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How will future climate change impact prescribed fire across the contiguous United States?

Check for updates

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As of 2023, the use of prescribed fire to manage ecosystems accounts for more than 50% of area burned annually across the United States. Prescribed fire is carried out when meteorological conditions, including temperature, humidity, and wind speed are appropriate for its safe and effective application. However, changes in these meteorological variables associated with future climate change may impact future opportunities to conduct prescribed fire. In this study, we combine climate projections with information on prescribed burning windows for ecoregions across the contiguous United States (CONUS) to compute the number of days when meteorological conditions allow for the safe and effective application of prescribed fire under present-day (2006–2015) and future climate (2051–2060) conditions. The resulting projections, which cover 57% of all vegetated area across the CONUS, indicate fewer days with conditions suitable for prescribed burning across ecoregions of the eastern United States due to rising maximum daily temperatures, but opportunities increase in the northern and northwestern United States, driven primarily by rising minimum temperatures and declining wind speeds.

More than a century-long history of fire suppression in the United States has led to the accumulation of combustible vegetation, or fuel, particularly in western forests that historically experienced frequent fire[1,2]. This fuel accumulation, combined with climate change and an increase in anthropogenic ignitions, has led to a substantial increase in catastrophic wildfire activity that is expected to worsen over the next century[3–5]. Prescribed fire is an important tool for mitigating wildfire risk by reducing biomass and changing forest structure[6–8]. It also promotes long-term stability in ecosystem carbon storage and ecological function[9–11], restoring and maintaining diversity in fire-adapted ecological communities[6,12,13]. Prescribed fire can be applied across large areas at lower cost than manual or mechanical fuel reduction methods, as well as in areas where topography or restricted access limit mechanical fuel reduction[14,15]. In some ecosystems, prescribed fire can also serve to mitigate the effects of carbon dioxide emissions from wildfires by aiding in forest carbon sequestration[7,9,16]. Furthermore, long-standing indigenous fire management has shown that prescribed fire can mitigate climate-induced influences on wildfire[17].

The majority of prescribed burning in the United States occurs in southeastern ecosystems and tallgrass prairie, both characterized by short fire return intervals[18] (~80% of burn area nationwide). In these regions public acceptance of prescribed burning is high, and prescribed fire is frequently applied at the wildland urban interface[19–21]. Although the western U.S. has a long history of advocacy for increased prescribed fire use by organizations such as the United States Forest Service, Bureau of Land Management, State Departments of Forestry, tribal coalitions, and the Nature Conservancy[4,22,23], the annual extent of prescribed fire has not increased to meet objectives, remaining relatively stable since 1998[4]. Prescribed fire application in the West is complicated by steep topography, heavy fuel loads, narrow burn windows due to air quality regulations and the absence of fire crews (often elsewhere working on wildfires)[22]. Fast changing environmental conditions also lead to significant challenges[24]. For example, recent prescribed fire escapes due to drier and windier than normal conditions have led to devastating wildfires[25].

Climate change is already having an impact on both wildfire and prescribed fire through increasing temperatures and variability in

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precipitation, which contribute to drier fuels and seasonally increasing fuel loads in some areas, making wildfires more severe and limiting prescribed fire opportunities[4,26–28]. This impact is especially evident across the western U.S. In Northern California, land managers cite narrow burn windows related to meteorological and fuel conditions as the biggest impediment to meeting prescribed burning objectives[29,30]. Research in California has demonstrated declines in available burning conditions driven by changes in relative humidity[31]. In the Southwest, persistent fuel moisture deficits lead to drought-stressed tree mortality[32,33], adding low-moisture fuel and driving extreme wildland fire behavior.

To date, the majority of fire research has focused on wildfire trends and effects[34,35]. However, prescribed fires, which are intentionally ignited under carefully chosen conditions (i.e. prescriptions) to achieve specific objectives, require a different research approach[34]. Safe and effective application of prescribed fire is only possible within prescription windows, or ranges of meteorological and fuel conditions that enable low intensity fire and adhere to air quality regulations[36,37]. Understanding how shifting weather patterns change the availability of suitable prescription windows is paramount to effectively identifying and leveraging available prescribed fire opportunities[4,38,39]. Previous work has highlighted potential regional climate impacts on available prescribed fire windows from increasing drought conditions and temperature, as well as reduced fuel moisture and relative humidity[31,40,41]. These previous studies applied uniform prescription ranges to areas including California[31], the southeastern US[40], and the western US[41], thus not accounting for impacts of local variability in prescription ranges. Here we examine the importance of local-scale variability in prescriptions by using a combination of locally to regionally varying prescription window information, landscape, and climate data to assess projected changes in future prescribed fire opportunities due to meteorological conditions across the CONUS (including the lower 48 states, excluding Alaska).

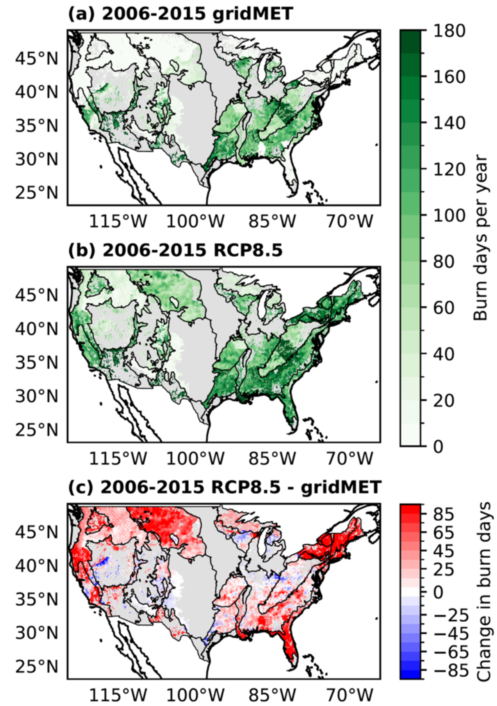

Fig. 1 | Number of days available for prescribed burning under present-day climate conditions. Burn day calculation based on (**a**) gridMET observational data and (**b**) the average of 18 MACA-downscaled CMIP5 models for the RCP8.5 scenario. **c** shows the difference between the RCP8.5 and gridMET burn days. Black lines represent ecoregion boundaries. Gray areas are regions where no prescription information is available.

Results

Present-day prescribed fire opportunities in models and data

We evaluated present-day and future opportunities for prescribed burning using a combination of prescriptions for 83 locations across the CONUS, gridded observational climate data from the Gridded Surface Meteorological (gridMET) Dataset[42], statistically downscaled climate data from 18 climate and earth system models participating in the Coupled Model Intercomparison Project version 5 (CMIP5)[43], and fuels data from the Landscape Fire and Resource Management Planning Tools (LANDFIRE)[44]. We used these data to compute burn days for each Environmental Protection Agency (EPA) Level II ecoregion[45] by evaluating daily gridMET data and CMIP5 simulations for RCP8.5 against prescriptions that fall within the EPA Level II ecoregion. Figure 1 compares average burn days for 2006–2015. Differences between the RCP scenarios are minimal for the 2006–2015 period, and differences between gridMET and CMIP5 are consistent across RCPs, thus only a comparison against RCP8.5 is shown. Both gridMET and CMIP5 produce the highest number of present-day burn days in the Warm Deserts, Ozark/Ouachita-Appalachian Forests, and Southeastern U.S. Plains (EPA ecoregions 10.2, 8.4, and 8.3 respectively). More than 100 burn days per year are also observed in areas of the Mixed Wood Plains (8.1) and Mediterranean California (11.1) in both datasets. The downscaled CMIP5 models for both RCP scenarios overestimate gridMET burn days over much of the CONUS, with small areas where burn days are underestimated in northern and western portions of the Southeastern USA Plains (8.3) and Ozark/Ouachita-Appalachian Forests (8.4), western Mixed Wood Plains (8.1), western Cold Deserts (10.1) and central Mediterranean California (11.1). Overestimates are largest in the northern Mixed Wood Plains (8.1), Atlantic Highlands (5.3), Mississippi Alluvial and Southern USA Coastal Plains (8.5), West-Central Semi-Arid Prairies (9.3), and the western portion of the Western Cordillera (6.2), where they exceed 95 burn days per year. These large differences are most likely due to a combination of underestimates of wind speed and overestimates of $RH_{\min}$ in areas of the CONUS which are larger than climate change induced changes in 2051–2060 (Supplementary Figures 3 and 4). Wind speed differences may be exacerbated by the different treatment of wind speeds among the two datasets. While MACA downscaling of the CMIP5 model output employs an analog approach that attempts to proxy atmospheric dynamics by assuming that similar patterns in weather have reasonably consistent sets of physical forcings[46], gridMET winds are interpolated to 4 km grid resolution from coarser-scale reanalysis data[42]. Since constraints associated with fuel condition and smoke transport are not included in our analysis, both gridMET and CMIP5 results likely present an overestimate of available burn days.

Future trends in prescribed fire opportunities

We have evaluated differences in burn days between present-day (2006–2015) and future conditions (2051–2060) for both RCP scenarios, as well as the difference in burn days in 2051–2060 between RCP4.5 and RCP8.5 using a small sample *t*-test in combination with controlling the FDR. Results are summarized in Fig. 2. Figure 2a shows differences between 2006–2015 and 2051–2060 for the RCP4.5 scenario. We see a decrease in burn days across much of the southeastern and eastern US, as well as portions of the Warm Deserts (10.2), western Mixed Wood Plains (8.1) and westernmost areas of the Western Cordillera (6.2). Smaller areas of increasing burn days can be seen primarily across the western US, including in the Mediterranean California ecoregion (11.1), the Cold Deserts (10.1) Western Cordillera (6.2) and West-Central Semiarid Prairies (9.3). Stippling indicates statistically significant differences, which are found in the southeastern US, Mediterranean California (11.1), Cold Deserts (10.1) and portions of the Western Cordillera (6.2). For the RCP8.5 scenario, differences in burn days between the present and mid-century increase in magnitude relative to RCP4.5, but their spatial distributions are consistent. Figure 2b shows larger areas of statistical significance, related to the larger magnitude of differences. The largest increase in magnitude is seen across the southeastern US, where decreases in burn days nearly double (Fig. 2c). We also see an increase in the increase in burn days in Mediterranean California (11.1;

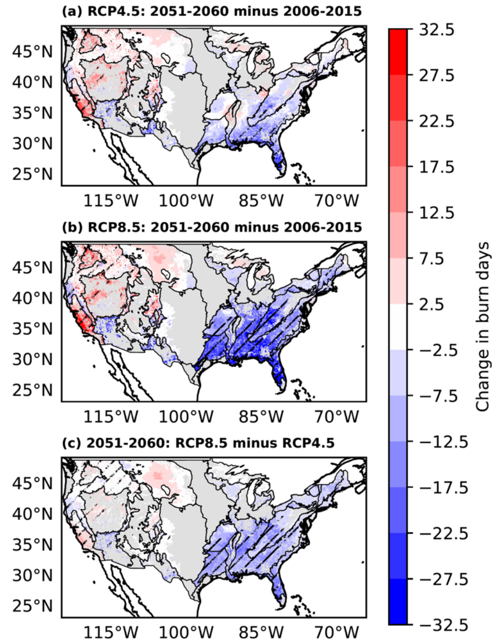

Fig. 2 | Multi-model mean difference in the number of burn days. a shows the difference between 2006–2015 and 2051–2060 for RCP4.5, (**b**) between 2005–2015 and 2051–2060 for RCP8.5, and (**c**) between RCP4.5 and RCP8.5 for 2051–2060. Stippling shows areas where differences are statistically significant after controlling for the FDR.

statistically significant), and in the West-Central Semiarid Prairies (9.3; not statistically significant).

Impacts of individual climate drivers on future changes in available burn days

Burn days were computed by evaluating climate data against four different constraints: minimum temperature (T_{min}), maximum temperature (T_{max}), minimum relative humidity (RH_{min}), and daily average wind speed (WS). Next, we considered how much each of these individual constraints on its own limits the availability of burn days and drives changes in burn days between the present day and the mid-century. We calculated burn days due to each individual climate variable alone (Fig. 3), as well as for all but one climate variable at a time (Supplementary Figure 5). The following discussion focuses on the results presented in Fig. 3.

Wind is the strongest overall constraint on burn days (Fig. 3j) and is projected to decrease over much of the CONUS in RCP4.5. Greater reductions are found over the western CONUS in RCP8.5, with patches of both increases and decreases of the same magnitude across the eastern United States (Supplementary Fig. 4). As a result of decreasing WS, burn days are projected to increase by 5 to 10 days in most locations across the CONUS in RCP4.5, except in areas within the Southeastern U.S. Plains (8.3) and Ozark/Ouachita-Appalachian Forests (8.4), where increases can reach up to 20 days (Fig. 3k). In RCP8.5 burn days increases are stronger relative to RCP4.5 in the West-Central Semiarid Prairies (9.3). Wind speeds increase and burn days decrease as a result by approximately 5 days within the Southeastern U.S. Plains (8.3) and Ozark/Ouachita-Appalachian Forests (8.4) (Fig. 3l). Significant uncertainties are associated with wind projections in climate models[47,48].

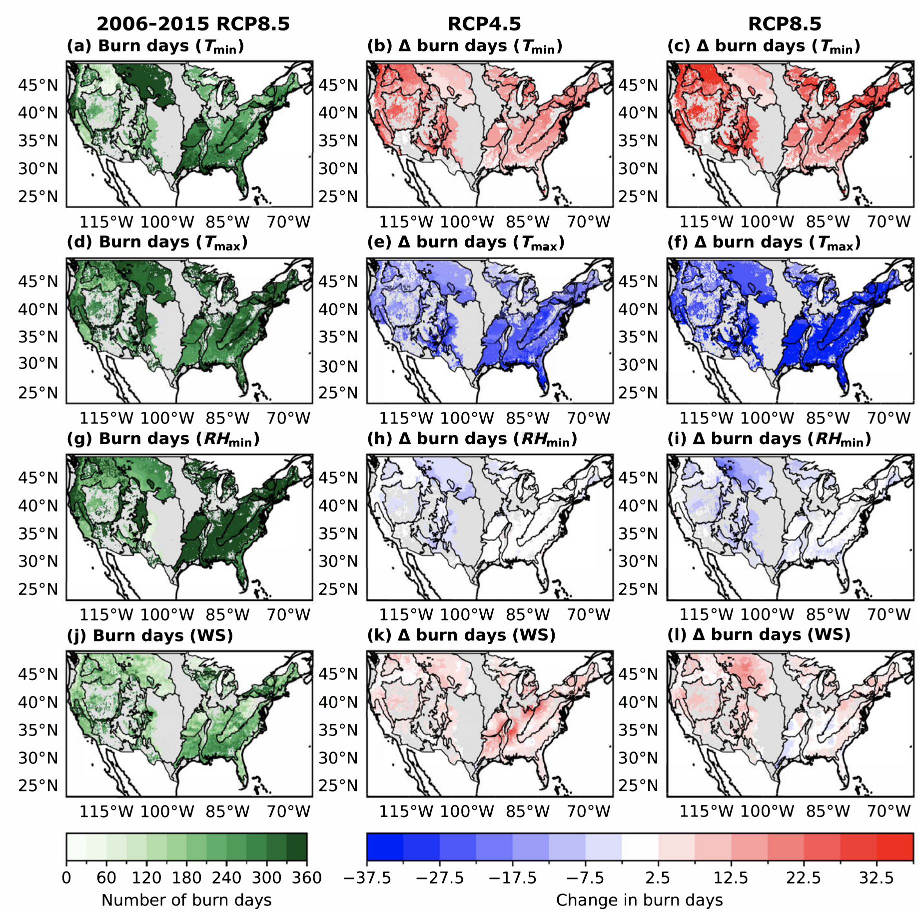

Fig. 3 | Burn opportunities due to individual climate variables. 2006–2015 values for RCP8.5 (left) are compared against changes from 2006–2015 to 2051–2060 for RCP4.5 (center) and RCP8.5 (right). Climate variables include minimum temperature (**a**–**c**), maximum temperature (**d**–**f**), minimum relative humidity (**g**–**i**) and wind speed (**j**–**l**).

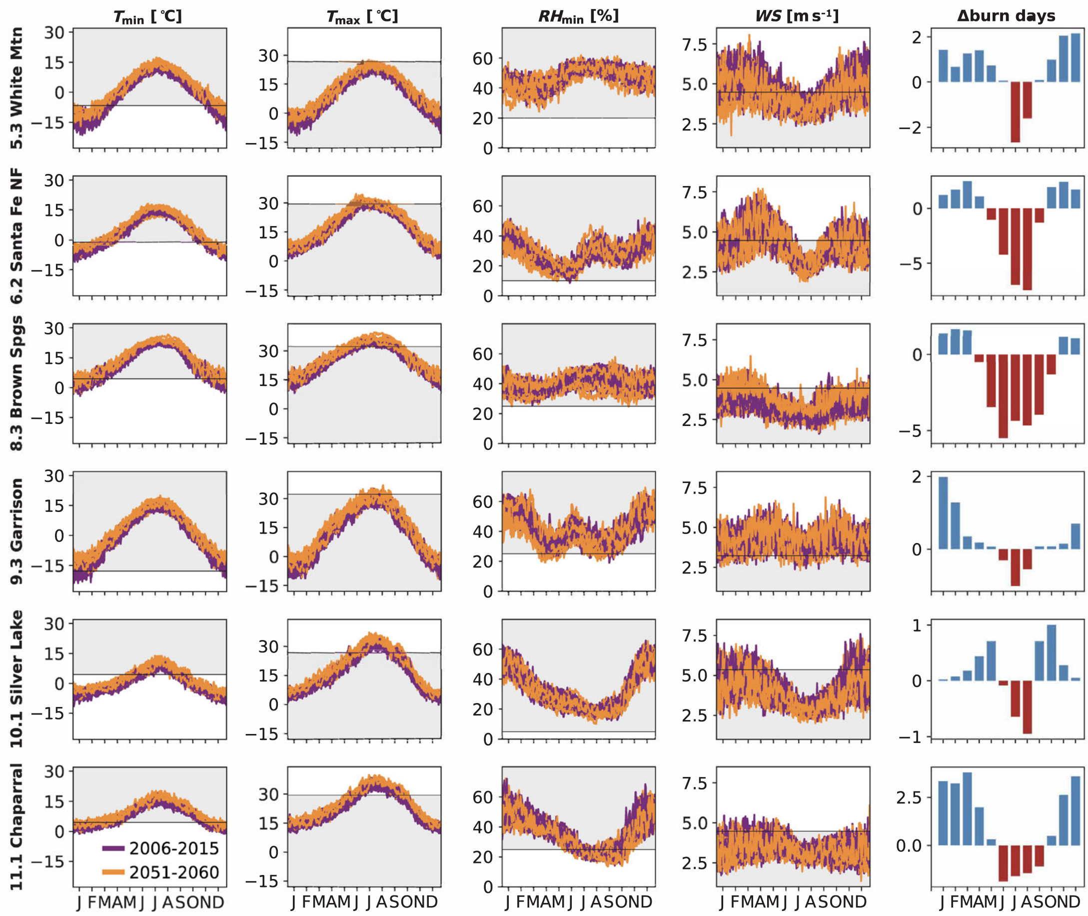

Fig. 4 | Annual variability of climate constraints for RCP4.5 CMIP5 simulations. Data from 18 models is shown, with each line representing one model. Columns represent T_{min}, T_{max}, RH_{min}, and WS (purple: 2006–2015, orange: 2051–2060), as well as model-average change in burn days between present day and future climate per month. Rows represent six sites in different ecoregions where different climate variables drive change in burn days. Prescription bounds are indicated by gray shading and black lines. Values within the gray shading are in prescription. Values that fall outside the gray shading are not in prescription.

Both T_{min} and T_{max} provide a strong constraint on present-day burn days in the Western Cordillera (6.2), Mediterranean California (11.1), Mississippi Alluvial and Southeastern USA Coastal Plains (8.5; Fig. 3a, c). In addition, T_{min} is also a strong constraint in the Mixed Wood Shield (5.2) and Upper Gila Mountain (13.1) ecoregions. In the other ecoregions, burn days as a result of temperature alone remain above 200 days per year (Fig. 3a, d). All climate models project temperature increases of up to 3 °C for both T_{max} and T_{min} across the CONUS between the present day and mid-century (Supplementary Figures 1, 2). These increases lead to an increase in burn days when low temperatures that were previously below the T_{min} limit rise to become in prescription (Fig. 3b, c), and fewer burn days when temperatures rise above the T_{max} constraint (Fig. 3e, f). Thus, maximum temperatures rising above the local T_{max} constraints lead to fewer burn days everywhere, and minimum temperatures rising above the T_{min} constraint everywhere result in an increase in burn days. For RCP4.5 the T_{max} constraint decreases burn days by between 10 and 30 days, with the strongest decreases in the eastern US. For RCP8.5 decreases exceed 30 days nearly everywhere, except for the southern portion of Mediterranean California (11.1). Increases in burn days related to T_{min} increases are largest in the western and northern US for both RCP scenarios. They are approximately 20 to 25 days for RCP4.5 and increase above 30 days for RCP8.5.

Minimum relative humidity is the overall weakest constraint on burn days. Minimum relative humidity limits burn days primarily in the South-Central Semiarid Prairies (9.4), and to a lesser extent in parts of the Western Cordillera (6.2) and southern Mediterranean California (11.1). RH_{min} is not a significant constraint in the remaining ecoregions, where it allows for between 250 and 365 burn days (Figs. 3e and 4e). Under climate change, daily minimum relative humidity in the multi-model mean decreases across much of the United States by up to 3%, with a small increase below 1% for limited areas along the California coast and in the southeastern corner of the West-Central Semiarid Prairies (Supplementary Figure 3). This widespread decrease is associated with decreases in available burn days predominantly in the West-Central Semiarid Prairies (9.3), Rocky Mountain region of the Western Cordillera (6.2), the South-Central Semiarid Prairies (9.4), and Mixed Wood Shield (5.2; Fig. 3h, i). These decreases are below 10 days for RCP4.5 but increase to up to 20 days in areas of the West-Central Semiarid Prairies (9.3) in RCP8.5.

Seasonal variability in available burn days

The results presented above focused on annual multi-model averages. However, seasonality plays an important role in how different climate drivers move days in and out of prescription. Figures 4 and 5 highlight how present and future seasonal climate variations impact burn days for individual locations representative of six ecoregions for RCP4.5 and RCP8.5, respectively. The locations were selected to capture the range of ecosystems and results (overall increases vs. decreases in burn days). The annual cycle of climate variables, including T_{min}, T_{max}, RH_{min}, and WS, for individual climate models is shown in columns 1 through 4. Column 5 shows the monthly multi-model mean change in burn days between the present day and future. All climate models project an increase in both minimum and maximum temperature throughout the year, which leads to an increase in burn days during the winter and shoulder seasons and a decrease in burn

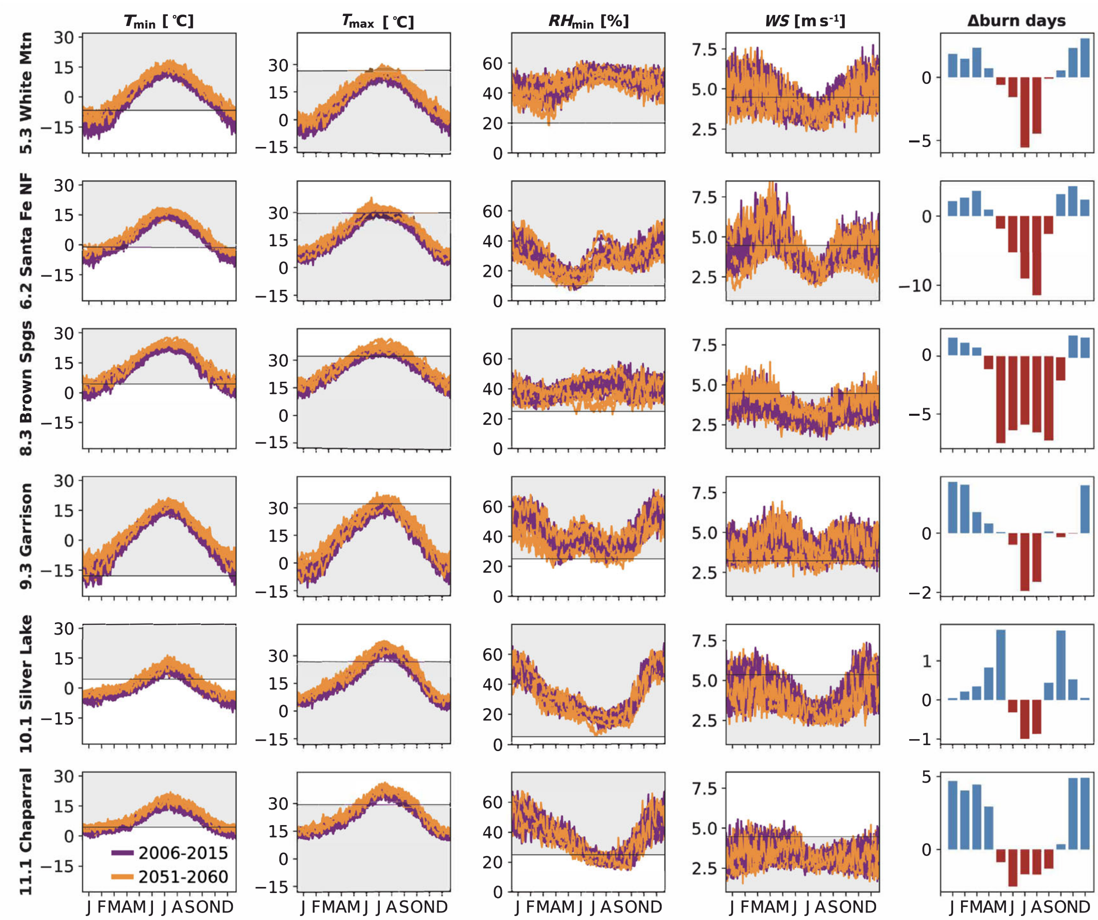

Fig. 5 | Annual variability of climate constraints for RCP8.5 CMIP5 simulations. Data from 18 models are shown, with each line representing one model. Columns represent T_{min}, T_{max}, RH_{min}, and WS (purple: 2006–2015, orange: 2051–2060), as well as model-average change in burn days between present day and future climate per month. Rows represent six sites in different ecoregions where different climate variables drive change in burn days. Prescription bounds are indicated by gray shading and black lines. Values within the gray shading are in prescription. Values that fall outside the gray shading are not in prescription.

days during the summer. Changes in relative humidity and wind speed exhibit much more inter-model variability than temperature. Clear climate-related trends are not observed for relative humidity, which is a weak constraint on burn days in general, as it falls within the prescription bounds almost entirely, except for the Chaparral site in Mediterranean California (11.1), where it is below the prescription bound from July to October. Wind provides the strongest constraint for the Garrison site in the West-Central Semiarid Prairies (9.3), where it is only within prescription for a few days throughout the year. For the White Mountain National Forest in the Atlantic Highlands (5.3), Santa Fe National Forest in the Western Cordillera (6.2), and Silver Lake National Forest in the Cold Deserts (10.1), wind is a constraint on burn days during the winter and shoulder seasons. It is a weak constraint during the winter and spring for the Chaparral site and Brown Springs. Wind speed decreases from 2006–2015 to 2051–2060 at three of the six sites (White Mountain, Silver Lake, and Chaparral), while increasing for Brown Springs. The wind speed decreases contribute to increasing burn days during the winter and shoulder seasons, while wind speed increases have the potential to contribute to decreasing burn days during the summer only at the White Mountain site. At Silver Lake, and for the Chaparral site, wind speeds are well below the prescription threshold during the summer for both present and future decades.

Discussion

As temperature and variability in precipitation increase with climate change, contributing to drying fuels and fuel build-up, we are already observing more severe wildfires and limitations on prescribed fire opportunities[26–28]. Rising maximum temperatures and declining moisture will continue to limit burning, especially in the Southeastern U.S. However, in many areas of the Western U.S., projected rising minimum temperatures and decreasing wind speeds present opportunities to expand prescribed fire application. In general decreasing burn days are projected during the summer, while burn days increase during the shoulder seasons.

Several caveats are important to note when considering the results presented here. First, while the meteorological factors we have examined do play an important role in safe application of prescribed fire, they provide only a first-order limit on burn days. For instance, we have not considered wind direction and atmospheric stratification, which are important constraints that govern smoke transport. However, smoke transport considerations are inherently local in nature, and relate to the location of the prescribed burn in relation to populations and surrounding topography. It would not be possible to consider smoke transport beyond the individual location for which prescriptions were originally developed. Fuel type and moisture content are equally important constraints, but adequate representations cannot be obtained from climate model projections. Fuel moisture is not an output in CMIP5 models, and fuel types are assumed static over time throughout the simulations we have analyzed, while we expect vegetation to change as a result of evolving climate conditions[49]. We acknowledge that as a result the specific numbers of burn days we present here are likely positively biased.

Finally, the availability of prescription information is not homogenous across our study area, with some ecoregions which cover a relatively small percentage of the CONUS featuring several prescriptions (e.g. ecoregion 5.2), while others cover larger areas, but have only one prescription (e.g. ecoregion 9.3, and 10.2).

Given these limitations, our results nonetheless strongly suggest that climate change will have an impact on prescribed burn opportunities that is dependent on the amount of future greenhouse gas emissions and resulting climate change, highly spatially variable, and driven by different aspects of climate change in different regions. Understanding and anticipating regional changes presents opportunities to adapt prescribed fire operations, policies that control its use, and long-term planning for ecological changes that will result from climate-fire interactions. It will be critical for researchers and managers to prepare for adaptation by exploring the edges of current burn prescriptions and increasing the rigor of ecological monitoring for desired and unanticipated outcomes[34]. As prescribed fire practice adapts to future conditions, it will become important to explore presently unutilized and novel conditions and consider seasonally expanding burn windows. Additional assessments of risk tradeoffs, such as smoke management concerns with nighttime ignitions versus margins for containing prescribed fire and heat stress on crews during daytime, will also gain importance. Future research and development of modeling tools that enable prescriptions to evolve to accommodate this kind of flexibility in policy and planning would be of great value. Finally, the ecological changes that accompany changing fire regimes in a future climate must be incorporated into long-term fire management and planning.

Methods

Data

Prescriptions are ranges of environmental conditions, including atmospheric temperature, relative humidity, and wind speed, that are considered safe for the application of prescribed fire at the individual sites for which prescriptions were developed. They are listed in prescribed fire plans issued by land management agencies planning and conducting prescribed burns. We collected prescribed fire plans for 83 locations across the CONUS from land management agencies including U.S. National and State Park Services, the U.S. Forest Service, U.S. Fish & Wildlife Service, U.S. Air Force, and the Coalition of Prescribed Fire Councils. We used minimum and maximum temperature, minimum and maximum wind speed, and minimum relative humidity in our analysis. We excluded maximum relative humidity because the maximum relative humidity values in the climate data we use occur at night, when prescribed fire operations are currently not, or very rarely, conducted. Rather the maximum relative humidity values listed in prescriptions refer to the daytime values that might be encountered during operations. Since nighttime values are significantly higher, maximum relative humidity would erroneously exclude most days from being suitable for burning. Some prescribed fire plans list broader required and more narrow desired parameter ranges. In these cases, we used the broader required ranges in our analysis. Other documents list ranges for low versus high-intensity fire behavior. In these cases, we used the low end of the low fire intensity range, and the high end of the high fire intensity range. Prescriptions typically also included fuel type and fuel moisture values. Fuel type was used to associate individual prescriptions to other locations with the same fuel type within areas with generally similar ecosystems. To define the extent of these regions, we used the EPA Level II ecoregion boundaries[45] (Fig. 6). Fuel type

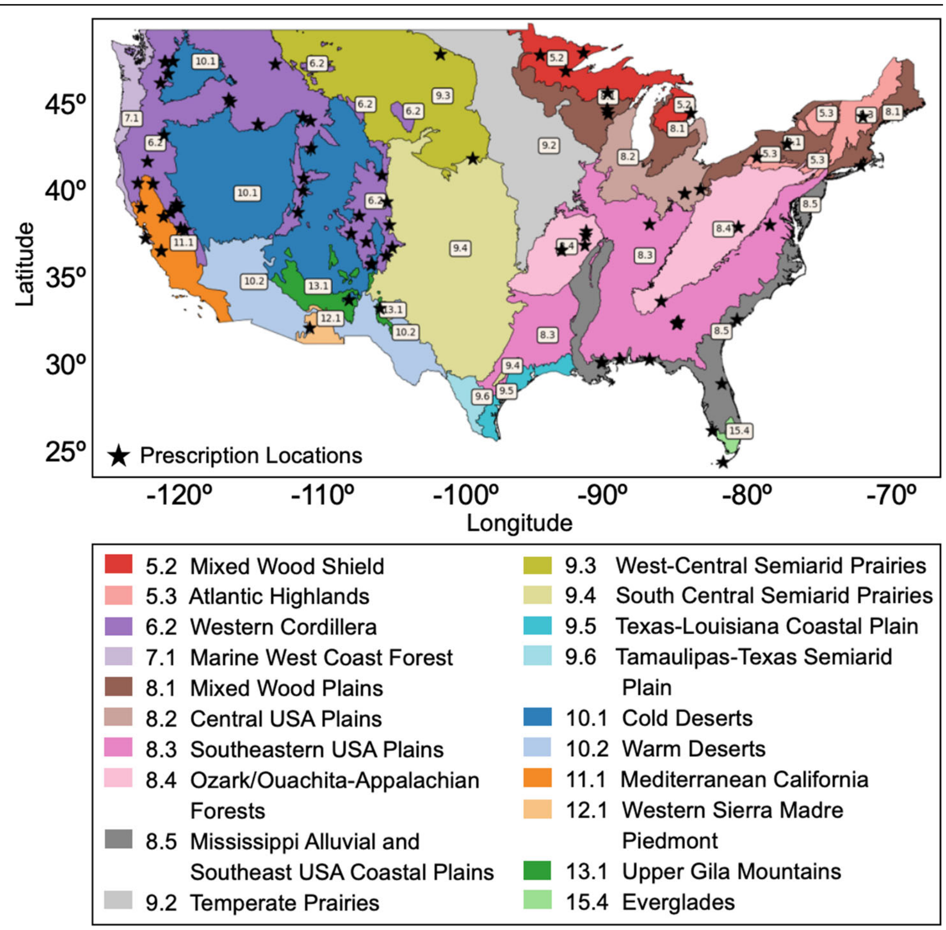

Fig. 6 | EPA Level II ecoregions and locations of prescription window data. Ecoregions are represented by different color fill. Black stars indicate locations of prescription data.

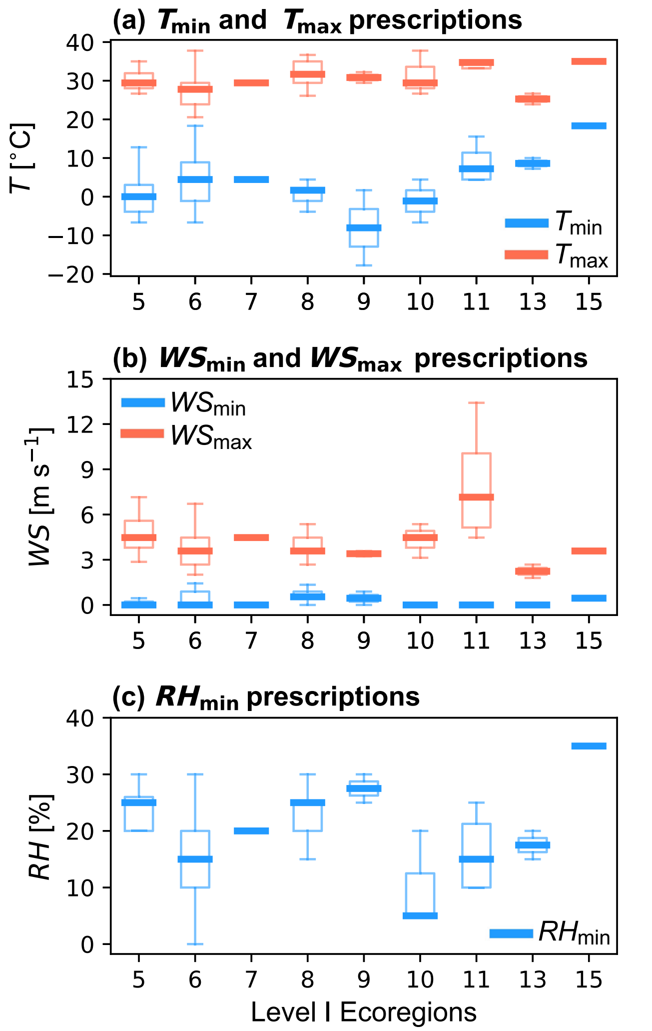

Fig. 7 | Ranges of prescriptions grouped by EPA Level I ecoregion. a minimum and maximum temperature, (**b**) minimum and maximum wind speed, and (**c**) minimum relative humidity. Prescription ranges highlight strong variability across as well as within ecoregions. The box-plot center lines represent the median of all prescriptions within the Level 1 ecoregion, the box limits represent the upper and lower quartiles, and the whiskers extend from the box to the farthest data point lying within 1.5x the interquartile range from the box.

information was obtained from Scott and Burgan Fire Behavior Fuel Models[50] available for the CONUS as part of LANDFIRE. While previous studies have evaluated viable burn days regionally considering spatially uniform ranges of prescription parameters[31,40,41], we have chosen to explicitly treat the spatial heterogeneity of prescriptions in this analysis. Figure 7 shows the ranges of the meteorological variables we consider for each EPA Level I ecoregion. We see large variability across ecoregions, with several instances of non-overlapping ranges (e.g. T_{min} and T_{max} for ecoregions 9, 13, and 15, or WS_{max} for ecoregions 11, 13, and 15) as well as large variability within those ecoregions that contain several prescriptions (Fig. 7).

We used two different climate datasets to evaluate burn days, including present-day (2006–2015) data from gridMET[42] at 4 km horizontal resolution and climate data from 18 CMIP5 models (Supplementary Table 1) for two future climate scenarios. We considered the mid-range Representative Concentration Pathways 4.5 (RCP4.5) scenario[46,51] which stabilizes radiative forcing from greenhouse gas emissions, and the RCP8.5 scenario[52], characterized by comparatively high greenhouse gas emissions. We analyzed CMIP5 data for the present day (2006–2015) and future (2051–2060). The mid-century future period of 2051–2060 was chosen because CMIP5 models do not project vegetation change in response to a changing climate. Thus, considering the end of the century would have larger uncertainties in terms of future vegetation distribution associated with it. CMIP5 data has been statistically downscaled to a 4 km horizontal resolution using Multivariate Adaptive Constructed Analogs (MACA)[53].

Burn day calculation

To apply the prescription information available to us to as large of an area as possible while maintaining the spatial heterogeneity of prescription ranges, we first extended the locations to which the prescription information can be applied by associating each prescription with an EPA Level II ecoregion. 16 of the 21 ecoregions across the CONUS contain one or more prescriptions (See Fig. 6 and Table 1). Within each EPA ecoregion boundary, prescriptions were then compared against the Scott and Burgan fuel model data from LANDFIRE. If the LANDFIRE fuel matched at least one fuel type listed in a prescription for the ecoregion, the prescription was applied to the grid cell. LANDFIRE Scott and Burgan data covers the CONUS at 30 m resolution. To match the climate data resolution of 4 km, we coarsened the LANDFIRE data using the mode of the fuel model. Additionally, some prescriptions list fuel types as Scott & Burgan fuel models, while others use Anderson fuel models. We converted Anderson to Scott and Burgan classifications by choosing fuel models that produce a similar fire spread rate[50] (see Table 2). If two or more prescriptions listing the same fuel types fell within one ecoregion, we used the prescription closest to the LANDFIRE grid cell. To identify the closest prescription, we used the Haversine formula for calculating distance on a sphere. This approach allowed us to expand data coverage to 57% of vegetated areas within the CONUS.

For each ecoregion, we looped over all 4 × 4 km grid cells where prescription information was available and evaluated the prescription against climate data for that grid cell to determine whether conditions on a given day are safe for burning or not. Using daily minimum and maximum temperature and wind speed, and minimum relative humidity, we counted a day as a burn day if temperature, wind speed, and RH values all fell within the prescription's ranges. If one or more of the climate variables fell outside of prescribed ranges, the day was not counted as a burn day. We repeated this process for years 2006 to 2015, and years 2051 to 2060, for both RCP4.5 and RCP8.5 projections. Annual burn days for the 10 years were then averaged. We also evaluated the role of individual meteorological variables as constraints by repeating this analysis with only one variable at a time, while assuming that all other variables are in prescription. Without the individual constraints, the number of burn days would be equal to 365 everywhere. Thus, the fewer burn day result, the stronger the constraint that the specific meteorological variable provides.

Statistical analysis

We evaluated the statistical significance of the differences between the number of burn days in the present day and the mid-century, as well as between RCP scenarios, using a small sample *t*-test for the difference between two means at a 95% significance level. We further accounted for the multiple hypothesis testing problem by controlling the false discovery rate (FDR)[54,55], and only considered differences statistically significant that the FDR procedure deemed significant. The FDR procedure sorts *N* hypothesis tests with *p* values in ascending order and determines a threshold value, p^*_{FDR}, such that we reject any *p* values greater than p^*_{FDR} according to Eq. (1):

$$p^*_{FDR} = \max_{i=1,\ldots,N}\left[p_{(i)} : p_{(i)} \leq (i/N)\alpha_{FDR}\right] \quad (1)$$

Table 1 | List of EPA Level I and Level II ecoregions, including number of prescription window data sites within each ecoregion, and % surface area covered

Level I Ecoregion	Level II Ecoregion	Number of Rx Sites	(%) Surface area in CONUS
5. Northern Forests	5.2 Mixed Wood Shield	5	2.83
	5.3 Atlantic Highlands	2	2.12
6. Northwestern Forested Mountains	6.2 Western Cordillera	35	12.29
7. Marine West Coast Forests	7.1 Marine West Coast Forests	1	3.86
8. Eastern Temperate Forests	8.1 Mixed Wood Plains	5	5.73
	8.2 Central USA Plains	3	2.22
	8.3 Southeastern USA Plains	6	10.10
	8.4 Ozark, Ouachita-Appalachian Forests	7	5.10
	8.5 Mississippi Alluvial and Southeast USA Coastal Plains	9	3.44
9. Great Plains	9.2 Temperate Prairies	0	7.37
	9.3 West-Central Semi-Arid Prairies	1	8.04
	9.4 South-Central Semi-Arid Prairies	1	9.77
	9.5 Texas-Louisiana Coastal Plain	0	0.89
	9.6 Tamaulipas-Texas Semi-Arid Plain	0	1.4
10. North American Deserts	10.1 Cold Deserts	2	10.38
	10.2 Warm Deserts	1	9.30
11. Mediterranean California	10.1 Mediterranean California	5	1.86
12. Southern Semi-Arid Highlands	12.1 Western Sierra Madre Piedmont	0	2.10
13. Temperate Sierras	13.1 Upper Gila Mountains	2	1.07
15. Tropical Wet Forest	15.4 Everglades	1	0.22

Table 2 | Conversion of Anderson Fuel Model to Scott and Burgan (S&B) Fuel Model

Anderson Fuel Model	S&B Fuel Model
FM1	GR2
FM2	GR2
FM3	GR7
FM4	SH5
FM5	GS2
FM6	SH4
FM7	SH4
FM8	TL3
FM9	TL9
FM10	TU2
FM11	SB1
FM12	SB2
FM13	SB2

Data availability

Climate and landscape data are freely available. Downscaled MACA data can be obtained at https://climate.northwestknowledge.net/MACA/ and LANDFIRE data is available at https://landfire.gov/fbfm40.php. Prescription window information is made available via github at https://github.com/ajonko/RxFire.

Code availability

Analysis code is available via github at https://github.com/ajonko/RxFire.

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Author contributions

A.J., A.A., T.B. and C.H. conceived the study, M.B., M.D., D.G., K.H., C.H. and J.R. collected prescription information, A.J., J.O., T.B. and A.G. conducted the analysis, and A.J. wrote the original manuscript; all authors edited the manuscript and participated in revisions.

Competing interests

The authors declare no competing interests.

Additional information

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