have been historically relatively low compared to the agency overall, averaging $1.4m/year, 2005-2020, they were modeled as a function of a constant only. For the Rest of the Forest Service (covering national contracts, the Washington, DC, office, and research stations), expenditures were also modeled as a function of the current month area burned on all national forests in regions 1-9, with current area burned instrumented by the total number of wildfires on national forests in regions 1-9 and the natural log of the sum of the population of counties containing national forest lands across each of the Forest Service regions 1-9. Because Department of the Interior expenditures were not available for physical regions like the Forest Service, total nationwide DOI expenditures, also reported monthly, were modeled with 2SLS methods, with expenditures specified as a function of current month area burned (instrumented with the number of wildfires on DOI lands across all of CONUS and the natural log of population in counties containing DOI lands in CONUS—i.e., excluding Alaska and Hawaii).

Because stationarity is required for regressors in the models described above, we also carried out several tests (augmented Dickey-Fuller, DFGLS, Phillips-Perron) of stationarity of the time series of real dollar monthly expenditures at the regional level for the Forest Service and the national level for DOI. All Phillips-Perron stationarity tests rejected a unit root at stronger than 1% for all Forest Service regions, Rest of Forest Service, and for the aggregate of DOI expenditures. Dickey-Fuller generalized least squares tests rejected stationarity for FS regions 1, 2, 8, 9, 10, and RFS when specifying lagged difference terms using the Schwarz Information Criterion but less commonly under other optimization criteria. We therefore evaluated the existence of long-term stable relationships (cointegrating relations) between RFS spending and CONUS area burned on Forest Service lands, and between DOI spending and CONUS area burned on DOI lands with a Johansen cointegration rank test for these two series. Rank tests could not reject nulls of no cointegration. Given the non-confirmatory test outcomes on cointegration, as a further examination of the possibility that expenditures were nonstationary, expenditures for RFS and DOI in aggregate were each modeled in first-differences, regressed on the first-differences of current and two months' lags of CONUS area burned. Tests with a small number of Monte Carlo iterations with those specifications produced unstable long-term projections (to late-century), with increasing variance and even negative expenditures projected for DOI. We therefore retained models of expenditures in levels as a function of area burned in levels for the projections reported here.

With monthly data on expenditures, it is natural to consider the existence of seasonal effects in spending that need to be accounted for. However, for the expenditures of the Forest Service and DOI, in nearly every case in every region, seasonality—measured with month indicator (dummy) variables—was found to be not statistically significant, after controlling for area burned. Therefore, we ignored potential seasonality in our expenditure models.

Finally, given the possibility of serial correlation in spending, we tested for residual serial correlation in the second stage equations of our suppression expenditure models. Durbin-Watson tests on the residuals confirmed nonsignificant serial correlation.

<u>Variable Preselection and Model Formulation for Area Burned</u>
Given accepted research, it has been shown that area burned in the United States can be adequately and accurately modeled as a function of temperature, moisture, and a variety of indices that derive from those two variables that determine flammability and rate of spread of wildfire. We tested a suite of climate variables that have been projected into the future by the Global Climate Models, downscaled using the Multivariate Adaptive Constructed Analogs (MACA) process (Abatzoglou 2013, Abatzoglou and Brown 2012). These climate variables included monthly average of daily maximum temperature, monthly total of daily precipitation, monthly average of vapor pressure deficit (VPD) and monthly total potential evapotranspiration

(PET). In the 2016 study, the single climate variable selected for inclusion in the 2016 model was the fiscal year annual average of daily maximum temperature. However, with the longer historical timeline, we chose to use monthly, regional observations as the basis for the area burned models for each agency. We tested the strength of the relationship between area burned and other climate variables in addition to temperature. Temperature has been shown to influence fuel moistures, fire season length, extreme fire weather, and lightning and storm tracks—all conditions that are known to influence area burned (Flannigan et al. 2009, Flannigan et al. 2016, McKenzie et al. 2004, Mueller et al. 2020, Romps et al. 2014, Wang et al. 2016). Abatzoglou and Kolden (2013) state that area burned is influenced by temperature, precipitation, and drought but contend that using temperature is merely a proxy for the many ways climate can influence wildfire. Precipitation has also been shown to have a strong link with area burned, particularly when standardized to percentile across an observed period (Abatzoglou and Kolden 2013, Holden et al. 2018, Keeley and Syphard 2017, Mueller et al. 2020, Riley et al. 2013). While we did test total monthly precipitation, we chose not to test the percentile of precipitation; finding a way to combine historical and projected data to provide reasonable percentile precipitation estimates by region and month may prove fruitful but was not completed in this study due to time constraints. Vapor pressure deficit (VPD) is a metric incorporating both temperature and relative humidity. VPD indicates how much moisture is in the air relative to the maximum amount of moisture that the air could hold. VPD has also been shown to correlate strongly with large fire events and area burned (Mueller et al. 2020, Seager et al. 2015, Williams et al. 2019). PET was included as a candidate variable because area burned has been found to correlate with drought (Abatzoglou and Kolden 2013, Lammon et al. 2014, McKenzie et al. 2017, Riley et al. 2013). We had initially hoped to include Energy Release Component (ERC) as a candidate variable due to its high documented correlation with area burned (Riley et al. 2013, Riley and Loehman 2016), but the computational time required for obtaining forecasts of ERC at spatial and temporal scales suitable for our analysis were beyond the study timeframe.

Research on human-caused fires indicates that local population and income can influence ignitions (Mercer and Prestemon 2005, Prestemon et al. 2013) and area burned (Prestemon et al. 2016). In addition, anecdotal evidence implies that as population increases, buildings and other structures increase, which diverts suppression efforts from land protection to point protection. This, too, could lead to increases in area burned, all else held constant. Increases in income are hypothesized to influence the extent of local power and influence, which has been shown to lead to increased suppression expenditures (Donovan et al. 2011). Such effects have been identified at small spatial scales, at the level of the county or smaller. However, less research exists on such relationships at such large spatial scales as whole collections of national forests (e.g., FS regions). Testing of area burned models that included population in the counties containing national forests or DOI lands revealed no significant effects. We estimated Poisson pseudo-maximum likelihood (PPML) models of regional area burned as a function of the level and first-difference of regional human population. Significances were uncommon across the 8 physical FS regions and 8 physical DOI regions and signs on parameter estimates were not consistent. Absence of evidence does not provide evidence of absence: population estimates in counties contain errors, and changes between months within the short time series of years therefore are unlikely to provide accurate information on the effects of humans on spending at the scale of the region. We concluded that the area burned in an entire region and the population in the counties of that region may not have been as spatially connected as would be required to identify significant effects of population on wildfire (and its spending).

Modeling of area burned should address the zero bound on area burned. One way to recognize this is through either log-transformation of area burned (assuming no months with zero area burned, in our case) or the application of models such as the Tobit or pseudo-Poisson maximum likelihood specifications. We evaluated linear models (which ignored zero-truncation) and PPML models under out-of-sample forecasting conditions over historical data. We found that PPML models out-performed linear models and avoided the possibility that projected area burned would be negative. We did not test all alternative functional forms that would recognize zero-truncation of the dependent variable (area burned). However, we tested the fit of a Negative binomial maximum likelihood (NBML) model. The NBML model had a slightly better fit out-of-sample, but random samples drawn during Monte Carlo simulation using that functional form sometimes did not allow for convergence of the likelihood function, making the method less reliable for simulations. Therefore, we opted to model area burned as using PPML models, as a function of monthly maximum daily temperature in degrees Kelvin, transformed by the natural logarithm, and monthly average vapor pressure deficit, also log-transformed. Exceptions to the two variable specifications were made for FS regions 3 and 5, where maximum temperature was dropped, and DOI regions 4, 5, and 6, where VPD was dropped.

The models we selected projected area burned as a function of the monthly average of maximum daily temperature and the monthly average of vapor pressure deficit (VPD). This combination of variables for projected area burned, although very highly correlated in the historical time series ($r > 0.92$ in all regions evaluated), performed better out of sample (random and end of series hold-out). Log-transformation of maximum temperature (in degrees Kelvin) and VPD (in kPa) slightly improved the out-of-sample fitness of the area burned projections. Modeling area burned requires some strong assumptions, that, in the face of a changing climate, could be difficult to justify. We expect climate change to alter forest and range ecosystem compositions, and vegetation changes will, in turn, alter how many acres burn and how often and intensely they burn. In this analysis, because hazardous fuels are not directly modeled, our models carry an assumption that these vegetation changes *will not matter* to either area burned, nor to the expenditures we make to suppress wildfire. It is possible that, to the extent these changes have already begun to occur across Federal wildlands, our models incorporate some of these changes in ecosystems, but we cannot test this possibility using an aggregate model structure alone.

Likewise, our projections assume that parametric relationships only account for the effects of wildland hazardous fuels management efforts that have been taking place in the historical time period. Because we do not include variables directly indexing such management, no what-if scenarios were carried out that would evaluate how Federal efforts to accelerate rates of hazardous fuel reduction would affect wildfire and suppression spending. Detailed vegetation modeling would be required to determine the extent to which climate-induced and management caused changes in hazardous fuels would occur and therefore have effects on wildfire and suppression expenditures.

Data

Temporal and geographic extent: The expenditure data are monthly, based on the Federal fiscal year (October 1 to September 30). We divided the United States into regions that coincide with the USFS regions and roughly with the Geographic Area Coordination Centers of the National Interagency Fire Center. Climate data is monthly also and is aggregated to these regions based on Federal lands only. Socioeconomic data is aggregated to regions based only on counties which include Federal lands. Fire data, also monthly, is based on actual fire ignition locations from the FPA FOD (fiscal years 1993-2018) (Short 2021). Monthly expenditure data for DOI are available nationally, while consistent monthly data for the FS are available nationally for fiscal years 2005-2020 by Forest Service Region, whose regional boundaries closely match GACC boundaries. Given the varying starting and end-dates of wildfire and suppression data, model data used in this study were truncated at the end of fiscal year 2018.

We used the Forest Service's 2020 Resources Planning Act Assessment (RPA) climate projections, which comprise 5 climate models projecting under the Representative Concentration Pathways (RCPs) RCP 4.5 and RCP 8.5 scenarios (Langner et al. 2020). The RPA climate data set is a subset of the MACAv2METDATA set (Abatzoglou and Brown 2012, Abatzoglou 2013). 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. The MACA method is a statistical downscaling method that uses historical observations to remove historical biases and match spatial patterns in climate model output.

The RPA data set contains the historical data (METDATA, 1979-2015), and the historical modeled data (1950-2005) and the future projections (2006-2099) (MACAv2-METDATA) for 5 climate models under two Representative Concentration Pathways (RCP 4.5, 8.5) (Table B1). Five climate models were selected to capture the future (2041-2059) range of the 20-model MACAv2-METDATA set (Langner et al. 2020). Rather than use an ensemble, a model that projected future change near the mean of all 20 projections was selected: NorESM1-M. The five models reflect the hottest projection (HadGEM2-ES365), the least warm projection (MRI-CGCM3), the wettest projection (CNRM-CM5), the driest projection (IPSL-CM5A-MR), and the middle of the range projection (NorESM1-M) (see http://maca.northwestknowledge.net/GCMs.php for detailed descriptions of these models). The data set and metadata are available at:

Historical: https://www.fs.usda.gov/rds/archive/catalog/RDS-2017-0070-2

Projections: https://www.fs.usda.gov/rds/archive/catalog/RDS-2018-0014

For this project, we added monthly vapor pressure deficit from MACAv2METDATA to the RPA historical and projected climate data sets. We also added four years' worth of monthly data to all variables in the RPA historical data set (2016-2019) from GRIDMET, which is the data set from which the RPA historical data were derived (Abatzoglou 2013).

We generated regional and national averages, monthly and annual, for maximum daily temperature, average VPD, total PET, minimum daily relative humidity, and the sum of daily precipitation. We created regional monthly averages by first converting all daily or monthly spatial data to Albers Equal Area Conic to ensure grid cells from differing datasets matched, and included only grid cells corresponding to Federal lands (USDA Forest Service or DOI) (Snyder 1987).

Most of the global climate models available in the MACAv2 data set have been evaluated for their performance relative to historical climate observations. Based on the analysis by Sheffield et al. (2013), at the conterminous US scale, the models that had the least bias in temperature included MRI-CGCM3, used in this study. For precipitation, the models with the least bias included CNRM-CM5 and NorESM1-M, used here. At the regional scale, the models that performed best included IPSL-CM5A-LR, used in this analysis. Simulations of the 20th century by CMIP5 models have been conducted for regions of the United States: Pacific Northwest (Rupp et al. 2013), Southeast (Rupp 2016), and for the Southwest (Rupp Pers. Comm.). Based on these regional analyses, the top five models, based on 18 metrics, included CNRM-CM5 and HadGEM2-ES, used in this analysis.

Figure B-1 shows the historical and projected maximum temperature and vapor pressure deficit area-weighted for nationwide by agency for the observed period and all modeled periods. The values of each variable during each time period differ by agency, but there are some trends to note. First, for both variables, values are higher for DOI lands than for Forest Service lands in the observed and backcast data, and that remains the case in the future periods. Second, for each agency, the median values across the ten futures for both variables are greater in the two future periods than for the backcast and observed periods, indicating increasingly hotter temperature extremes, and drier conditions expected on average. Compared with backcast values, maximum monthly temperatures for both DOI and Forest Service lands are expected to increase by nearly 2 degrees by mid-century and more than 3 degrees by late century on average across the 10 futures, with the greatest increases projected under the hottest (HadGEM2-ES365) and driest (IPSL-CM5A-MR) projections under RCP 8.5 for both agencies. Average projections of VPD for the U.S. across the ten futures show expected increases by 0.1 kPa at mid-century and 0.2

kPa at late century for Forest Service lands, and by 0.2 and 0.3 for DOI lands for the two time periods, respectively. In all cases for both variables and both agencies, the range in average values across the ten futures for the U.S. is greater at late century than for mid-century, corresponding with increasing uncertainty in the climate model projections over time. While the projected values for both variables differ by region, there are consistent trends by region (Appendix Figures B-1 and B-2). Increases in both maximum temperature and VPD are also expected for each region at mid-century and late century. Average projected maximum temperature was greatest in the Southern region for both agencies at mid-century and late century, while the greatest increases in maximum temperature were projected in the Eastern region. For VPD, on average across the ten futures, the greatest values were projected for Forest Service lands in the Southwestern region and for DOI lands in the Pacific Southwest, while the greatest increases were projected for both agencies' lands in the Southwestern region.

Area burned (in acres) and number of fires were provided by Karen Short from the Fire Program Analysis Fire Occurrence Database (Short 2021). This dataset includes point locations, discovery dates, and final area burned estimates from individual agency fire reports estimates that were aggregated by month and jurisdictional agency for FY1993 to 2018. Additional FS data for FY19 were obtained from FIRESTAT, as noted above. We were unable to acquire and properly compile additional FY19 data from DOI due to time constraints. We used area burned for CONUS (excluding Alaska) for both FS and DOI expenditure modeling, although we also projected Alaska spending for the Forest Service separately without making projections of area burned. Although spending in Alaska (Region 10) for the Forest Service is low, averaging less than $1m/year, wildfire area burned on DOI lands in Alaska are more significant. Alaska represents a significant acreage in many years (averaging 37%, 1993-2018, but ranging from 3% to 93% of total DOI area burned), but a much smaller expenditure (we only have five years of expenditure data by region, but the average is 8%, and the range is from 4-14% of total DOI expenditures). With this level of variability, and a clear disconnect between area burned and expenditures, along with inadequate data for modeling Alaska expenditures separately, we chose to not model area burned in Alaska and used projected CONUS area burned as the dependent variable in projecting total nationwide expenditures for both DOI and expenditures only for non-region spending for the category Rest of Forest Service. For Forest Service regions, 1-9, however, we model expenditures as a function of each region's area burned. For Forest Service Region 10 (Alaska), we model it as simply a constant.

Suppression expenditure data: All expenditures are in constant 2020 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 Forest Service were monthly, 2005-2020. For the Department of the Interior, data were also monthly, 2013-2020. The national level data are from NIFC, and the FS regional data are derived from historical reports, the Foundation Financial

Information System (FFIS) database (2005-2012), and the Financial Management Modernization Initiative (FMMI) since 2012.

Projections

To generate a no-further-climate change average for area burned and expenditures for 2006-2018 for FS and DOI, we averaged the historical data. In addition, we produced a median of the backcast of the regression models using historical modeled climate variables. The projections for midcentury represent an average of 2041-2059, and late-century are an average of 2081-2099 (the year 2100 is not included in the MACA dataset).

We used the projected climate data in our selected models to generate future area burned for midcentury and late-century, and then used area burned in the expenditure projections. We also calculated a change in area burned from recent to the two future periods. There are two possible methods of projecting with the climate values from the GCMs: (1) use the historical observed data as the base and use the projected climate data to estimate the change, or (2) use the climate model backcast projection as the base and the projected data as the change. We report both in this document.

The Monte Carlo simulations involved (1) randomly sampling from monthly observations of area burned and backcast historical climate over fiscal years 2006-2018, monthly observations of FS suppression expenditures over fiscal years 2006-2018, and monthly observations of DOI suppression expenditures over fiscal years 2013-2018; (2) estimating statistical relationships for area burned and suppression spending with the randomly sampled data; (3) projecting area burned and spending through fiscal year 2099 with the estimated parameters; and (4) repeating steps (1)-(3) 500 times for each of the climate projections (each of the 10 GCM x RCP combinations). Monte Carlo projection results are summarized 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 10 climate projections. We generated projected expenditures and area burned for each of the climate models. Results were also summarized in tabular form, reporting historical observed, historical modeled (fiscal years 2006-2018) for area burned and expenditures for the Forest Service and DOI and their total, including 80% and 90% upper and lower bounds and medians for mid-century and late-century.

Results

Area burned modeling results

Area burned model estimates are reported in Table B-1. Models indicate good fit and high significance of both maximum temperature and VPD. Constant terms are also significant in most cases. Pseudo-R^2's indicate that a sizeable portion of historical variation is explained by the data in most regions for both agencies. Generally, VPD is positively related to area burned. In cases when maximum temperature is included as an additional predictor, maximum temperature is negatively signed. In cases when VPD is not present (DOI regions 4, 5, and 6), maximum temperature is positively signed. Because maximum temperature is positively correlated with VPD, the latter set of results is expected. For any given value of VPD, a lower temperature means that relative humidity is lower, and thus fires would be expected to burn hotter.

Expenditure modeling results

Expenditure equation estimates are reported in Table B-2. Models indicate that current month area burned and two lags of area burned are usually significant for each region or aggregate modeled. Because the two lags were not significant in initial estimates of the Rest of Forest Service model, those lags were dropped for reporting and for models used in Monte Carlo projections.

Projections

Area Burned Projections

Area burned projections for the FS and DOI in aggregate are shown in Figures B-2 through B-4. (Regional detail of median area burned across all climate projections is presented in Appendix figures C-3 through C-6.) In the left panel of each of these figures is reported the median and the upper and lower bounds of an 80% confidence band for the total of FS plus DOI (48-state CONUS). The confidence bands only account for parameter uncertainty in the regional area burned models across the ten climate projections. In the right panel in each is the median for each of the ten climate projections. Figure B-2 is for total (FS + DOI), Figure B-3 is FS only, and Figure B-4 is DOI only. In all figures, it is apparent that late-century area burned varies widely across projections, with the highest area burned projected by the HadGEM2-ES365 (hot) climate model under the RCP 8.5 scenario. The lowest area burned projections emerged from the least-warm model, MRI-CGCM3 under the RCP 4.5 scenario. The figures demonstrate clearly how late-century area burned varies widely across climate projections, a result that might have been expected, given the wide variability across projections in late-century maximum temperature and VPD (Figure B-1).

Tables B-3 through B-5 report the Monte Carlo area burned projections numerically. Tables are organized to show observed area burned over our benchmark years of 2006-2018, model projections of area burned over the benchmark years using backcast climate data from each of the GCM x RCP projections, and then projections of median area burned in mid-century (2041-2059) and late-century (2081-2099). The "All Scenario Median" and the 80% and 90% upper and lower confidence bounds reported are based on the combined 10 climate projections x 500 iterations/projection = 5,000 total iterations.

Table B-3 shows the total of area burned for the FS and DOI. Broadly, the table shows general agreement between observed area burned for CONUS (3.92 million acres/year, 2006-2018) and backcast area burned for the same period (medians of the 10 climate projections range from 3.20-4.91 million acres/year). By mid-century, when compared to observed historical area burned, area burned in aggregate for FS + DOI is projected to be 21% to 251% higher and by late-century 35% to 1929% higher. Compared to backcast historical climate, these percentages range from 22% to 201% higher in mid-century and 65% to 1641% higher in late-century. The medians across all climate projections are 104% and 237% by mid- and late-century compared to observed historical and 106% and 241% compared to modeled historical area burned.

Table B-4 reports the results for just the FS CONUS lands. Variability is similar to that shown in Table B-3. Just as for the FS + DOI in aggregate, there is wide variation across the ten climate projections. Across all ten climates for the FS, median area burned is 94% and 244% higher by mid- and late-century, respectively, compared to observed historical area burned, and 129% and 306% higher by mid- and late-century when compared to modeled historical area burned.

Table B-5 shows the same results but for DOI lands in CONUS. Here again, there is wide variation across the ten climate projections and demonstrates the same trends as reported for FS lands in CONUS. Compared to observed historical (2006-2018) area burned in CONUS, DOI median area burned in CONUS is projected to be 114% and 226% higher by mid- and late-century, respectively. Compared to modeled historical, median area burned is projected to be 83% and 180% higher in mid- and late-century, respectively.

It is notable that the median values for area burned, 2006-2018, using backcast climate (maximum temperature, VPD) variables (second column of values in tables B3 through B5) reveal possible statistical biases produced by each of the climate projections (GCM x RCP scenario). Combined FS + DOI (Table B-3) has little overall bias when measured by the "all projections median" value (3.88 million acres/year) versus the observed value (3.92 million acres/year). For the Forest Service, however, the backcast projections tend to under-predict in the 2006-2018 benchmark period (1.51 million acres/year backcast versus 1.79 million acres/year observed), while the opposite is shown for DOI (2.33 million acres/year backcast versus 2.00 million acres/year observed). Because no climate projection can perfectly predict the backcast values of all climate variables, the lack of perfect alignment of median backcast predictions with the historical area burned is not unexpected, although particular GCMs tend to predict lower and others higher than the observed area burned. For example, the "least warm" model (at RCP 4.5 and 8.5) predicts the lowest, while the "dry" and "hot" models (at 4.5 and 8.5) predict the highest in the 2006-2018 backcast for both FS and DOI. Those tendencies to predict low or high might in part explain the lower and upper ranges of projected area burned outcomes projected for mid- and late-century shown in the tables.

<u>Expenditure Projections</u>

Graphs showing projections of expenditures are reported in figures B-4 through B-6. Just as for area burned, each figure has a left panel showing the median and 80% upper and lower bound projections of expenditures across all 10 climate projections, while the right panel in each shows the median projections for each of the 10 climate projections. Clear in all cases is that the high variability, particularly in late-century, in area burned is translated into high variability in projected expenditures.

Data from the graphs are summarized in tables B-6 through B-8. Data in the tables are reported in the same way as for area burned projections, enabling comparisons between annual totals of area burned observed and projected in the benchmark historical period of 2006-2018. Like for area burned, the "All Scenario Median" and the 80% and 90% upper and lower confidence bounds reported are based on the combined 10 climate projections x 500 iterations/projection = 5,000 total iterations. As reported in Table B-6, in mid-century compared to observed historical, median expenditures (in 2020 dollars) range from 24% lower to 121% higher, and for late-century 16% lower to 1353% higher. Compared to modeled historical, they range from 26% higher to 190% higher by mid-century and 42% to 1805% higher when compared to modeled historical. In aggregate across FS + DOI, median projected real expenditures across all ten climate projections are 22% and 90% higher by mid- and late-century, respectively. When compared to projected expenditures, they are 83% and 186% higher for mid- and late-century, respectively.

Tables B-7 and B-8 document how variability across projections in future expenditures is connected closely to variability in area burned. Across all climate projections, FS (Table B-7) median suppression spending is projected to be 16% higher and 85% higher in mid- and late-century compared to observed historical and 109% and 234% higher when compared to modeled historical. Comparable figures for DOI (Table B-8) are 57% and 128% higher in median suppression spending by mid- and late-century, respectively, when compared to observed historical and 48% and 114% higher when compared to modeled historical spending.

Discussion and Conclusions

The models developed here show that expenditures respond to changes in area burned as expected, and that area burned increases with increasing vapor pressure deficit and, in some cases, average maximum temperature. Area burned is projected to increase by double or triple-digit percentages across most of the ten projections we evaluated. Real dollar suppression expenditures are projected to increase by similarly large percentages.

While vapor pressure deficit and temperature are only two of several climate measures that have been linked to wildfire area burned, we found that unbiased backcasts of area burned and expenditures could be obtained from parameterizing these simple relationships. However, model simplicity likely trades off with higher uncertainty in making projections, so definitive conclusions about the long-run status of wildfire and associated suppression on Federal lands in the United States may not be warranted without acknowledgment of these uncertainties. In the following section, we detail several reasons why uncertainty is large when envisioning the evolution of wildfire and expenditures.

Wildfire area burned and suppression spending display high uncertainty in their projected futures, particularly by late-century. We note that actual FS spending (and total FS + DOI spending) since 2015 has exceeded even the 80% uncertainty upper bound modeled in this report, hinting that structural changes might be underway that will lead to spending that remains well above projected median levels indefinitely. Additional modeling, perhaps directed at finer spatial scales and accounting more directly for hazardous fuels, could reduce uncertainties and help to reduce biases in model predictions. Nevertheless, it is possible that, even with improved models based on historical data, there will be structural changes in how fires burn under novel climates and novel vegetation assemblages, how fire managers apply suppression resources under shifting wildfire regimes, and in the unit costs of suppression resources over time. Such changes would imply that the projections reported here provide progressively less useful guidance, moving from mid- to late-century.

Caveats and Assumptions

Our models involve a number of assumptions, violation of any of which would alter both the projected changes in spending and the ranges of our confidence bands. These assumptions, loosely grouped into aggregation bias (over space and time), omitted variable bias (including climate, fire and socioeconomic variables) and modeling limitations, are discussed in more detail below. Even with these caveats and assumptions, however, our models, along with the literature we have cited (and much that we have not) provide evidence that both wildfire extent and suppression expenditures are expected to increase with climate change. Our models, specifically, show that vapor pressure deficit and/or temperature can account for significant increases in area burned and that expenditures increase with increases in area burned.

<u>Aggregation</u>

The statistical models of area burned and of suppression spending are estimated using data aggregated to regions and nationwide. Such aggregation, in the presence of heterogeneity in area burned and spending processes, would bias parameter estimates in unknown directions. Aggregation across space and time can interact with biases associated with omitted variables (next caveat), resulting in findings of insignificance when in fact significant effects exist (i.e., it can raise statistical Type II error rates). For both the FS and the DOI models of area burned, the fact that each region's area burn function was estimated separately allowed for the relationship between wildfire and climate to differ across regions. Even so, the assumption involved for the reported models is that fine-scale (finer than region level) wildfire area burned responds identically to climate variables within that region. The FS models of the relationship between suppression spending area burned were also allowed to vary across regions, but they still forced the spending-burn relationship (i.e., real dollars per acre) to be constant within each region. For the Department of the Interior, because total departmental spending was modeled as a function of total area burned, the spending relationship to area burned implied constant spending per acre. A similar forcing assumption was implied by non-regional spending of the Forest Service.

Omitted variables

Our statistical models of area burned and expenditures are parsimonious, with area burned specified as a function of monthly maximum daily temperature and/or vapor pressure deficit. There is little doubt that potentially influential variables are omitted in our chosen specifications. Thus, these models assume that any omitted variables are orthogonal to the included variables, so that errors in projections are contained in error terms that are unrelated to the included variables. Alternatively, it could be that the omitted variables are perfectly correlated with the included variables, in which case parameter estimates for included variables completely contain the effects of the perfectly correlated omitted variables, and no bias would exist in resulting projections.

One key factor potentially missing from the suppression spending models is direct attention to human populations, which can lead to higher demands to protect property at the expense of area burned and which can affect the distributions of aggregate wildland fuels. In addition, a specific kind of omitted variables bias would emerge if past wildfires are negatively related to future wildfires in the same locations, then wildfire area burned modeled without attention to this process would be biased upward compared to reality. Although we tested for the relationship between spending and human population levels and changes and found inconsistent and usually non-significant effects, it is still possible that finer scale modeling of area burned could reveal robust effects.

Recent research has concluded both that temperature is a reasonable measure of climate change, but also that temperature is an insufficient measure of climate change influences on wildfire. In a statistical analysis of the relationship between meteorological variables and area burned in Canada, Flannigan and Harrington (1988) found that long sequences of days without rain, low relative humidity, and maximum temperatures were the best predictors of area burned, while rainfall and number of dry days per month were not significant. Romps et al. (2014) evaluated the impacts of climate change on lightning and found that (a) the precipitation projections do not show overall increases that would lead to increased lightning, and (b) increased temperature is the major controlling factor leading to increased lightning projections. Temperature has been shown to lead to a need for additional precipitation to hold fuel moistures constant (Flannigan et al. 2016). This results from the changes in amount of water the air can hold at higher temperatures—as temperatures increase the air can hold more water, which leads to drying of fuels, even if precipitation stays the same. Flannigan et al. (2016) also conclude that increasing temperatures lead to an increased number of extreme fire weather days.

For these analyses, we relied on mapping the association between temperature and vapor pressure deficit and area burned into the future. However, the association between temperature and area burned has been demonstrated to be relatively weak in the absence of some form of a dryness metric (Littell et al. 2009). It is reasonable to expect that temperature is only one, and perhaps not the most important one, of the climate variables affecting wildfire. However, this is a testable, and as yet untested, hypothesis in relation to projecting aggregate wildfire extent and expenditures. We show here only that temperature and vapor pressure deficit are significant, in the absence of other climate measures, in affecting area burned. The combination of VPD and maximum daily temperature in our models increased the goodness-of-fit of our models out-of-sample compared to inclusion of these and other combinations of variables and also when those measures were excluded.

In our models, many variables found in other research to affect both wildfire and suppression were assumed constant throughout the projections, when it is unlikely that constancy will be maintained to the end of this century. Thus, each of these assumptions represents an omitted variable. We assumed that wildfire suppression strategies and technology do not change, and so we did not need to include variables representing that change. We assumed that suppression will not become more or less effective at limiting wildfire. We assumed that wildland fuels management rates remain unchanged, in relation to overall wildfire activity. Research shows that management of aggregate fuels on landscapes can affect how wildfires burn, likely affecting suppression productivity and hence area burned or other damages upon which suppression is focused (Loudermilk et al. 2014, Mercer et al. 2005, 2007; Thompson et al. 2013). However, Bessie and Johnson (1995) compared the composite influences of fuels and climate and concluded that climate was the driving force in year over year changes in area burned. Nevertheless, the lack of direct statistical accounting for the effects of climate or management efforts to reduce hazardous fuels adds a degree of uncertainty to the projections that may not be reflected in our projections. Furthermore, models assume that allocations of suppression efforts across threatened people, property, and resources will be allocated in the same ways, in response to wildfire, as they have in the past. Because historical data on suppression spending and area burned reflect averages of policies to protect people, property, and resources, substantial changes in the ratios of these variables threatened by wildfires in the future could affect spending in ways not accounted for in our projections.

In this analysis, the general approach and structure of wildfire management was assumed constant over time. However, consequences to wildfires and costs from climate changes are outside the range of reliable futuring over long time frames, except that new climates will modify human activities and probably require alternative management approaches. Even within the near future (10 to 20 years) analyzed in the Quadrennial Fire Review (QFR) (https://www.forestandrangelands.gov/QFR/documents/2014QFRFinalReport.pdf) there exists "a strong possibility that today's regional wildland fire management dynamics will shift as a result of climate and environmental factors". Furthermore, the QFR identified the potential for a shock-type wildfire event to instigate a fundamental realignment of Federal land and fire management functions that would clearly alter the relationship between area burned and management cost. It is doubtful that biologists and foresters in 1900 could have predicted the magnitude of wildfire sizes, behaviors, damages to human and natural resources, and costs experienced today let alone the types of equipment and suppression responses that occur. Due to the increased uncertainty of both natural and human consequences of future climate, future management cost projections should be evaluated with caution.

We also assume constant socioeconomic variables, including prices, population, and income. If the per-unit cost of labor, capital, and other purchased inputs into suppression production were to rise at a rate higher than inflation, then suppression expenditures would tend to be higher, possibly also leading to lower overall suppression effort and then to greater area burned. Generally, wages and capital costs have not been rising faster than inflation in the last 20 years. However, as the economy and overall wealth grows, these per-unit prices of these inputs might.

Our projections indicate that, under some climate projections, area burned would increase several fold over historical rates. As the projected annual area burned increases, however, this means that substantially more acres would need to reburn, or that wildfire would need to move into areas that historically have not burned, in order for these fires to have adequate fuel. Thus, our models would overestimate the projected area burned, at least in forested landscapes. Conversely, in drier, range ecosystems, it is possible that increases in burning rates could lead to the potential for more fire, as reburning rates are expected to be higher in these ecosystems. For these ecosystems, our models would underestimate the projected area burned. It is not known at what burning rate these limiting conditions would be reached in either forest or range ecosystems. Hope et al. (2016) capped their Canadian area burned estimates assuming a 20-year fire return interval, equivalent to burning 5% of the wildland each year. Our results suggest that by late-century, an average of nearly 6 million FS acres per year could burn, or about 3% of all FS land, and we felt we had little justification for, in the absence of a statistically modeled relationship, artificially capping our area burned estimates. Additionally, because the United States has wide variation across ecoregions in wildfire return intervals (Greenberg and Collins 2021), simple solutions such as artificial caps would possibly add more uncertainty to our projections, not less. It is possible that such relationships can be estimated, which would be an area worthy of additional study and modeling efforts.

Modeling

We assumed that the included information from climate projections was adequate to capture uncertainty regarding the effects of temperature and vapor pressure deficit on area burned on Federal lands. We assumed that these systems could be approximated by an exponential relationship, with no significant biases or added uncertainty due to spatial autocorrelation and no significant effects of our assumption of mean-variance proportionality. More fundamentally, because our models could only be based on historical relationships among variables, we assume that those relationships will endure to the end of the century. Our models make long-run projections, without evaluating which factors that are typically assumed fixed might be variable in the long-run, such as fire regimes, biomes, and suppression strategies. In addition, even at aggregate scales, the highly-modified forest and grassland ecosystems of U.S. Federal lands may not bear much relation to either natural ecosystems or to ecosystems expected in the distant future under climate change (McKenzie and Littell 2016).

Any model is an abstraction, a simplification of reality. In this analysis, we used only five climate models under each RCP scenario. Thus, we assumed that five global climate model realizations of future climate under the increased radiative forcing of either 4.5W/m^2 or of 8.5W/m^2 were sufficient to capture uncertainty regarding the temperature and climate futures on Federal lands. Undoubtedly, additional projections under each RCP would have narrowed the variability in the future. However, these five climate models allow us to explore a hot versus a warm future and a wet versus a dry future. The large end of century projections by the Hadley model under RCP 8.5 portend hot temperatures and increased wildfire area burned. In contrast, the Least Warm model (MRI-CGCM3) projects the least change in area burned. While our Monte Carlo simulations address uncertainty in the estimated coefficients as well as uncertainty reflected in the multiple GCM temperature projections, we did not incorporate any within-GCM uncertainty. The assumption here is that the multiple models can proxy for uncertainty within the GCMs.

Uncertainty in wildfire projection exists even at the incident level, over the timeframe of hours to days, and is compounded when working at decadal or century-long scales (Riley and Thompson 2016). One reason for compounding uncertainty is that shifts in vegetation assemblies and even biomes are likely during this timeframe due to climate change, meaning fire regimes will also shift (Lenihan et al. 2003, Loehman et al. 2014). Take, for example, the changes in fuels and vegetation documented since the turn of the 20th century (Loope and Gruell 1973, Gruell 1983, Gruell 2001). By first removing Indian burning (Lewis 1973, Barrett 1980), and then attempting to remove wildfires, European settlement altered vegetation composition and structure, insect outbreaks, and wildfire behavior beyond recognition in just 100 years of relatively subtle climate changes. Feedbacks between shifting vegetation assemblies, changing climate, and altered ignition patterns will be complex and may produce no-analog states.

Caveat summary

Wildfire and fire management, including suppression, is a complex system where individual factors interact in complex, non-linear, unpredictable ways. What happens in one component of the system will cascade through the system altering other components, and these cascades are multidirectional. Climate change is expected to influence ignition patterns, fire weather, ecological community composition, local community development, and our willingness and ability to manage wildfire. Each of these changes will reverberate through the system, adding uncertainty about the future of wildfire and suppression spending that may not be adequately captured by the simple statistical relationships that drive the results presented in this study.

Literature Cited

Abatzoglou JT. 2013. Development of gridded surface meteorological data for ecological applications and modelling. International Journal of Climatology 33:121–131. Doi:10.1002/joc.3413

Abatzoglou JT, Brown TJ. 2012. A Comparison of Statistical Downscaling Methods Suited for Wildfire Applications, International Journal of Climatology 32(5):772–780. Doi:10.1002/joc.2312

Abatzoglou JT, Kolden CA. 2013. Relationships between climate and macroscale area burned in the western United States. International Journal of Wildland Fire 22:1003–1020. http://dx.doi.org/10.1071/WF13019

Abatzoglou JT, Juang CS, Williams AP, Kolden CA, Westerling AL. 2021. Increasing synchronous fire danger in forests of the western United States. Geophysical Research Letters 48(2):e2020GL091377. https://doi.org/10.1029/2020GL091377

Abt KL, Prestemon JP, Gebert KM. 2009. Wildfire suppression cost forecasts for the US Forest Service. Journal of Forestry107(4):173-178.

Barrett SW. 1980. October. Indian fires in the pre-settlement forests of western Montana. In Proceedings of the Fire History Workshop. USDA Forest Service, General Technical Report RM-81, Fort Collins, Colorado (pp. 35-41).

Bessie WC, Johnson EA. 1995. The Relative Importance of Fuels and Weather on Fire Behavior in Subalpine Forests. Ecology 76:747–762. Doi:10.2307/1939341

Donovan GH, Prestemon JP, Gebert K. 2011. The effect of newspaper coverage and political pressure on wildfire suppression costs. Society and Natural Resources 24(8):685-698.

Executive Office of the President. 2016. Climate Change: The Fiscal Risks Facing the Federal Government—A Preliminary Assessment (November 2016), 73 pages. https://obamawhitehouse.archives.gov/sites/default/files/omb/reports/omb_climate_change_fiscal_risk_report.pdf

Flannigan MD, Amiro BD, Logan KA, Stocks BJ, Wotton BM. 2006. Forest Fires and Climate Change in the 21ST Century. Mitigation and Adaptation Strategies for Global Change 11:847–859. Doi: 10.1007/s11027-005-9020-7

Flannigan MD, Harrington JB. 1988. A study of the relation of meteorological variables to monthly provincial area burned by wildfire in Canada (1953–80). Journal of Applied Meteorology 27:441–452.

Flannigan MD, Krawchuk MA, De Groot W, Wotton BM, Gowman LM. 2009. Implications of changing climate for global wildland fire. Int J Wildland Fire 18: 483–507. Doi: 10.1071/wf08187

Flannigan MD, Logan KA, Amiro BD, Skinner WR, Stocks BJ. 2005. Future Area Burned in Canada. Clim Change 72: 1–16. Doi: 10.1007/s10584-005-5935-y

Flannigan MD, Wotton BM, Marshall GA, De Groot WJ, Johnston J, Jurko N, Cantin AS. 2016. Fuel moisture sensitivity to temperature and precipitation: climate change implications. Climatic Change 134: 59. Doi:10.1007/s10584-015-1521-0

Gao P, Terando AJ, Kupfer JA, Varner JM, Stambaugh MC, Lei TL, Hiers JK. 2021. Robust projections of future fire probability for the conterminous United States. Science of the Total Environment 789:147872. https://doi.org/10.1016/j.scitotenv.2021.147872

Greenberg CH, Collins B. 2021. Fire Ecology and Management: Past, Present, and Future of US Forested Ecosystems. Springer. 502 pages. https://doi.org/10.1007/978-3-030-73267-7

Gruell GE. 1983. Fire and vegetative trends in the Northern Rockies: interpretations from 1871-1982 photographs. Gen. Tech. Rep. INT-158. Ogden, UT: U.S. Department of Agriculture, Forest Service, Intermountain Research Station. 117 p.

Gruell GE. 2001. Fire in Sierra Nevada forests: a photographic interpretation of ecological change since 1849. Mountain Press. Photographs.

Holden ZA, Swanson A, Luce CH, Jolly WM, Maneta M, Oyler JW, Warren DA, Parsons R, Affleck D. 2018. Decreasing fire season precipitation increased recent western US forest wildfire activity. Proceedings of the National Academy of Sciences 115(36):E8349-8357.

Hope ES, McKenney DW, Pedlar JH, Stocks BJ, Gauthier S. 2016. Wildfire Suppression Costs for Canada under a Changing Climate. PloS ONE 11(8): e0157425. Doi:10.1371/journal.pone.0157425

Jolly WM, Cochrane MA, Freeborn PH, Holden ZA, Brown TJ, Williamson GJ, and others. 2015. Climate-induced variations in global wildfire danger from 1979 to 2013. Nature: Communications 6: 7537. Doi: 10.1038/ncomms8537. Pmid:26172867

Langner LL, Joyce LA, Wear DN, Prestemon JP, Coulson DP, O'Dea CB. 2020. Future scenarios: A technical document supporting the USDA Forest Service 2020 RPA Assessment. Gen. Tech. Rep. RMRS-GTR-412. Fort Collins, CO: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station. 34 p. https://doi.org/10.2737/RMRS-GTR-412

Lenihan JM, Drapek R, Bachelet D, Nielsen RP. 2003.Climate change effects on vegetation distribution, carbon, and fire in California. Ecological Applications 13(6): 1667-1681.

Lewis HT. 1973. Patterns of Indian burning in California: ecology and ethnohistory (No. 1). Ballena Press.

Littell JS, McKenzie D, Peterson DL, Westerling AL. 2009. Climate and wildfire area burned in western U.S. ecoprovinces, 1916-2003. Ecological Applications 19(4):1003-1021.

Littell JS, Peterson DL, Riley KL, Liu Y, Luce CH. 2016. A review of the relationships between drought and forest fire in the United States. Global Change Biology 22(7):2353-2369. Doi: 10.1111/gcb.13275.

Liu Y, Goodrick S, Heilman W. 2014. Wildland fire emissions, carbon, and climate: Wildfire–climate interactions. Forest Ecology and Management 317:80-96.

Loehman RA, Reinhardt E, Riley KL. 2014. Wildland fire emissions, carbon, and climate: Seeing the forest and the trees–A cross-scale assessment of wildfire and carbon dynamics in fire-prone, forested ecosystems. Forest Ecology and Management 317:9-19.

Loope LL, Gruell GE. 1973. The ecological role of fire in the Jackson Hole area, northwestern Wyoming. Quaternary Research 3(3):425-443.

Loudermilk EL, Stanton A, Scheller RM, Dilts TE, Weisberg PJ, Skinner C, Yang J. 2014. Effectiveness of fuel treatments for mitigating wildfire risk and sequestering forest carbon: A case study in the Lake Tahoe Basin. Forest Ecology and Management 323(1):114-125.

McKenzie D, Gedalot ZM, Peterson DL, Mote P. 2004. Climatic change, wildfire, and conservation. Conservation Biology 18:890-902.

McKenzie D, Littell JS. 2016. Climate change and the eco-hydrology of fire: will area burned increase in a warming western U.S.? Ecological Applications 27(1):26-36. doi: 10.1002/eap.1420

Mercer DE, Prestemon JP. 2005. Comparing production function models for wildfire risk analysis in the Wildland-Urban Interface. Forest Policy and Economics 7(5):782-795.

Mercer DE, Prestemon JP, Butry DT, Pye JM. 2007. Evaluating alternative prescribed burning policies to reduce net economic damages from wildfire. American Journal of Agricultural Economics 89(1):63-77.

Mitchell RJ, Liu Y, O'Brien JJ, Elliott KJ, Starr G, Miniat CF, et al. 2014. Future climate and fire interactions in the southeastern region of the United States. Forest Ecology and Management 327: 316–326. Doi: 10.1016/j.foreco.2013.12009..003

Motta V. 2019. Estimating Poisson pseudo-maximum-likelihood rather than log-linear model of a log-transformed dependent variable. RAUSP Management Journal 54 (4):508-518. https://doi.org/10.1108/RAUSP-05-2019-0110

Mueller SE, Thode AE, Margolis EQ, Yocom LL, Young JD, Iniguez JM. 2020. Climate relationships with increasing wildfire in the southwestern US from 1984 to 2015. Forest Ecology and Management 460:117861.

Parks, S.A., and J.T. Abatzoglou. (2020). Warmer and Drier Fire Seasons Contribute to Increases in Area Burned at High Severity in Western US Forests From 1985 to 2017. Geophysical Research Letters 47(22), e2020GL089858.

Prestemon JP, Abt KL, Gebert K. 2009. Suppression cost forecasts in advance of wildfire seasons. Forest Science 54: 381–396.

Prestemon JP, Hawbaker TJ, Bowden M, Carpenter J, Brooks MT, Abt KL, Sutphen R, Scranton S. 2013. Wildfire Ignitions: A Review of the Science and Recommendations for Empirical Modeling. Gen. Tech. Rep. SRS-GTR-171. Asheville, NC: USDA-Forest Service, Southern Research Station. 20 p

Prestemon JP, Shankar U, Xiu A, Talgo K, Yang D, Dixon E IV, McKenzie D, Abt KL. 2016. Projecting wildfire area burned in the south-eastern United States, 2011–60. International Journal of Wildland Fire 25(7): 715-729. DOI: http://dx.doi.org/10.1071/WF15124

Riley KL, Thompson MP. 2016. Uncertainty in modeling wildland fire. P. 193-213 In: Riley, Karin L., Matthew P. Thompson, and Peter Webley (editors). Uncertainty in Natural Hazards. New York City: Wiley and American Geophysical Union Books.

Riley KL and Loehman RA. 2016. Mid-21st century climate changes increase predicted fire occurrence and fire season length, Northern Rocky Mountains, US. Ecosphere 7(11), e01543. https://doi.org/10.1002/ecs2.1543

Riley KL, Williams AP, Urbanski SP, Calkin DE, Short KC, O'Connor CD. 2019. Will landscape fire increase in the future? A systems approach to climate, fire, fuel, and human drivers. Current Pollution Reports 5(2):9-24. doi: /10.1007/s40726-019-0103-6

Romps DM, Seeley JT, Vollaro D, Molinari J. 2014. Projected increase in lightning strikes in the United States due to global warming. Science 346(6211):851-854.

Rupp DE. 2016. An evaluation of 20th century climate for the Southeastern United States as simulated by Coupled Model Intercomparison Project Phase 5 (CMIP5) global climate models. US Geological Survey.

Rupp D E. 2016. Pers. Comm. Figures from an analysis of the Southwestern United States.

Rupp DE., Abatzoglou JT, Hegewisch KC, Mote PW. 2013. Evaluation of CMIP5 20th century climate simulations for the Pacific Northwest USA. Journal of Geophysical Research: Atmospheres 118:10,884-10,906.

Seager R, Hooks A, Williams AP, Cook B, Nakamura J, Henderson N. 2015. Climatology, variability, and trends in the US vapor pressure deficit, an important fire-related meteorological quantity. Journal of Applied Meteorology and Climatology 54(6):1121-1141.

Sheffield J, Barrett, AP, Colle B, Fernando D N, Fu R, et al. 2013. North American Climate in CMIP5 experiments. Part I: Evaluation of historical simulations of continental and regional climatology. Journal of Climate 26: 9209-9245

Short KC. 2021. Spatial wildfire occurrence data for the United States, 1992-2018 [FPA_FOD_20210617] (5th Edition). Fort Collins, CO: Forest Service Research Data Archive. https://doi.org/10.2737/RDS-2013-0009.5.

Snyder JP. 1987. Map Projections: A Working Manual. U.S. Geological Survey Professional Paper 1395. Washington, DC: United States Government Printing Office.

Thompson MP, Vaillant NM, Haas JR, Gebert KM, Stockmann KD. 2013. Quantifying the Potential Impacts of Fuel Treatments on Wildfire Suppression Costs. Journal of Forestry 111(1):49-58.

U.S. Census Bureau. 2021. Population, Population Change, and Estimated Components of Population Change: April 1, 2010 to July 1, 2019 (CO-EST2019-alldata). https://www.census.gov/data/tables/time-series/demo/popest/2010s-counties-total.html#par_textimage. Data obtained 9/2/2021.

USDA Forest Service. 2016. Climate change & fiscal risk: wildland fire technical supplement. Report prepared for the White House Office of Management and Budget by the USDA Forest Service. https://obamawhitehouse.archives.gov/sites/default/files/omb/assets/techdocs/Wildland%20Fire%20Technical%20Supplement.pdf).

Wang X, Thompson DK, Marshall GA, et al. 2015. Increasing frequency of extreme fire weather in Canada with climate change. Climatic Change 130: 573. Doi:10.1007/s10584-015-1375-5

Westerling AL, Hidalgo HG, Cayan DR, Swetnam TW. 2006. Warming and earlier spring increase western U.S. forest wildfire activity. Science 313(5789):940-943. DOI: 10.1126/science.1128834

Williams AP, Abatzoglou JT, Gershunov A, Guzman-Morales J, Bishop DA, Balch JK, Lettenmaier DP. 2019. Observed impacts of anthropogenic climate change on wildfire in California. Earth's Future 7(8):892-910.

Table B-1. Area burned equation estimates for the USDA Forest Service and Department of Interior regions, Poisson pseudo-maximum likelihood models, in acres, monthly data, 2006 – 2018, 324 observations.

	Constant		Ln(Tmax) [a]		Ln(VPD) [b]		Pseudo R^2
Forest Service Region 1	650	**	-113	**	10.9	***	0.80
	(300)		(53)		(2.5)		
Forest Service Region 2	1064	***	-186	***	13.3	***	0.64
	(203)		(36)		(2.0)		
Forest Service Region 3	706	***	-123	***	9.0	***	0.53
	(207)		(36)		(1.6)		
Forest Service Region 4	9.08	***			6.2	***	0.75
	(0.32)				(0.9)		
Forest Service Region 5	708	**	-123	**	8.4	***	0.43
	(343)		(60)		(2.8)		
Forest Service Region 6	9.64	***			6.6	***	0.74
	(0.20)				(0.7)		
Forest Service Region 8	795	***	-138	***	9.0	***	0.37
	(217)		(38)		(2.2)		
Forest Service Region 9	429	***	-74	***	5.6	***	0.25
	(99)		(17)		(1.1)		
Department of the Interior Region 1	949	***	-165	***	11.0	***	0.67

	Constant		Ln(Tmax) [a]		Ln(VPD) [b]		Pseudo R^2
	(253)		(45)		(2.4)		
Department of the Interior Region 2	507	***	-88	***	6.3	***	0.47
	(176)		(31)		(1.5)		
Department of the Interior Region 3	832	***	-145	***	10.5	***	0.53
	(132)		(23)		(1.4)		
Department of the Interior Region 4	-511	***	92	***			0.66
	(76)		(13)				
Department of the Interior Region 5	-313	***	56	***			0.43
	(52)		(9)				
Department of the Interior Region 6	-559	***	100	***			0.69
	(68)		(12)				
Department of the Interior Region 8	769	***	-133	***	9.0	***	0.46
	(107)		(19)		(1.2)		
Department of the Interior Region 9	937	***	-163	***	9.3	***	0.53
	(149)		(26)		(1.4)		

Notes: Standard errors in parentheses; *** indicates significance at 1%, ** at 5%, * at 10%.

[a] Month average of the daily maximum temperature, in degrees Kelvin

[b] Month average of daily average vapor pressure deficit

Table B-2. Suppression expenditure equation estimates for the USDA Forest Service and Department of Interior regions, two-staged least squares linear regression models, in real inflation-adjusted (2020 dollars), monthly data, 2005 – 2019 (USDA Forest Service), 180 observations (regions 1-9) or 192 observations (Region 10, 2005-2020), or 2013-2017 (Department of the Interior), 60 observations.

	Constant		Acres Burned$_t$[a]		Acres Burned$_{t-1}$		Acres Burned$_{t-2}$		Root Mean Squared Error (Million)
Forest Service Region 1	1,241,545		114	***	191	***	65	***	11
	(918,254)		(16)		(12)		(11)		
Forest Service Region 2	-1,284		262	***	157	***	-37		7.5
	(674,614)		(56)		(22)		(23)		
Forest Service Region 3	-2,276,364		240	***	120	***	82	***	19
	(2,256,614)		(78)		(24)		(18)		
Forest Service Region 4	1,144,299		132	***	87	***	54	***	12
	(1,034,860)		(18)		(12)		(11)		
Forest Service Region 5	1,872,268		334	***	324	***	163	***	38
	(3,487,242)		(46)		(28)		(27)		
Forest Service Region 6	-358,264		425	***	222	***	150	***	27
	(2,353,933)		(61)		(34)		(31)		
Forest Service Region 8	3,674,111	***	-75	*	62	***	34		10
	(851,406)		(43)		(21)		(21)		
Forest Service Region 9	218,831		296	*	116	***	72	***	2.7
	(370,317)		(155)		(22)		(22)		

	Constant		Acres Burned$_t$[a]		Acres Burned$_{t-1}$		Acres Burned$_{t-2}$		Root Mean Squared Error (Million)
Forest Service Region 10	116,583	***							0.5
	(36,300)								
Rest of Forest Service	21,700,000	***	52	***					46
	(4,286,596)		(17)						
Department of the Interior Total	15,100,000	***	24	**	83	***	14	**	20
	(3,406,863)		(10)		(9)		(7)		

Notes: Standard errors in parentheses; *** indicates significance at 1%, ** at 5%, * at 10%.

[a] Instrumented in 2SLS estimation with current month number of wildfires reported, human population

Table B-3. Total Department of the Interior + USDA Forest Service area burned projected (CONUS), median values, Monte Carlo 500 iterations per climate projection (GCM x RCP scenario); "All Projections Median" and the 80% and 90% bounds reported in this table are based on the combined 10 projections x 500 iterations/projection = 5,000 total iterations.[a]

		Area Burned Observed Historical Median	Area Burned Modeled Historical Median	Area Burned Projected Future Median	Area Burned Projected Future Median	Change from Observed Historical Median	Change from Observed Historical Median	Change from Modeled Historical Median	Change from Modeled Historical Median
		2006 - 2018	2006 - 2018	2041 - 2059	2081 - 2099	2041 - 2059	2081 - 2099	2041 - 2059	2081 - 2099
		------------------------ Million Acres --------------------				-------------------------- Percent -------------------------			
CNRM-CM5 x RCP 4.5	Wet	3.92	4.90	6.00	8.89	53	127	22	82
HadGEM2-ES x RCP 4.5	Hot	3.92	4.91	10.84	17.10	177	336	121	248
IPSL-CM5A-MR x RCP 4.5	Dry	3.92	4.63	8.19	8.30	109	112	77	79
MRI-CGCM3 x RCP 4.5	Least Warm	3.92	3.20	4.75	5.29	21	35	49	65
NorESM1-M x RCP 4.5	Middle	3.92	3.76	7.94	9.82	103	150	111	161
CNRM-CM5 x RCP 8.5	Wet	3.92	3.97	8.59	23.16	119	491	116	484
HadGEM2-ES x RCP 8.5	Hot	3.92	4.57	13.75	79.54	251	1,929	201	1,641
IPSL-CM5A-MR x RCP 8.5	Dry	3.92	4.11	9.40	28.17	140	618	129	586
MRI-CGCM3 x RCP 8.5	Least Warm	3.92	3.47	4.94	10.28	26	162	42	196

		Area Burned Observed Historical Median	Area Burned Modeled Historical Median	Area Burned Projected Future Median	Area Burned Projected Future Median	Change from Observed Historical Median	Change from Observed Historical Median	Change from Modeled Historical Median	Change from Modeled Historical Median
		2006 - 2018	2006 - 2018	2041 - 2059	2081 - 2099	2041 - 2059	2081 - 2099	2041 - 2059	2081 - 2099
		------------------------ Million Acres --------------------				-------------------------- Percent -------------------------			
NorESM1-M x RCP 8.5	Middle	3.92	3.99	10.54	24.99	169	537	164	525
	All Projections Median	3.92	3.88	7.99	13.21	104	237	106	241
	All Projections 80% Lower		2.32	3.58	4.57				
	All Projections 80% Upper		7.14	17.61	59.64				
	All Projections 90% Lower		2.08	3.16	3.88				
	All Projections 90% Upper		8.30	22.21	88.70				

[a] Note that median values shown in this table will not generally be equal to the median values for the USDA Forest Service plus the median values of the Department of the Interior.

Table B-4. Total USDA Forest Service area burned projected, median values, Monte Carlo 500 iterations per climate projection (GCM x RCP scenario); "All Projections Median" and the 80% and 90% bounds reported in this table are based on the combined 10 projections x 500 iterations/projection = 5,000 total iterations.

		Area Burned Observed Historical Median	Area Burned Modeled Historical Median	Area Burned Projected Future Median	Area Burned Projected Future Median	Change from Observed Historical Median	Change from Observed Historical Median	Change from Modeled Historical Median	Change from Modeled Historical Median
		2006 - 2018	2006 - 2018	2041 - 2059	2081 - 2099	2041 - 2059	2081 - 2099	2041 - 2059	2081 - 2099
		Million Acres				Percent			
CNRM-CM5 x RCP 4.5	Wet	1.79	1.92	2.79	4.11	56	130	45	114
HadGEM2-ES x RCP 4.5	Hot	1.79	2.29	5.69	10.39	219	482	149	354
IPSL-CM5A-MR x RCP 4.5	Dry	1.79	1.74	3.59	3.56	101	100	106	105
MRI-CGCM3 x RCP 4.5	Least Warm	1.79	1.20	1.85	2.01	4	12	54	67
NorESM1-M x RCP 4.5	Middle	1.79	1.46	3.09	4.42	73	148	111	202
CNRM-CM5 x RCP 8.5	Wet	1.79	1.69	3.99	14.76	123	726	136	773
HadGEM2-ES x RCP 8.5	Hot	1.79	1.96	8.11	56.32	354	3,053	313	2,767
IPSL-CM5A-MR x RCP 8.5	Dry	1.79	1.60	4.11	14.59	130	717	157	814
MRI-CGCM3 x RCP 8.5	Least Warm	1.79	1.20	1.73	4.13	-3	131	45	245

		Area Burned Observed Historical Median	Area Burned Modeled Historical Median	Area Burned Projected Future Median	Area Burned Projected Future Median	Change from Observed Historical Median	Change from Observed Historical Median	Change from Modeled Historical Median	Change from Modeled Historical Median
		2006 - 2018	2006 - 2018	2041 - 2059	2081 - 2099	2041 - 2059	2081 - 2099	2041 - 2059	2081 - 2099
		------------------------ Million Acres --------------------				--------------------------- Percent --------------------------			
NorESM1-M x RCP 8.5	Middle	1.79	1.48	4.80	13.28	169	643	225	798
	All Projections Median	1.79	1.51	3.46	6.14	94	244	129	306
	All Projections 80% Lower		0.78	1.26	1.62				
	All Projections 80% Upper		3.30	9.40	40.29				
	All Projections 90% Lower		0.62	1.05	1.30				
	All Projections 90% Upper		4.14	13.12	67.43				

Table B-5. Total Department of the Interior area burned projected, median values, Monte Carlo 500 iterations per climate projection (GCM x RCP scenario); "All Projections Median" and the 80% and 90% bounds reported in this table are based on the combined 10 projections x 500 iterations/projection = 5,000 total iterations.

		Area Burned Observed Historical Median	Area Burned Modeled Historical Median	Area Burned Projected Future Median	Area Burned Projected Future Median	Change from Observed Historical Median	Change from Observed Historical Median	Change from Modeled Historical Median	Change from Modeled Historical Median
		2006 - 2018	2006 - 2018	2041 - 2059	2081 - 2099	2041 - 2059	2081 - 2099	2041 - 2059	2081 - 2099
		------------------------ Million Acres -------------------				-------------------------- Percent -------------------------			
HadGEM2-ES x RCP 4.5	Hot	2.00	2.74	5.17	7.57	159	279	89	176
IPSL-CM5A-MR x RCP 4.5	Dry	2.00	2.87	4.54	4.80	128	140	58	67
MRI-CGCM3 x RCP 4.5	Least Warm	2.00	2.01	2.85	3.27	43	64	42	63
NorESM1-M x RCP 4.5	Middle	2.00	2.34	4.07	5.21	104	161	74	122
CNRM-CM5 x RCP 8.5	Wet	2.00	2.29	4.49	9.20	125	361	96	302
HadGEM2-ES x RCP 8.5	Hot	2.00	2.68	5.93	19.54	197	878	122	630
IPSL-CM5A-MR x RCP 8.5	Dry	2.00	2.44	5.23	12.96	162	549	115	432
MRI-CGCM3 x RCP 8.5	Least Warm	2.00	2.20	3.08	5.77	54	189	40	162
NorESM1-M x RCP 8.5	Middle	2.00	2.50	5.66	10.72	183	437	126	328

	Area Burned Observed Historical Median	Area Burned Modeled Historical Median	Area Burned Projected Future Median	Area Burned Projected Future Median	Change from Observed Historical Median	Change from Observed Historical Median	Change from Modeled Historical Median	Change from Modeled Historical Median
	2006 - 2018	2006 - 2018	2041 - 2059	2081 - 2099	2041 - 2059	2081 - 2099	2041 - 2059	2081 - 2099
	------------------------ Million Acres -------------------				--------------------------- Percent --------------------------			
All Projections Median	2.00	2.33	4.26	6.51	114	226	83	180
All Projections 80% Lower		1.47	2.24	2.83				
All Projections 80% Upper		3.89	7.23	18.07				
All Projections 90% Lower		1.33	2.01	2.47				
All Projections 90% Upper		4.28	8.35	22.86				

Table B-6. Total Department of the Interior + USDA Forest Service real (2020 dollars) suppression spending projected, median values. Monte Carlo 500 iterations per climate projection (GCM x RCP scenario); "All Projections Median" and the 80% and 90% bounds reported in this table are based on the combined 10 projections x 500 iterations/projection = 5,000 total iterations.[a]

		Expenditures Observed Historical Median	Expenditures Modeled Historical Median	Expenditures Projected Future Median	Expenditures Projected Future Median	Change from Observed Historical Median	Change from Observed Historical Median	Change from Modeled Historical Median	Change from Modeled Historical Median
		2006 - 2018	2006 - 2018	2041 - 2059	2081 - 2099	2041 - 2059	2081 - 2099	2041 - 2059	2081 - 2099
		Billion Dollars				Percent			
CNRM-CM5 x RCP 4.5	Wet	2.00	1.54	2.24	3.35	12	68	45	117
HadGEM2-ES x RCP 4.5	Hot	2.00	1.48	3.12	5.36	56	168	111	263
IPSL-CM5A-MR x RCP 4.5	Dry	2.00	1.55	2.44	2.71	22	36	57	74
MRI-CGCM3 x RCP 4.5	Least Warm	2.00	1.17	1.52	1.67	-24	-16	30	42
NorESM1-M x RCP 4.5	Middle	2.00	1.30	2.58	3.15	29	58	99	142
CNRM-CM5 x RCP 8.5	Wet	2.00	1.42	2.66	9.55	33	378	87	573
HadGEM2-ES x RCP 8.5	Hot	2.00	1.52	4.42	29.00	121	1,353	190	1,805
IPSL-CM5A-MR x RCP 8.5	Dry	2.00	1.39	2.99	8.81	50	341	115	532
MRI-CGCM3 x RCP 8.5	Least Warm	2.00	1.20	1.51	3.03	-24	52	26	153

		Expenditures Observed Historical Median	Expenditures Modeled Historical Median	Expenditures Projected Future Median	Expenditures Projected Future Median	Change from Observed Historical Median	Change from Observed Historical Median	Change from Modeled Historical Median	Change from Modeled Historical Median
		2006 - 2018	2006 - 2018	2041 - 2059	2081 - 2099	2041 - 2059	2081 - 2099	2041 - 2059	2081 - 2099
		Billion Dollars				Percent			
NorESM1-M x RCP 8.5	Middle	2.00	1.36	3.49	8.51	75	326	156	525
	All Projections Median	2.00	1.33	2.44	3.80	22	90	83	186
	All Projections 80% Lower		0.85	1.18	1.43				
	All Projections 80% Upper		2.16	5.26	21.60				
	All Projections 90% Lower		0.72	1.03	1.23				
	All Projections 90% Upper		2.47	6.64	34.05				

[a] Note that median values shown in this table will not generally be equal to the median values for the USDA Forest Service plus the median values of the Department of the Interior.

Table B-7. Total USDA Forest Service real (2020 dollars) suppression spending projected, median values. Monte Carlo 500 iterations per climate projection (GCM x RCP scenario); "All Projections Median" and the 80% and 90% bounds reported in this table are based on the combined 10 projections x 500 iterations/projection = 5,000 total iterations.

		Expenditures Observed Historical Median	Expenditures Modeled Historical Median	Expenditures Projected Future Median	Expenditures Projected Future Median	Change from Observed Historical Median	Change from Observed Historical Median	Change from Modeled Historical Median	Change from Modeled Historical Median
		2006 - 2018	2006 - 2018	2041 - 2059	2081 - 2099	2041 - 2059	2081 - 2099	2041 - 2059	2081 - 2099
		------------------- Billion Dollars -----------------------				------------------------ Percent --------------------------			
CNRM-CM5 x RCP 4.5	Wet	1.52	1.02	1.66	2.50	9	65	63	146
HadGEM2-ES x RCP 4.5	Hot	1.52	0.97	2.31	4.29	52	183	138	343
IPSL-CM5A-MR x RCP 4.5	Dry	1.52	0.94	1.67	1.85	10	22	77	96
MRI-CGCM3 x RCP 4.5	Least Warm	1.52	0.69	0.94	1.08	-38	-29	37	57
NorESM1-M x RCP 4.5	Middle	1.52	0.80	1.79	2.35	18	55	124	193
CNRM-CM5 x RCP 8.5	Wet	1.52	0.93	1.88	8.18	24	439	102	780
HadGEM2-ES x RCP 8.5	Hot	1.52	1.00	3.48	26.52	129	1,649	248	2,556
IPSL-CM5A-MR x RCP 8.5	Dry	1.52	0.90	2.13	6.88	41	354	136	662
MRI-CGCM3 x RCP 8.5	Least Warm	1.52	0.73	0.96	1.99	-37	31	32	172

		Expenditures Observed Historical Median	Expenditures Modeled Historical Median	Expenditures Projected Future Median	Expenditures Projected Future Median	Change from Observed Historical Median	Change from Observed Historical Median	Change from Modeled Historical Median	Change from Modeled Historical Median
		2006 - 2018	2006 - 2018	2041 - 2059	2081 - 2099	2041 - 2059	2081 - 2099	2041 - 2059	2081 - 2099
		------------------- Billion Dollars -----------------------				------------------------ Percent ---------------------------			
NorESM1-M x RCP 8.5	Middle	1.52	0.85	2.62	7.05	73	365	207	725
	All Projections Median	1.52	0.84	1.75	2.80	16	85	109	234
	All Projections 80% Lower		0.46	0.69	0.85				
	All Projections 80% Upper		1.57	4.18	18.85				
	All Projections 90% Lower		0.29	0.47	0.62				
	All Projections 90% Upper		1.82	5.46	30.98				

Table B-8. Total Department of the Interior real (2020 dollars) suppression spending projected, median values. Monte Carlo 500 iterations per climate projection (GCM x RCP scenario); "All Projections Median" and the 80% and 90% bounds reported in this table are based on the combined 10 projections x 500 iterations/projection = 5,000 total iterations.

		Expenditures Observed Historical Median	Expenditures Modeled Historical Median	Expenditures Projected Future Median	Expenditures Projected Future Median	Change from Observed Historical Median	Change from Observed Historical Median	Change from Modeled Historical Median	Change from Modeled Historical Median
		2006 - 2018	2006 - 2018	2041 - 2059	2081 - 2099	2041 - 2059	2081 - 2099	2041 - 2059	2081 – 2099
		------------------- Billion Dollars -----------------------				------------------------ Percent --------------------------			
CNRM-CM5 x RCP 4.5	Wet	0.45	0.52	0.60	0.81	32	78	15	56
HadGEM2-ES x RCP 4.5	Hot	0.45	0.52	0.81	1.14	78	152	56	121
IPSL-CM5A-MR x RCP 4.5	Dry	0.45	0.55	0.73	0.78	62	72	34	42
MRI-CGCM3 x RCP 4.5	Least Warm	0.45	0.44	0.54	0.59	19	30	23	34
NorESM1-M x RCP 4.5	Middle	0.45	0.46	0.68	0.83	51	84	48	80
CNRM-CM5 x RCP 8.5	Wet	0.45	0.49	0.74	1.35	63	199	52	178
HadGEM2-ES x RCP 8.5	Hot	0.45	0.51	0.95	2.65	110	486	86	417
IPSL-CM5A-MR x RCP 8.5	Dry	0.45	0.51	0.84	1.72	86	280	67	241
MRI-CGCM3 x RCP 8.5	Least Warm	0.45	0.45	0.56	0.93	25	106	26	109

		Expenditures Observed Historical Median	Expenditures Modeled Historical Median	Expenditures Projected Future Median	Expenditures Projected Future Median	Change from Observed Historical Median	Change from Observed Historical Median	Change from Modeled Historical Median	Change from Modeled Historical Median
		2006 - 2018	2006 - 2018	2041 - 2059	2081 - 2099	2041 - 2059	2081 - 2099	2041 - 2059	2081 – 2099
		------------------- Billion Dollars			-----------------------	------------------------ Percent			---------------------------
NorESM1-M x RCP 8.5	Middle	0.45	0.51	0.90	1.54	98	240	76	200
	All Projections Median	0.45	0.48	0.71	1.03	57	128	48	114
	All Projections 80% Lower		0.36	0.46	0.55				
	All Projections 80% Upper		0.67	1.12	2.55				
	All Projections 90% Lower		0.33	0.42	0.49				
	All Projections 90% Upper		0.74	1.27	3.13				

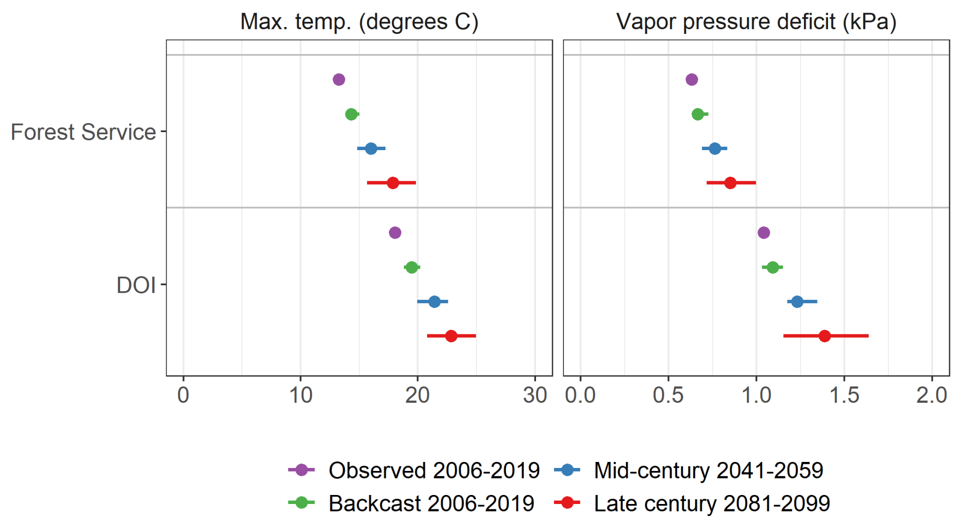


Figure B-1. Average (median) monthly maximum temperature and vapor pressure deficit on Forest Service and Department of Interior lands for the historical observed period (2006-2019) and for the ten plausible projected climate futures (5 GCMs x 2 RCPs) used in the projections for the backcast (2006-2019), mid-century (2041-2059) and late century periods (2081-2099). In the backcast, mid-century, and late century periods, the point indicates the median of average values across all ten plausible futures, while the bars represent the range in average values across all futures.

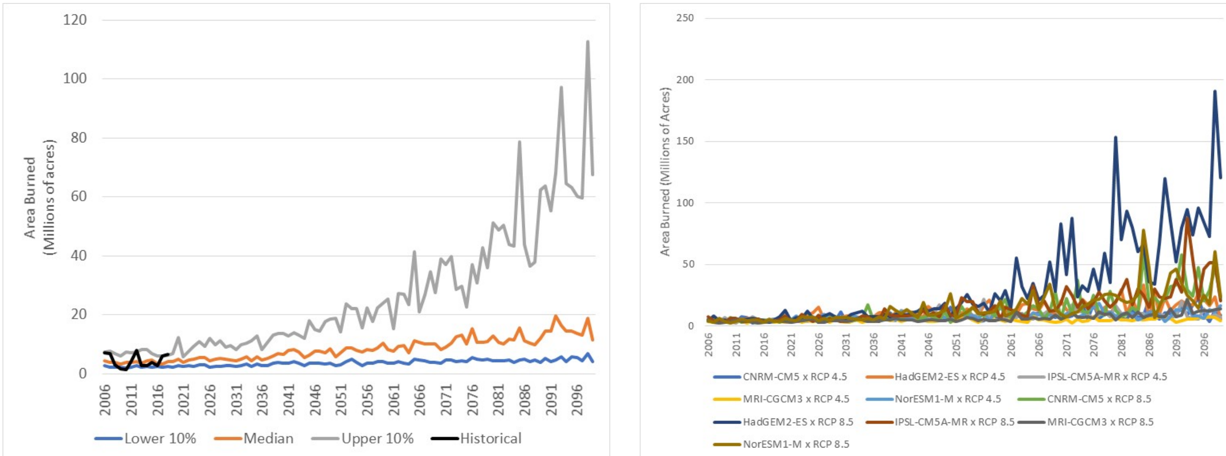


Figure B-2. Total Department of the Interior + USDA Forest Service area burned, projected, by fiscal year, all climate projections combined, and median by scenario. Monte Carlo 500 iterations per GCM x RCP scenario (i.e., 5,000 iterations included in this figure).

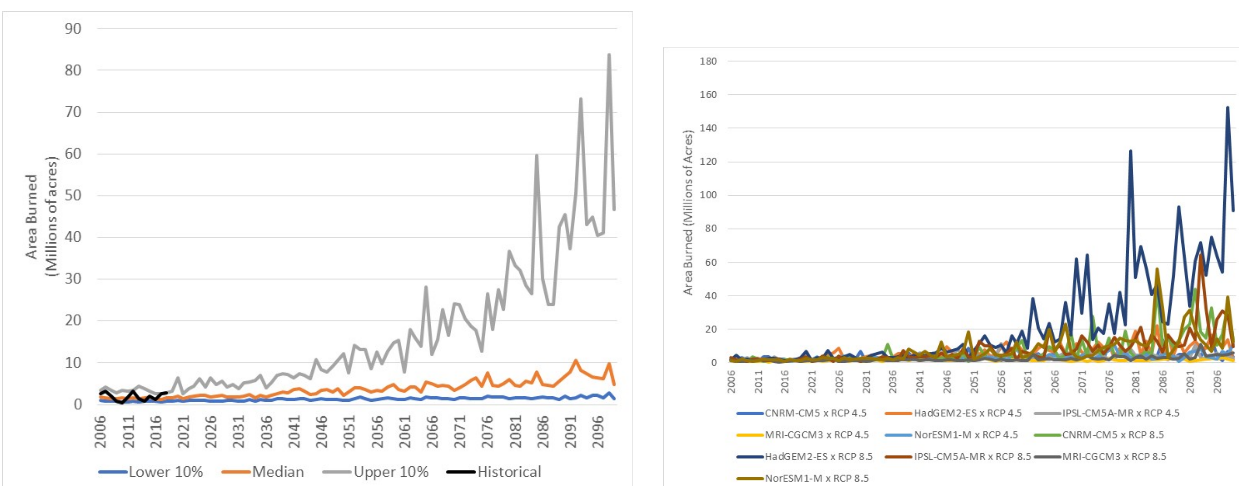


Figure B-3. USDA Forest Service area burned, projected, by fiscal year, all climate projections combined, and median by scenario. Monte Carlo 500 iterations per GCM x RCP scenario (i.e., 5,000 iterations included in this figure).

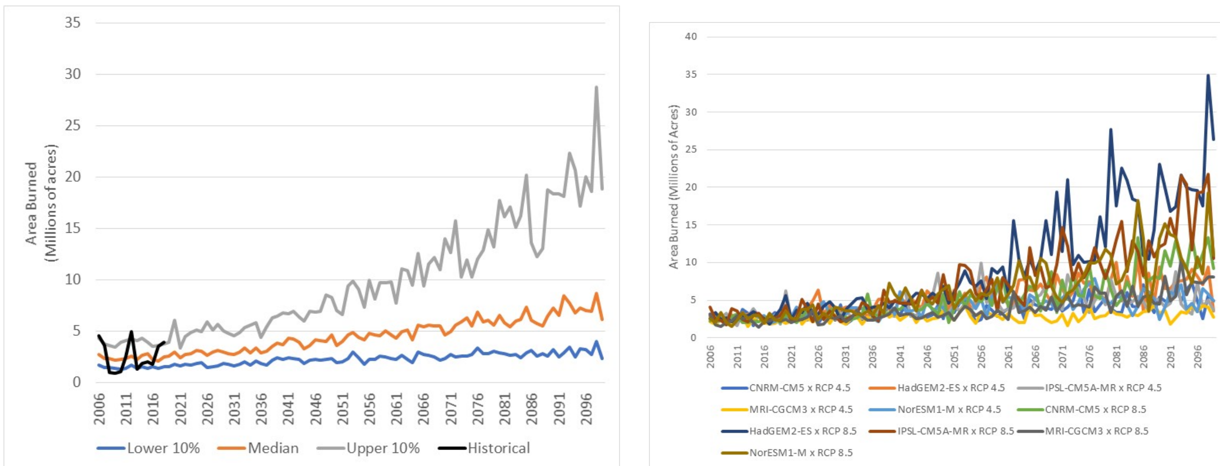


Figure B-4. Department of the Interior area burned, projected, by fiscal year, all climate projections combined, and median by scenario. Monte Carlo 500 iterations per GCM x RCP scenario (i.e., 5,000 iterations included in this figure).

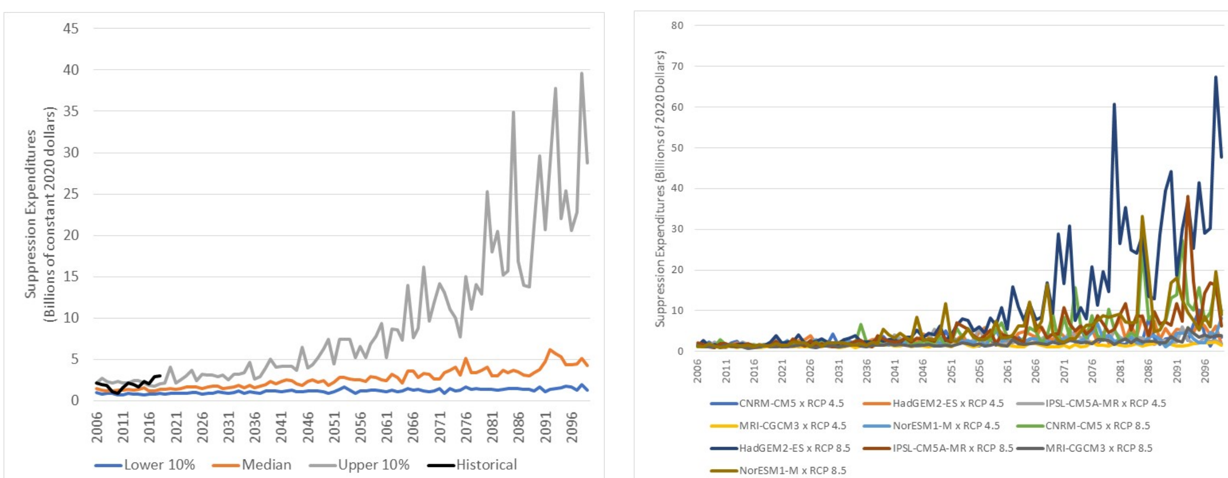


Figure B-5. Total Department of the Interior + USDA Forest Service suppression expenditures, projected, by fiscal year (inflation adjusted 2020 dollars), all climate projections combined, and median by scenario. Monte Carlo 500 iterations per GCM x RCP scenario (i.e., 5,000 iterations included in this figure). See Table B-2 for statistical models underlying the Monte Carlo projections presented in this figure.

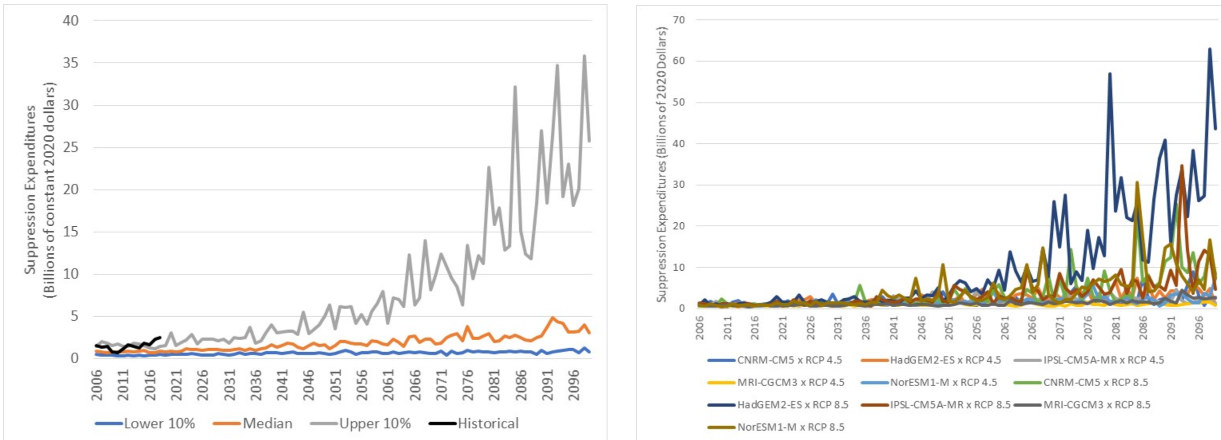


Figure B-6. USDA Forest Service suppression expenditures, projected, by fiscal year (inflation adjusted 2020 dollars), all climate projections combined, and median by scenario. Monte Carlo 500 iterations per GCM x RCP scenario (i.e., 5,000 iterations included in this figure).

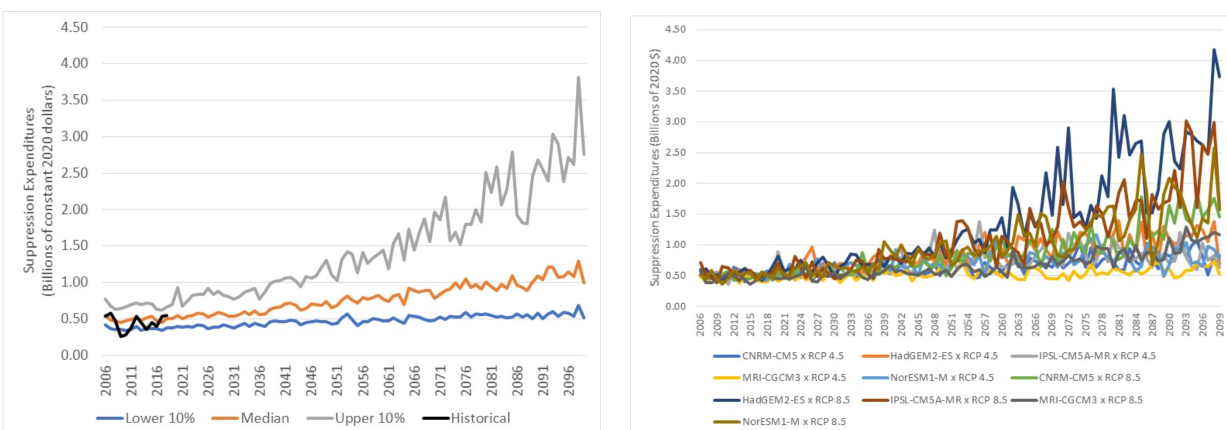


Figure B-7. Department of the Interior suppression expenditures, projected, by fiscal year (inflation adjusted 2020 dollars), all climate projections combined, and median by scenario. Monte Carlo 500 iterations per GCM x RCP scenario (i.e., 5,000 iterations included in this figure).

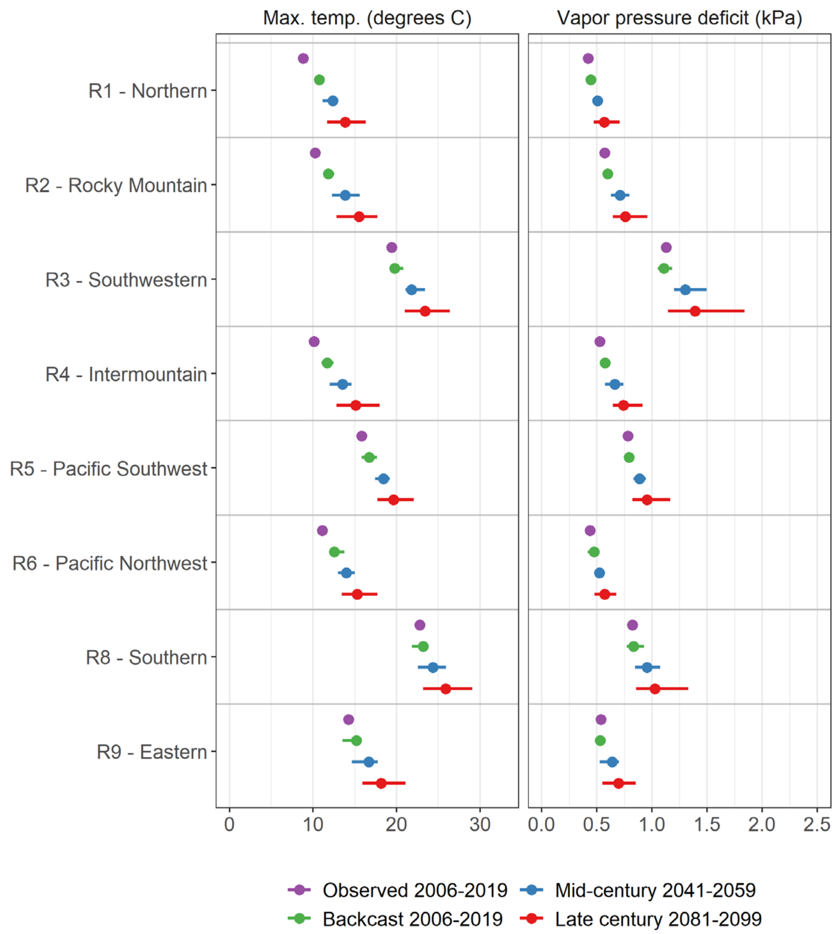


Figure C-1. Average (median) monthly maximum temperature and vapor pressure deficit by region on Forest Service lands for the historical observed period (2006-2019) and for the ten plausible futures (5 GCMs x 2 RCPs) used in the projections for the backcast (2006-2019), mid-century (2041-2059) and late century periods (2081-2099). In the backcast, mid-century, and late century periods, the point indicates the median of average values across all ten plausible futures, while the bars represent the range in average values across all futures. Both variables were used in regional models for FS lands, with the exception of models for regions 3 and 5, which only used VPD.

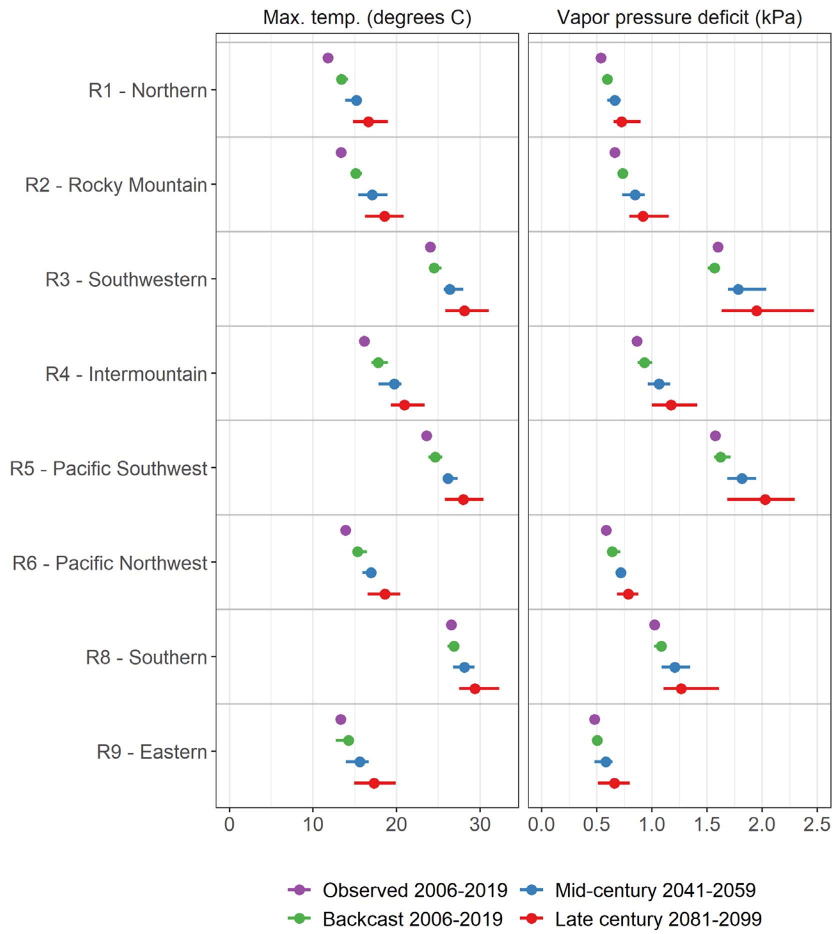
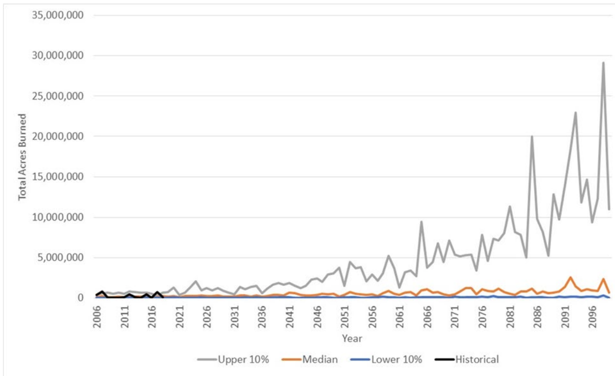
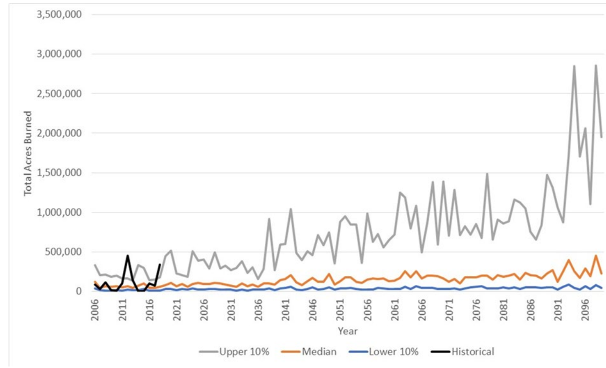


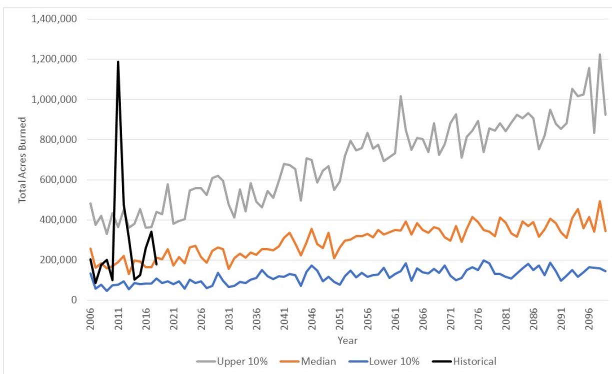
Figure C-2. Average (median) monthly maximum temperature and vapor pressure deficit by region on Department of Interior lands for the historical observed period (2006-2019) and for the ten plausible futures (5 GCMs x 2 RCPs) used in the projections for the backcast (2006-2019), mid-century (2041-2059) and late century periods (2081-2099). In the backcast, mid-century, and late century periods, the point indicates the median of average values across all ten plausible futures, while the bars represent the range in average values across all futures. Both variables were used in models for DOI lands, with the exception of regions 4, 5, and 6, which only used maximum temperature.



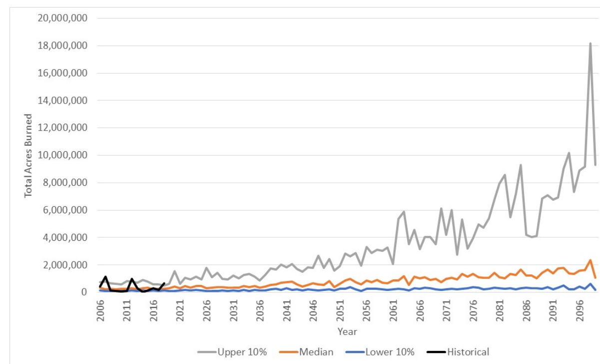
Region 1



Region 2

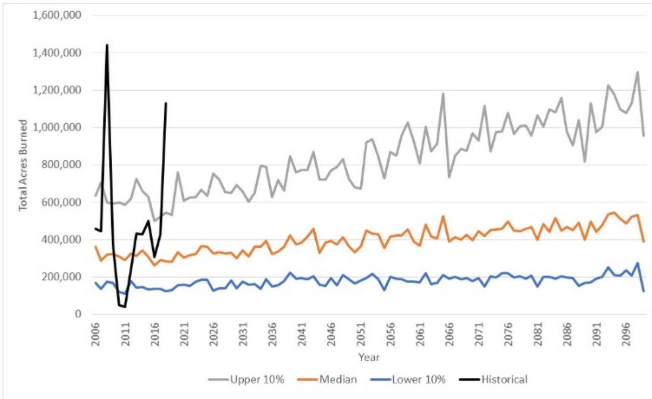


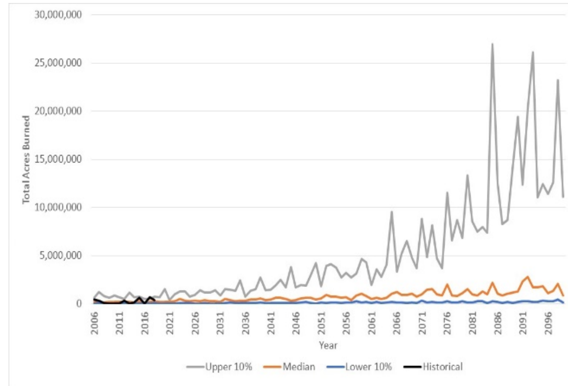
Region 3



Region 4

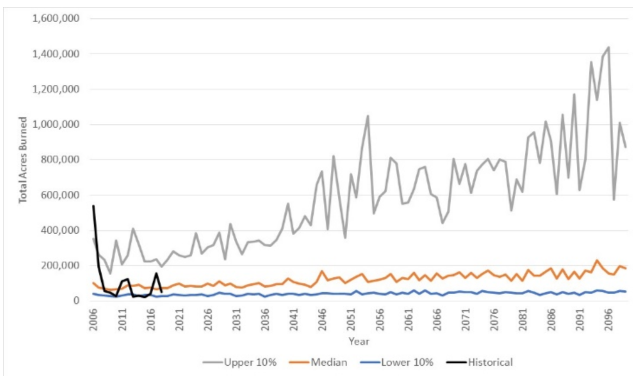
Figure C-3. USDA Forest Service regions 1-4 median and 80% upper and lower bounds of area burned projections, all climate projections combined. Monte Carlo 500 iterations per GCM x RCP scenario (i.e., 5,000 iterations included in this figure).

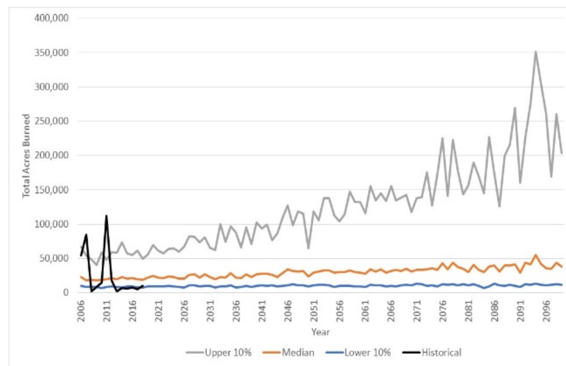




Region 5

Region 6

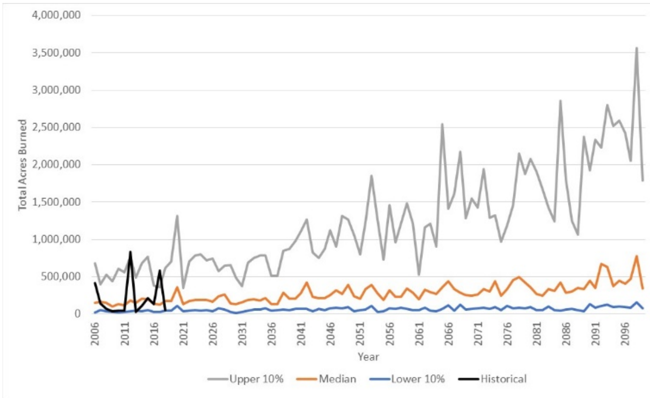




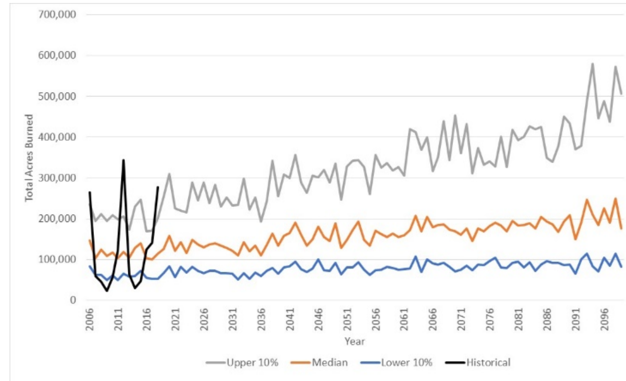
Region 8

Region 9

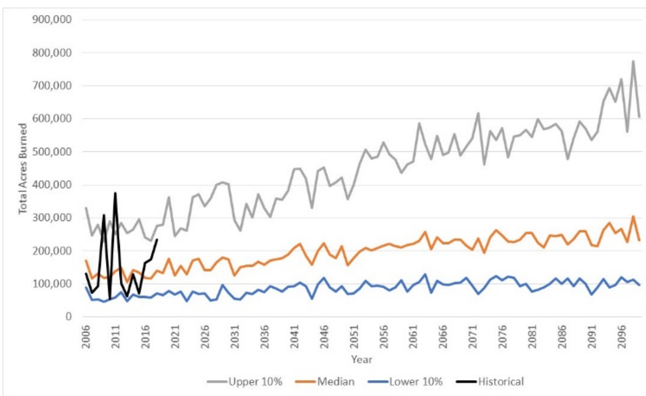
Figure C-4. USDA Forest Service regions 5-9 median and 80% upper and lower bounds of area burned projections, all climate projections combined. Monte Carlo 500 iterations per GCM x RCP scenario (i.e., 5,000 iterations included in this figure).



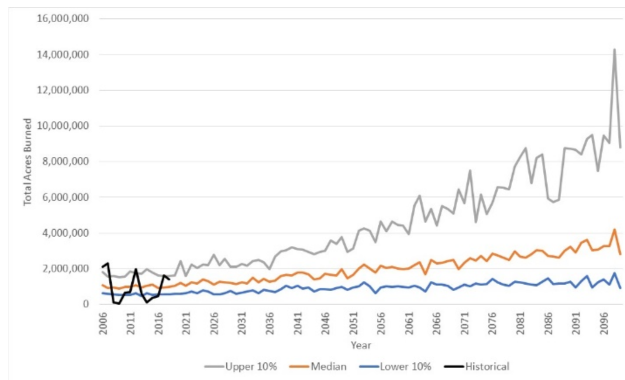
Region 1



Region 2

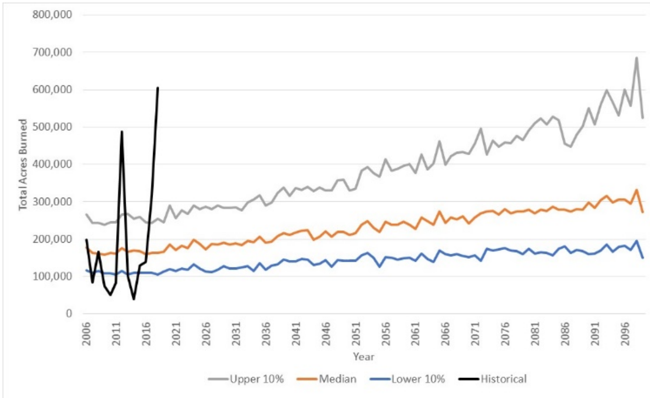


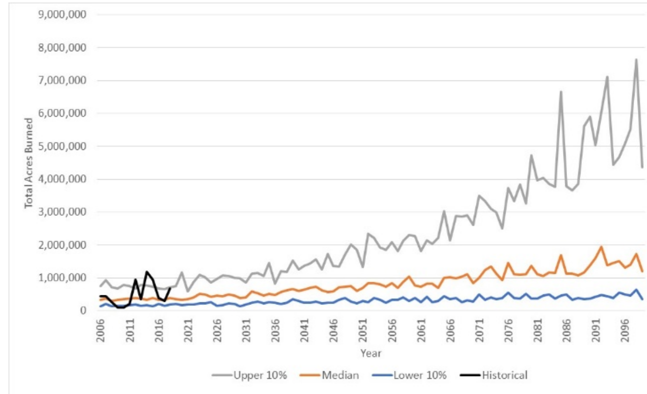
Region 3



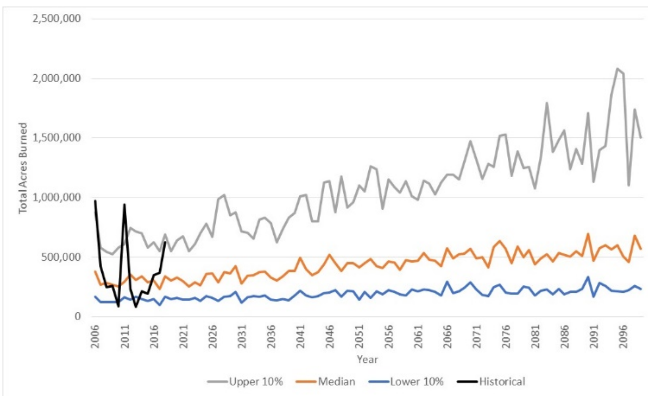
Region 4

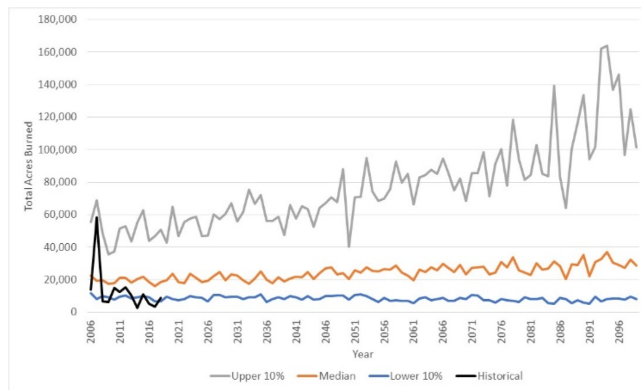
Figure C5. Department of the Interior median and 80% upper and lower bounds of area burned projections on lands contained in the boundaries of FS regions 1-4, all climate projections combined. Monte Carlo 500 iterations per GCM x RCP scenario (i.e., 5,000 iterations included in this figure).





Region 5 Region 6





Region 8 Region 9

Figure C-6. Department of the Interior median and 80% upper and lower bounds of area burned projections on lands contained in the boundaries of FS regions 5-9, all climate projections combined. Monte Carlo 500 iterations per GCM x RCP scenario (i.e., 5,000 iterations included in this figure).