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Main Text （~7785 words)
Figures 1 to 7

**Abstract (250 words)**

The air quality impact of increased wildfires in a warming climate has often been overlooked in current model projections, owing to the lack of interactive fire emissions of gases and particles responding to climate change in Earth System Model (ESM) projection simulations. Here we combine multi-ensemble projections of wildfires in three ESMs from the Sixth Coupled Model Intercomparison Project (CMIP6) with an empirical statistical model to predict fine particulate ($PM_{2.5}$) pollution in the late 21$^{st}$ century under a suite of Shared Socioeconomic Pathways (SSPs). Total $CO_2$ emissions from fires over western North America during August–September are projected to increase from present-day values by 60–110% (model spread) under a strong-mitigation scenario (SSP1-2.6), 100–150% under a moderate-mitigation scenario (SSP2-4.5), and 130–260% under a low-mitigation scenario (SSP5-8.5) in 2080–2100. We find that enhanced wildfire activity under SSP2-4.5 and SSP5-8.5 could cause a two- to three-fold increase in $PM_{2.5}$ pollution over the US Pacific Northwest during August–September. Even with strong mitigation under SSP1-2.6, $PM_{2.5}$ in the western US would increase ~50% by mid-century. By 2080–2100 under SSP5-8.5, the 95$^{th}$ percentile of late summer daily $PM_{2.5}$ may frequently reach unhealthy levels of 55–150 μg/m$^3$. In contrast, chemistry-climate models using prescribed fire emissions of particles not responding to climate change simulate only a 7% increase in $PM_{2.5}$. The consequential pollution events caused by large fires during 2017–2020 might become a new norm by the late 21$^{st}$ century, with a return period of every 3 to 5 years under SSP5-8.5 and SSP2-4.5.

**Significance Statement (120 words)**

Record-setting fires in the western US over the last decade caused severe air pollution, loss of human life, and property damage. Enhanced drought and increased biomass in a warmer climate may fuel larger and more frequent wildfires in the coming decades. Applying an empirical statistical model to fires projected by Earth system models including climate-ecosystem-socioeconomic interactions, we show that fine particulate pollution over the US Pacific Northwest could double to triple during late summer to fall by the end of the 21$^{st}$ century under intermediate- and low-mitigation scenarios. The historic fires and resulting pollution extremes of 2017–2020 could occur every 3 to 5 years under 21$^{st}$

century climate change, posing challenges for regional air quality management and threatening public health.

**Main Text**

**Introduction**

Wildfires contribute 15–30% of atmospheric primary fine particle ($PM_{2.5}$) emissions in the United States (1), with implications for ecosystems, human health, and climate (2-5). Marked increases in wildfire burned area over the western US in recent decades have been linked to anthropogenic climate change and land management practices (4, 6-8). Increasing emissions from wildfires have caused summertime $PM_{2.5}$ levels to rise in some western US regions despite efforts to control anthropogenic emissions (9-11). Millions of people were exposed to very unhealthy or hazardous $PM_{2.5}$ concentrations (150–650 $\mu g/m^3$ for 24-h average) for extended periods during recent large wildfires around the world (11-17). Exposure to dense smoke from fires has detrimental effects on human health (3, 18-20), with an economic cost due to short-term smoke exposure estimated to be $11–20 billion per year in the continental US (21). The US Clean Air Act allows for screening of air quality exceedances caused by "exceptional events," such as wildfires, from counting towards a non-attainment determination (22). Understanding the extent to which wildfire emissions in a future climate influence $PM_{2.5}$ exceedances thus has implications for designing effective air quality policies.

A number of studies have projected enhanced wildfire activity over the western US under a warming climate during the 21st century (23-27). However, owing to the lack of interactive fire emissions of gases and particles responding to climate change in current chemistry-climate models, projections of future $PM_{2.5}$ air quality generally overlook the impacts of changing fires (28-31). A few studies estimated future fire emissions using statistical regressions of burned area and climate variables and fed these emissions into an offline chemical transport model to estimate future $PM_{2.5}$ air quality (26, 32-35). These studies suggested 80–170% increases in fire emissions of primary aerosols by the 2050s, which resulted in 46–70% increases in surface organic carbon concentrations (a key component in fire smoke). Using fire emissions simulated by a process-based fire model driven by archived meteorological fields from a chemistry-climate model, several studies estimated 50–90% increases in mean organic carbon concentrations over the continental US by the late 21st century (23,

36). These results have large uncertainties, as the statistical or offline fire models typically do not include feedbacks among climate, land use, ecosystem dynamics, and anthropogenic influences through ignition and suppression (2, 37-39).

Here we leverage the Sixth Coupled Model Intercomparison Project (CMIP6) multi-model and multi-ensemble simulations of fire $CO_2$ emissions responding to changes in climate, vegetation, and population distributions, combined with a multiple linear regression (MLR) model developed from historical observations, to project wildfire impacts on $PM_{2.5}$ means and extremes over the western US under a suite of Shared Socioeconomic Pathways (SSPs; see *Methods*). The process-based fire models in CMIP6 are greatly improved compared to those in CMIP5, with better representation of the impacts of fuel wetness on fire occurrence and spread, enhanced fire spread rate in forest crowns, and ability to simulate multi-day fires (40-51). Our statistical model considers the influence of both local and regional fires, as well as inter-state smoke transport, air stagnation, and other meteorological conditions. We compare our MLR-predicted $PM_{2.5}$ with that simulated in the chemistry-climate models using prescribed fire emissions of gases and particles not responding to climate change (see *Methods*) (29). We show that drought and increased biomass under a warmer climate in the Pacific Northwest during the late 21$^{st}$ century increase the risk of fires, causing a two- to three-fold increase in $PM_{2.5}$ levels in late summer to fall.

## Results

### Observed correlations between fires and $PM_{2.5}$ air quality

[Figure 1 about here]

We first use historical observations to investigate the extent to which the interannual variability of $PM_{2.5}$ means and extremes at US surface sites can be explained by regional versus local fires as well as meteorological conditions. The observed relationships will serve as a basis for developing the MLR model used to predict future $PM_{2.5}$ levels from fire $CO_2$ emissions and meteorology available from CMIP6 Earth system models. We correlate surface $PM_{2.5}$ observations averaged over a 2°×2° grid with fire $CO_2$ emissions integrated over a box with size varying from 2.5°×2.5° to 20°×20° centered at that grid during May–November from 1997 to 2020, using simple linear regression and multiple linear

regression (MLR, see *Methods*). We consider four meteorological variables: surface temperature, precipitation, relative humidity, and air stagnation, which have been previously shown to be correlated with surface $PM_{2.5}$ (11, 52).

During August and September, when fires peak seasonally over the Pacific Northwest under the present-day climate (53), mean $PM_{2.5}$ levels at western US sites show strong correlations ($r^2$ = 0.5–0.9) with regional fire $CO_2$ emissions summed over a box of 10°×10° to 15°×15°, indicating the importance of regional smoke transport (11) (Fig.1a). In comparison, the correlations are much weaker ($r^2$ < 0.5) during May–July and October–November (Fig.S1), and are statistically insignificant ($p$ > 0.05) at most eastern US sites, where fire is not the dominant source of surface $PM_{2.5}$. In the following analyses we thus focus on the US Pacific Northwest (solid black box on Fig.1b) during August and September.

The MLR model, including the impacts from meteorological variables, achieves higher correlations ($r^2$ = 0.7–0.9; Fig.1b) compared to a simple linear regression with fires alone ($r^2$ = 0.5–0.9; Fig.1a). Fire $CO_2$ emissions on average explain 66% of the observed $PM_{2.5}$ interannual variability during August–September in the Pacific Northwest (Fig.1c), with air stagnation index being the second most important predictor (11%), consistent with our prior work suggesting that air stagnation played an important role in the accumulation of $PM_{2.5}$ during the historic 2017 and 2018 fire seasons (11). The contributions from relative humidity, temperature, and precipitation are each less than 10%. A larger increase in correlation ($r^2$) with meteorology is found in July and October than August or September, suggesting a more important role of meteorology in controlling $PM_{2.5}$ during these months (Fig.S1). These correlations confirm that it is important to consider impacts from both fires and meteorology for a robust estimation of changes in future $PM_{2.5}$ air quality.

We next examine the relationship between regional fires and $PM_{2.5}$ extremes defined as the 95$^{th}$ percentile (q95) of available daily $PM_{2.5}$ measurements from all sites within a 2°×2° grid for August and September (see *Methods* and Fig.S2). We still use monthly mean meteorological variables instead of extremes in the MLR model, since the q95 $PM_{2.5}$ in observations may not coincide with days having extreme meteorological conditions (i.e., heat wave, stagnation) and there are larger uncertainties in the predicted climate extremes than mean states. Significant correlations are observed between fire $CO_2$ emissions and the q95 $PM_{2.5}$ at most western US sites in August and September, based on simple linear

regression ($r^2$ = 0.5–0.9; Fig.1d) and MLR ($r^2$ = 0.7–0.9; Fig.1e). Fire $CO_2$ emissions explain 70% of the observed $PM_{2.5}$ interannual variability on average at US Pacific Northwest sites (Fig.1f), dominating over meteorological impacts.

The interannual variability of both mean and q95 $PM_{2.5}$ during August–September averaged over US Pacific Northwest sites shows a strong correlation ($r^2$ = 0.8–0.9) with regional total fire $CO_2$ emissions over western North America (Fig.1g-h). In the 2017, 2018, and 2020 fire seasons, the western US experienced record-breaking wildfires burning ~50% more than the average area over the past two decades (54-56). The q95 $PM_{2.5}$ averaged over the US Pacific Northwest sites during August–September was 76 μg/m$^3$ in 2017, 44 μg/m$^3$ in 2018, and 95 μg/m$^3$ in 2020, respectively, exceeding the US National Ambient Air Quality Standard of 35 μg/m$^3$.

These MLR analyses demonstrate significant interannual correlations of surface $PM_{2.5}$ pollution with regional fire $CO_2$ emissions and meteorology over the western US during August–September. Cross validation further confirms the robustness of the MLR model in predicting $PM_{2.5}$ (*SI Appendix,* Text S1). We obtain regression coefficients for the MLR model using the relationships of $PM_{2.5}$, fires, and meteorological conditions observed in August–September during the period 1997–2020. Then we drive the MLR model with the monthly time series of fire $CO_2$ emissions and meteorological variables simulated by CMIP6 Earth system models under different climate change scenarios to predict $PM_{2.5}$ throughout the 21$^{st}$ century (see *Methods*).

**Evaluating variability of fires simulated by CMIP6 models**

[Figure 2 about here]

To establish the robustness of future projections, we examine how well three CMIP6 models, the Community Earth System Model version 2 (CESM2) (57), the Geophysical Fluid Dynamics Laboratory Earth System Model version 4.1 (GFDL-ESM4.1) (58) and the Centre National de Recherches Météorologiques Earth System Model version 2 (CNRM-ESM2-1) (59), simulate historical fires. We use satellite observations of burned area from the MODerate Resolution Imaging Spectrometer (MODIS) (60) and satellite-based estimates of fire $CO_2$ emissions from the Global Fire Emissions Database (GFED4s) (61, 62) and the Quick Fire Emissions Dataset (QFED2.5) (63). Observations show hotspots of burned area and fire $CO_2$ emissions over the Pacific Northwest in August and

September (Fig.2a-b). We investigate the extent to which models capture the interannual variability of fires over this region relative to their respective mean state. Evaluating normalized interannual variability provides insights into the sensitivity of simulated fires to meteorological and climatic variability, which is critical to establish the robustness of projected fire responses to climate change.

We first examine the land-only experiments (see *Methods*) driven by observation-based meteorological forcings to allow direct comparison with the observed fires in space and time. The land-only simulations generally capture the observed normalized interannual variability of burned area ($r^2$ = 0.32–0.67) and fire $CO_2$ emission ($r^2$ = 0.25–0.60) over western North America (Fig.2c-d), despite mean-state biases (Fig.S3). Above-normal fire activity is observed and simulated in years such as 1988, 2006, 2012, 2017, 2018, and 2020, associated with severe drought conditions (64-69). The CESM2 model performs best in simulating the interannual variability of burned area ($r^2$ = 0.67; $p$ < 0.01) and fire $CO_2$ emission ($r^2$ = 0.60–0.64; $p$ < 0.01). For comparison, the correlations for burned area are $r^2$ = 0.49 ($p$ < 0.01) for CNRM-ESM2-1, and $r^2$ = 0.32 ($p$ < 0.05) for GFDL-ESM4.1. The amplitude of the observed interannual variability of fire $CO_2$ emissions (represented as standard deviation in Fig.2) is also best captured by CESM2: s.d. = 36.4%, compared to s.d. = 55.9–56.2% in observations, s.d. = 28.3% in GFDL-ESM4.1, and 20.6% in CNRM-ESM2-1.

The fully coupled ocean-land-atmosphere experiments allow us to project future fires under varying climate change scenarios. These coupled model simulations are driven by model-generated climate and thus are not expected to capture the timing and location of the observed fires during historical periods. Therefore, we evaluate the hemispheric to regional patterns in burned area and fire $CO_2$ emissions, as well as the strength of interannual variability during the 1997–2014 period. Both the land-only and coupled experiments from all three models simulate the salient features of the spatial patterns of fire burned area and $CO_2$ emissions across the Northern Hemisphere, such as capturing fire hotspots over western North America and Mediterranean Europe in August and September (Figs.S4-S7). The models simulate reasonable fire interannual variability over these hotspots areas, despite large mean-state biases. Over western North America, total fire $CO_2$ emissions in August and September are overestimated by a factor of two in CESM2, and factors of 4–5 in GFDL-ESM4.1 and CNRM-ESM2-1, compared to the estimates from two satellite-based fire emission inventories (Fig.S3b). Similar high biases have previously been identified in CMIP5 Earth system models (23, 41) and by the CMIP6 Fire

Model Intercomparison Project (40). These studies suggest possible biases in the simulated fuel load (biomass), fire response to human activities, and fuel consumption rate applied in the models (40, 41, 70).

We conclude that the three CMIP6 Earth system models have moderate ability to simulate changes in fire emissions in response to variations in climate and vegetation, despite varying levels of mean-state biases. To gauge the uncertainties of our $PM_{2.5}$ predictions associated with these biases, we compare MLR predictions driven by the relative changes of fire $CO_2$ emissions versus those driven by the absolute emission changes in each model. For CESM2, with small mean-state biases in historical fire $CO_2$ emissions, we find an overall consistent magnitude of western US mean $PM_{2.5}$ predictions between the two MLR models (top panels in Fig.S8). For GFDL-ESM4.1 and CNRM-ESM2-1, with high mean-state biases in historical fire $CO_2$ emissions, the MLR model driven by the absolute changes of fire emissions predicts much larger $PM_{2.5}$ in 2080–2020, with the $PM_{2.5}$ prediction driven by relative changes agreeing better with that driven by the CESM2 model (bottom panels in Fig.S8). Thus, we conclude that it is more reasonable to use the relative change of fire $CO_2$ emissions to drive the MLR prediction of future $PM_{2.5}$ levels.

**Changes in climate and fires in the 21st century**

[Figure 3 about here]

We next investigate changes in climate and fires over western North America in the 21st century from the CMIP6 coupled Earth system simulations under four climate change scenarios: SSP1-2.6 (low societal vulnerability combined with radiative forcing of 2.6 W $m^{-2}$ by 2100), SSP2-4.5 (intermediate societal vulnerability, 4.5 W $m^{-2}$ forcing), SSP3-7.0 (high societal vulnerability, 7.0 W $m^{-2}$ forcing) and SSP5-8.5 (fossil-fueled development, high emissions, 8.5 W $m^{-2}$ forcing) (71, 72). While studies have suggested that fire seasonality may change in a warming climate (73-75), our MLR model predictions build upon the strong correlation between $PM_{2.5}$ and fires during August–September over the Pacific Northwest under present-day climate. To investigate whether it is reasonable to focus on August–

September under future climate, we examine fire seasonality and spatial pattern over North America under SSP5-8.5 (Fig.3).

All three models project a lengthening of the fire season over the Pacific Northwest in a warmer climate, with elevated fire $CO_2$ emissions spanning from May to November during 2080–2100 under SSP5-8.5 compared to July to October at present (Fig.3a). Nevertheless, all three models suggest fire $CO_2$ emissions in the late 21$^{st}$ century peak in August and September, similar to the current climate. Therefore, we continue to focus our projections on changes in fires and $PM_{2.5}$ air quality in August and September. During August and September, fire $CO_2$ emissions are projected to increase significantly ($p$<0.05) over western North America (Fig.3b) and Mediterranean Europe (Figs.S9-S10) in the late 21$^{st}$ century under SSP5-8.5, according to our multi-ensemble and multi-model projections. These regions are particularly susceptible to water scarcity in a warming climate (76, 77), which could impact regional air quality via vegetation feedbacks (78).

[Figure 4 about here]

Figure 4 illustrates the temporal evolution of surface temperature, soil moisture, vegetation carbon mass, burned area, and fire $CO_2$ emissions from CESM2, which best simulates the observed interannual variability of fires, as discussed previously (Fig.2). Changes in fire $CO_2$ emissions and burned area from the other two models are also shown for comparison. CESM2 projects a ~2K increase in August–September mean surface temperature over western North America by the 2040s (versus present day), with little difference across the SSPs (Fig.4a). Surface temperatures among scenarios diverge afterwards, with a 7.5K increase under SSP5-8.5 compared to a 2K increase under SSP1-2.6 by the late 21$^{st}$ century (versus present day). Following climate warming and rising $CO_2$ concentrations, which stimulates vegetation growth, CESM2 simulates a decrease in surface soil moisture and an increase in vegetation carbon mass (Fig.4b-c), both providing more favorable conditions for fires. Under the SSP3-7.0 and SSP5-8.5 high-warming scenarios, CESM2 projects a ~10% decrease in surface soil moisture by the end of the 21$^{st}$ century. The projected decrease is consistent with the overall drying trend projected by 13 CMIP6 models (79), attributed primarily to enhanced evaporative demand and water use by vegetation in a warmer climate (80). Vegetation carbon mass shows a ~50% increase by

2100 under SSP5-8.5, partly driven by $CO_2$ fertilization, increased temperature, and land use changes (81-83).

Following the projected trends in climate and vegetation, CESM2 shows 50–120% increases in burned area and 110–250% increases in fire $CO_2$ emissions among different SSPs by 2100 over western North America (Fig.4d,g; Table S2). The different increases in fires among the scenarios reflect impacts from both climate and population distributions (37). The projected increases in fire $CO_2$ emissions are ~250% under the SSP3-7.0 and SSP5-8.5 extreme warming scenarios, more than twice that under the SSP1-2.6 climate mitigation scenario. We note a smaller increase in fire burned area under SSP5-8.5 (100%) compared to SSP3-7.0 (120%) (red versus yellow lines in Fig.4g). This may be related to the larger population projected under SSP5-8.5 (84) and thus stronger effects of fire suppression (85, 86). The influence of population density on fire suppression is also evident in historical simulations (Fig.S11). Across all scenarios, the projected increases in fire $CO_2$ emissions are about twice those in burned area (Fig.4), indicating increased emission efficiency per area burned driven partly by increased vegetation biomass or increased fire duration in a warming climate.

All three models project substantial increases in burned area and fire $CO_2$ emissions in the late 21$^{st}$ century, although the magnitudes of the projected changes, the spatial patterns, and the spreads across scenarios and across ensemble members differ (Fig.4 and Figs.S9-S10). The projected percentage increase in fire $CO_2$ emissions per degree warming is ~40% in CESM2 and GFDL-ESM4.1 and ~20% in CNRM-ESM2-1. Under SSP5-8.5 by the late 2100s, the projected increase in fire $CO_2$ emissions over western North America is 260% from GFDL-ESM4.1, 240% from CESM2, and 130% from CNRM-ESM2-1 (Fig.4d-f). GFDL-ESM4.1 shows the largest cross-scenario spread, with a 70% increase in fire $CO_2$ emissions under SSP1-2.6 and a 260% increase under SSP5-8.5 by the late 21$^{st}$ century (Fig.4e). Among the three models, CNRM-ESM2-1 has the simplest fire module but has the greatest number of ensembles (see *Methods* and Table S1). The larger ensemble spread for both historical and future simulations in CNRM-ESM2-1 results in a better estimate of the influence of the internal climate variability on fire emissions. There are also some inter-model differences in the spatial distribution of the projected fire increases over western North America (Figs.S9-S10). CESM2 shows larger increases of fire burned area and emissions over the northern Great Plains, while CNRM-ESM2-1 and GFDL-

ESM4.1 simulate larger increases over the Pacific Northwest. These results highlight the importance of multi-model and multi-ensemble projections to access uncertainties.

**Comparison with previous studies**

A few prior studies have estimated changes in fire emissions in the 21st century. Here we present a brief comparison with our results. Under SSP2-4.5 by midcentury, the three CMIP6 models we consider projected a 60–80% increase in fire emissions over western North America. Our projected changes are smaller than the ~150% increase projected by a statistical fire model considering impacts from climate but not land use and population density (26). This is consistent with the smaller increase in fire carbon emissions over western North America during 1960s–2010s from the CESM2 coupled historical simulations using interannually varying versus fixed-1850 land use and population density (Fig.S11). Increased population density leads to greater fire suppression, wood harvest, and conversion of natural land (i.e. forest) to managed land (i.e. cropland), resulting in reduced forest biomass available for burning (40, 43, 87). Our projection of 60–80% increase in fire $CO_2$ emissions over western North America is higher than the 45% increase projected by an offline process-based fire model driven by archived meteorological fields (23). The larger changes from our projection may be related to a positive feedback between fire and climate, e.g. increased fire risk due to enhanced surface temperature caused by fire-induced damage in vegetation canopy, which is not included in the offline simulation (37, 42, 88). The comparisons suggest that it is important to consider the impacts from climate, land use, and population influence for a robust projection of fires and feedbacks.

**Increasing $PM_{2.5}$ pollution from wildfires in a warming climate**

[Figure 5 about here]

Changes in fire $CO_2$ emissions and meteorology projected by three CMIP6 Earth system models are used to drive the MLR model to predict $PM_{2.5}$ over the western US under four SSP scenarios (Fig.5, Table S2). The MLR model driven by historical fires generally captures the observed variability and increasing trend of western US $PM_{2.5}$ in August–September during 1997–2020, demonstrating the credibility of the MLR-based $PM_{2.5}$ estimations (red versus black lines in Fig.5d-f). The MLR model driven by simulated future fires projects August–September mean $PM_{2.5}$ levels at western US sites to increase by approximately 50% in the coming decades (2020–2050), even under the SSP1-2.6 strong-mitigation scenario with global $CO_2$ emissions cut severely and reaching net-zero around 2050. Under

the “middle-of-the-road” SSP2-4.5 scenario, $CO_2$ emissions hover around current levels before falling mid-century, but do not reach net-zero by 2100 (71, 72); wildfire emissions and resulting $PM_{2.5}$ pollution would continue to increase after 2050 and almost double by 2100 compared to present-day levels (green lines in Figs.4d-f and 5d-f). Under SSP5-8.5, with $CO_2$ emissions roughly double present levels by 2050 (71, 72) and western US summer mean temperature rising 6–8 K by the end of the century (Fig.4a), mean $PM_{2.5}$ levels resulting from increasing wildfires during August–September could double to triple compared to present-day levels (red lines in Fig. 5d-f), reaching 15–45 μg/m$^3$ for the US Pacific Northwest and northern California by the late 21$^{st}$ century (Fig.5a-c; Table S2). These $PM_{2.5}$ increases are primarily driven by marked increases in fire emissions in the warming climate (Fig.S12), with a small contribution from increasing stagnation frequency (Fig.S13).

In contrast, $PM_{2.5}$ simulated directly by chemistry-climate models, using prescribed fire emissions of aerosol precursors responding to changes in land use but not climate (see *Methods*), do not show significant changes (+7%) throughout the 21$^{st}$ century under SSP5-8.5 (tan lines in Fig.5d-f). The prescribed fire emissions show little trend over western North America during the 21$^{st}$ century (Fig.S14). The minor changes in anthropogenic emissions from the combustion of fossil fuels over western North America are not accounted for in our MLR $PM_{2.5}$ predictions.

[Figure 6 about here]

We next examine changes in $PM_{2.5}$ extremes predicted by our MLR model in response to enhanced fire activity under the intermediate-mitigation SSP2-4.5 and low-mitigation SSP5-8.5 scenarios (Fig.6). We predict considerable deterioration of $PM_{2.5}$ air quality over the western US in the 21$^{st}$ century under SSP5-8.5, caused by fires. By 2080–2100 under SSP5-8.5, the q95 of daily $PM_{2.5}$ in August–September is 20–170 μg/m$^3$ at Pacific Northwest sites, with 72–96% (model spread) of the sites experiencing q95 $PM_{2.5}$ above the 35 μg/m$^3$ US national standard, 52–68% above the unhealthy level (55 μg/m$^3$), and 0–8% above the very unhealthy level (150 μg/m$^3$; Fig.6a-c). The q95 $PM_{2.5}$ in August–September averaged over US Pacific Northwest sites exceeds the 35 μg/m$^3$ US national standard by mid-21$^{st}$ century under both SSP2-4.5 and SSP5-8.5 (Fig.6d-f). By the late 21$^{st}$ century, the estimated q95 $PM_{2.5}$

levels averaged over US Pacific Northwest sites in individual models and ensembles could reach as much as 85–125 μg/m$^3$ under SSP2-4.5 and 115–155 μg/m$^3$ under SSP5-8.5.

[Figure 7 about here]

Large fires burning across the US West in 2017, 2018, 2020, and 2021 caused historic levels of air pollution, loss of human life, and property damage (12, 54, 56). Unhealthy to hazardous concentrations of $PM_{2.5}$ (55–500 μg/m$^3$) were recorded at sites in the US Pacific Northwest and California for extended periods during summer to fall (11, 12). We use extreme value theory to examine whether these historically consequential events are more likely to occur in a future climate under intermediate and high emissions scenarios (*Methods*). We analyze large samples of q95 $PM_{2.5}$ at each site over the US Pacific Northwest during August–September from historical extremes (2017, 2018, and 2020), all historical observations for 1997–2020, and the MLR projections for 2080–2100 (Fig.7). We find that the shape of the exceedance probability distribution of q95 $PM_{2.5}$ during the late 21$^{st}$ century under SSP5-8.5 resembles that for the historic $PM_{2.5}$ extremes of 2017, 2018, and 2020 caused by fires: ~70% of sites have q95 $PM_{2.5}$ exceeding the 35 μg/m$^3$ US national standard, compared to only 16% for average conditions observed during the past two decades (Fig.7a). Under SSP2-4.5, the $PM_{2.5}$ distribution also shows a substantial shift towards extreme conditions. Figure 7b shows the return period of the q95 $PM_{2.5}$ at US Pacific Northwest sites, fitted using a generalized extreme value distribution, from historical observations and the MLR $PM_{2.5}$ predictions. For a range of return periods (e.g., 5, 10, 20 years), the estimated q95 $PM_{2.5}$ would double to triple in the MLR projections compared with historical observations. The return period of the recent pollution extremes of 2017, 2018, and 2020 (with a mean August–September q95 $PM_{2.5}$ of 72 μg/m$^3$) would decrease to approximately 5 years in the late 21$^{st}$ century under SSP2-4.5 and to 3 years under SSP5-8.5.

**Conclusions and Implications**

Using an empirical statistical model driven by observations and CMIP6 Earth system model projections of fire $CO_2$ emissions and meteorology, we project western US $PM_{2.5}$ air quality in the 21$^{st}$ century under a suite of Shared Socioeconomic Pathways (SSPs). Late summer to fall $PM_{2.5}$ pollution over the US Pacific Northwest is projected to double to triple by 2080–2100 due to enhanced fire activity associated with drought and increased biomass under intermediate (SSP2-4.5) and high warming scenarios (SSP5-8.5). Even with strong mitigation under SSP1-2.6, western US $PM_{2.5}$

pollution would increase ~50% by mid-century. The occurrence of four severe fire years in quick succession during 2017–2021 over the western US raises the possibility that climate change is already driving strong changes in fire regimes that may be underestimated by our models. Our study suggests that severe $PM_{2.5}$ air pollution caused by these historic fire events could occur every 5 years in the late 21$^{st}$ century under an intermediate climate change scenario (SSP2-4.5). Air quality exceedances caused by wildfires can be classified as 'exceptional events,' which are not counted towards a non-attainment determination, according to the US Environmental Protection Agency. However, a considerable increase in the frequency of fire-driven exceedances may complicate this policy, as these events become a new norm in the changing climate. The large spread across climate change scenarios highlights the co-benefits of climate mitigation for wildfires and air pollution. Multi-agency collaborations, addressing climate mitigation, air quality, and forest management, are needed to minimize the adverse health impacts projected to result from fire smoke.

## Materials and Methods

### 1. Data availability

The data from three CMIP6 models used in this study (89-91) are publicly available at https://esgf-node.llnl.gov/projects/cmip6/. Surface observations of $PM_{2.5}$, meteorological variables from reanalysis datasets, satellite observations of burned area, and fire emission inventories are publicly available through the links provided at the corresponding references as described below.

### 2. Multi-linear regression model

The multiple linear regression (MLR) model is developed using observational datasets of surface $PM_{2.5}$ concentrations, meteorological variables, and fire $CO_2$ emissions over western North America during 1997–2020. This observation-based MLR model is then applied to predict future $PM_{2.5}$ levels driven by fire $CO_2$ emissions and meteorology projected by the CMIP6 Earth system models. Considering that climate model projections are more robust on larger scales, all observational datasets and CMIP6 model fields used for the MLR analysis are averaged onto a 2°×2° grid. The MLR model predicts the mean and the 95$^{th}$ percentile of $PM_{2.5}$ at each 2°×2° grid $d$ and month $i$ in the form of:

$$\mathrm{PM2.5}_{d,i}(t) = \beta_{d,i}\mathrm{Fire}_{d,i}(t) + \sum_{k=1}^{4}\beta_{d,i,k}\mathrm{Met}_{d,i,k}(t) + b_{d,i} \quad (1)$$

where Fire(t) is the anomaly time series of fire $CO_2$ emissions in percentage relative to the present-day climatology, Met(t) is the anomaly time series of meteorological variables (i.e., surface temperature, precipitation, relative humidity, and air stagnation) relative to the present-day climatology; $\beta$ and b are regression coefficients fitted by the MLR. We select these four meteorological variables that have been previously identified to be correlated with surface $PM_{2.5}$ (11, 52). We performed the regression by adding and deleting prediction parameters stepwise to obtain the best fit based on the Akaike Information Criterion. The relative importance of each predictor is determined using a bootstrap approach described in (92). The performance of the MLR model is tested using leave-one-out cross-validation (*SI Appendix,* Text S1).

The observation-based MLR model is applied to predict mean and the 95$^{th}$ percentile of surface $PM_{2.5}$ concentrations at each 2°x2° grid, driven by monthly time series of fire $CO_2$ emissions and meteorology projected by the CMIP6 Earth system models under a suite of climate change scenarios over the course of the 21$^{st}$ century. To ensure that we only apply the MLR predictions at locations where $PM_{2.5}$ levels are primarily driven by fire emissions, we limit our analysis to western US grid cells where the observed correlation $r^2$ from the MLR model is greater than 0.5 during August and September; as such, sites located in urban areas with large anthropogenic influence are filtered out. For $PM_{2.5}$ prediction at each valid grid, we calculate the anomaly time series (in percentage relative to the present-day 1990–2010 climatology) of total fire $CO_2$ emissions in a projected future climate, integrated over a regional box where the maximum correlation with $PM_{2.5}$ is found based on historical observations (Fig.1). This approach thus accounts for the influence of regional smoke transport. Anomaly time series of meteorological variables in the future climate are calculated as the absolute differences from the present-day 1990–2010 climatology for each valid 2°×2° grid.

**3. Observational datasets**

Daily observations of $PM_{2.5}$ at surface monitoring sites during 1997–2020 are obtained from the US Environmental Protection Agency's Air Quality System (https://www.epa.gov/aqs). To maximize data availability, we include $PM_{2.5}$ measured with both the Federal Reference Methods and non-Federal Reference Methods, as a strong linear correlation ($r^2$=0.92) between these two methods has been found at co-located monitors (93). To be consistent with the other datasets used for the MLR analysis

as well as to increase the statistical power and robustness of the analysis, we average all available daily surface $PM_{2.5}$ observations onto a 2°x2° grid. For each month at each 2°x2° grid cell, we calculate the average and the 95$^{th}$ percentile of available daily $PM_{2.5}$ from all sites within that grid. Most grids have sample sizes of 50–200 daily $PM_{2.5}$ observations each month; only grids with at least 20 samples per month are considered in our analyses (Fig.S2).

To represent the intensity and severity of wildfires, we use satellite observations of burned area and satellite-based estimations of fire $CO_2$ emissions, consistent with the datasets available from the CMIP6 fire models. The monthly burned area is from the Collection 6 Moderate Resolution Imaging Spectrometer (MODIS) climate model grid burned area product (2000–2020, 0.25°x0.25°) (60). Fire emissions of $CO_2$ are obtained from the Global Fire Emissions Dataset version 4 with small fires (GFED4s, 1997–2020, 0.25°x0.25°) based on satellite-retrieved burned area (61, 62), and the Quick Fire Emission Dataset version 2.5 (QFED2.5, 2001–2019, 0.1°x0.1°) based on satellite-observed fire radiative power (63). The MLR model only uses fire $CO_2$ emissions from GFED4s averaged onto a 2.0x2.0 grid while both GFED4s and QFED2.5 are used to evaluate the CMIP6 fire models.

The MLR analysis includes four meteorological variables that have been previously identified to have correlations with surface $PM_{2.5}$ (11, 52): surface temperature, precipitation, relative humidity, and air stagnation (*SI Appendix*, Text S2). Monthly mean surface temperature, precipitation and relative humidity are obtained from the European Centre for Medium-Range Weather Forecasts Reanalysis version 5 (ERA5, 1997–2020, 0.1°x0.1°) (94). The air stagnation index is obtained from the U.S. National Centers for Environmental Information (95). All original datasets are averaged onto a 2°x2° grid for the MLR analysis.

**4. CMIP6 Fire Models**

We use simulations from three CMIP6 Earth system models (CESM2, GFDL-ESM4.1 and CNRM-ESM2-1) that archived $CO_2$ emissions from fires and meteorological variables needed for the MLR model. The models' horizontal resolutions range from 1.0 to 1.5° (Table S1). Vegetation structure and functioning in all three models (e.g., leaf area index) respond to changes in climate. GFDL-ESM4.1 simulates daily vegetation distribution (58, 96-98) while CESM2 and CNRM-ESM2-1 use prescribed land use and land cover change files (49, 59). Fire $CO_2$ emissions in all three CMIP6 models are simulated dynamically, coupled to climate and vegetation (*SI Appendix,* Text S3) (42, 43, 45-47, 50,

51, 99). However, these models do not calculate fire emissions of particles or non-$CO_2$ gases, so atmospheric chemistry in these models is not coupled to interactive fire emissions responding to climate change.

Two sets of experiments from these models are used: (1) Land-only experiments (LAND-HIST experiment from the Land Use Model Intercomparison) driven by the observation-based meteorological forcings (derived from dynamic downscaling of the 20$^{th}$-Century Reanalysis) (100, 101); (2) Coupled land-atmosphere-ocean historical simulations (CMIP6 HIST experiment) and future projections (from the Scenario Model Intercomparison Project) driven by emissions of greenhouse gases and aerosols under four Shared Socioeconomic Pathways: SSP1-2.6, SSP2-4.5, SSP3-7.0, SSP5-8.5 (71). The land-only experiments driven by observed climate allow for direct comparison with observations in space and time in order to understand biases related to the modeling of fire dynamics (Fig.2). The coupled model simulations are used to understand changes in fires under climate change scenarios, which serve as a key predictor for future $PM_{2.5}$ levels (Figs.5-7). To understand the drivers of the temporal evolution of historical fires (Fig.S11), we analyze three CESM2 coupled-model experiments: (1) with all historical forcings (HIST): (2) the control simulation with pre-industrial forcings, including constant land cover and land use, land management, and population density at 1850 levels (pi-Control) (102); (3) with all historical forcings same as HIST but with land use held constant at 1850 levels as in pi-Control (HIST_NoLU) (101).

**5. Chemistry-climate model $PM_{2.5}$ simulations using prescribed fire emissions**

We compare the MLR-based estimations of $PM_{2.5}$ driven by interactive fires responding to climate change with $PM_{2.5}$ directly simulated by three chemistry-climate models (103-105). In these chemistry-climate models, fire emissions of particles are prescribed for both historical and future simulations. Historical simulations of these models use fire emissions of gases and particles from GFED version 4 with small fires (GFED4s) for 1997–2014, and historical reconstructions from the Fire Model Intercomparison project prior to 1997 (28, 48). Future fire emissions of gases and particles are prescribed based on the spatial distribution of the 2005–2014 climatology from GFED4s, and consider the impacts from land use but not climate change (29). There are no substantial trends nor interannual variability in biomass burning emissions of aerosols used for future $PM_{2.5}$ projections from

these chemistry-climate models (Fig.S14). Future $PM_{2.5}$ levels simulated by these chemistry-climate models thus reflect the impacts from changes in anthropogenic emissions and meteorology, but overlook the impact of climate-driven increases in fire emissions of aerosols and aerosol precursors.

**6. Calculation of exceedance probability and return period**

To examine how prevalent the recent $PM_{2.5}$ pollution extremes caused by fires in 2017, 2018 and 2020 may be in a warming climate, we compare the exceedance probability and return period of the 95$^{th}$ percentile (q95) of daily $PM_{2.5}$ in August–September at US Pacific Northwest sites from historical observations with MLR projections under SSP2-4.5 and SSP5-8.5 scenarios.

The exceedance probability is calculated as 1-$F_n$, where $F_n$ is the empirical cumulative distribution function, calculated as $F_n(t) = \frac{1}{n}\sum_{i=1}^{n} \mathbf{1}_{X_i \le t}$, where *n* is the total number of the predicted monthly q95 $PM_{2.5}$ at each site in the US Pacific Northwest in August and September. $\sum_{i=1}^{n} \mathbf{1}_{X_i \le t}$ is the number of events with the predicted q95 $PM_{2.5}$ smaller than a given q95 $PM_{2.5}$ level of t.

The return levels and return periods are estimated using extreme value theory (106). Extreme value theory has been used in previous studies to estimate return levels and days of ozone pollution events under present and future climates (107-109). Here in this study, we perform the extreme event analysis with the extRemes package in R (110) using large samples of q95 $PM_{2.5}$ at each site in the US Pacific Northwest during August–September from historical extremes (2017, 2018, and 2020), from all historical observations for 1997–2020, and from the MLR projections for 2080–2100. The observed and MLR-predicted q95 $PM_{2.5}$ are fitted using a generalized extreme value distribution function. The 95% confidence intervals are estimated based on the delta method using the parameter covariance (110).

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**Figures:**

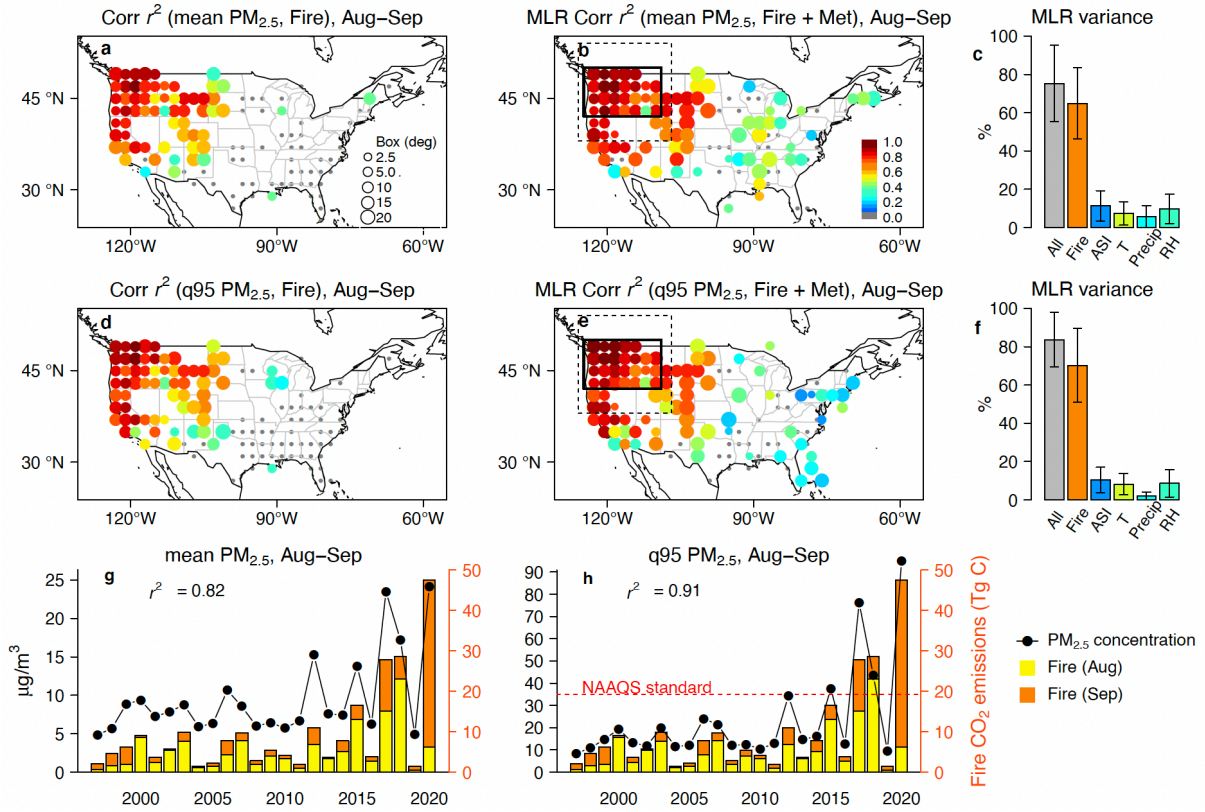


**Figure 1. Observed correlations between fires and surface $PM_{2.5}$ air quality.** (a-c) Correlation $r^2$ of mean $PM_{2.5}$ averaged over each 2 °x2 ° grid with regional total $CO_2$ emissions from fires in August–September during 1997–2020 derived from simple linear regression (a) versus multiple linear regression (MLR) with consideration of meteorological variables (b), and the variance explained over the US Pacific Northwest (solid black box on b) by each predicting variable (c). The width of the box (in degrees), within which regional total fire emissions are best correlated with $PM_{2.5}$ at that site, is given in the right corner in (a). The $r^2$ values are color-coded for sites with significant correlations, with gray indicating sites with insignificant correlations ($p > 0.05$). (d-f) Same as (a-c) but for the 95$^{th}$ percentile (q95) of available daily $PM_{2.5}$ observations at each grid in August–September. (g-h) Time series of the mean and q95 $PM_{2.5}$ in August–September averaged over US Pacific Northwest sites from 1997 to 2020, along with regional total $CO_2$ emissions from fires integrated over western North America (dashed black box on b).

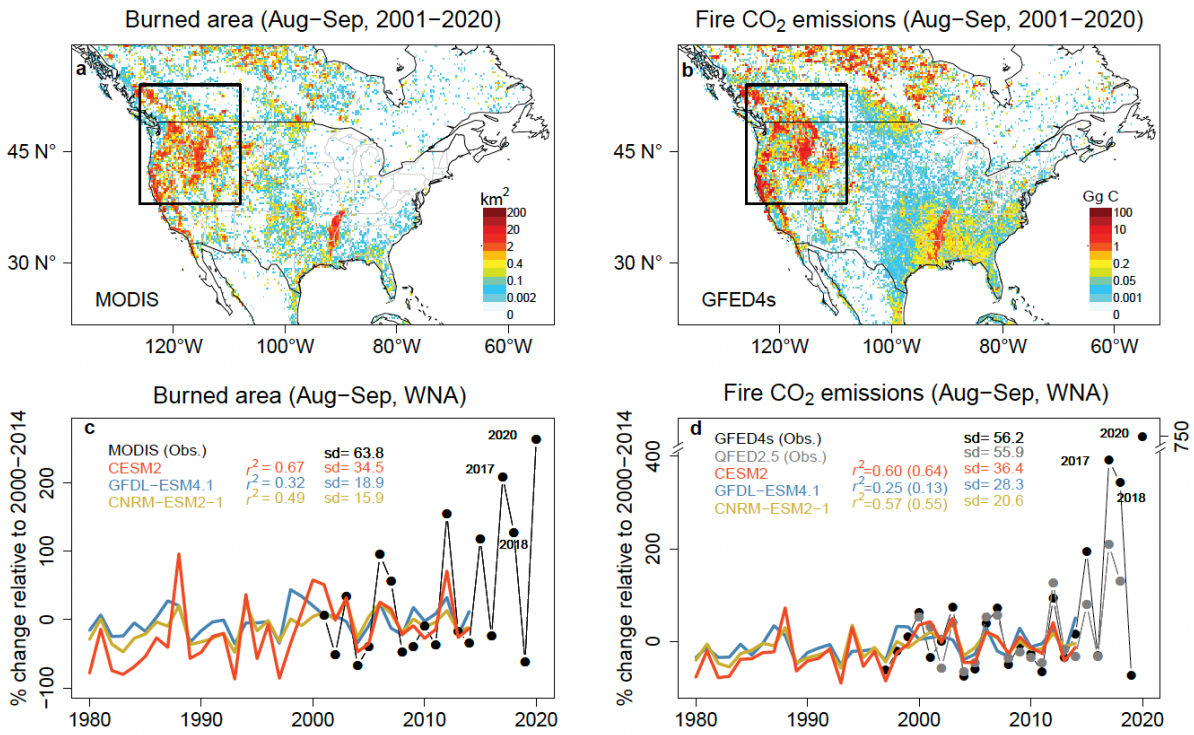


**Figure 2. Evaluating model simulations of fires over western North America.** (a-b) The 2001–2020 climatology of August–September total burned area from MODIS satellite observations and fire $CO_2$ emissions from GFED4s over North America. (c) The relative changes of August–September total burned area over western North America (WNA, black box on map) from 1980 to 2020 versus 2000–2014 averages from MODIS satellite observations (black) and from three CMIP6 land-only experiments (solid lines). (d) same as (c) but for fire $CO_2$ emissions from two satellite-based inventories (black for GFED4s and gray for QFED2.5) and from three CMIP6 land-only experiments (solid lines). Standard deviations (sd, in percentage) and correlations $r^2$ between models and observational datasets (QFED2.5 in parentheses) are shown in c and d.

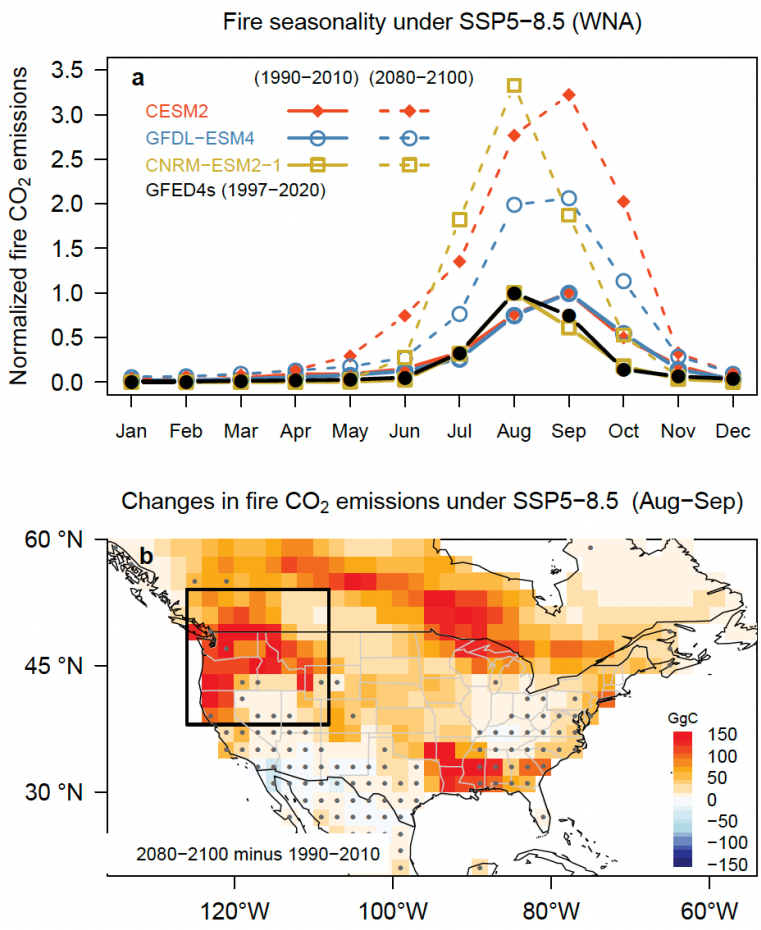


**Figure 3. Changes in fire seasonality in the late 21st century.** (a) Monthly mean fire $CO_2$ emissions over western North America under present day (1990–2010, solid lines) and SSP5-8.5 (2080–2100, dashed lines) normalized by the month with peak emissions at present day from CMIP6 coupled model experiments. Also shown are satellite-based estimates for present-day climate (black). (b) Multi-model and multi-ensemble mean changes in $CO_2$ emissions from fires (in Gg C) in August–September during the late 21st century under SSP5-8.5 (2080–2100 minus 1990–2010). The results are first averaged across the available ensemble members from each model (3 for CESM2, 1 for GFDL-ESM4.1, and 5 for CNRM-ESM2-1), and then averaged across the models. Stippling indicates grids with less than two models show statistically significant ($p < 0.05$) changes or where the three models do not agree in sign. For each model, a change is defined significant if >50% of the ensemble changes are statistically significant ($p < 0.05$).

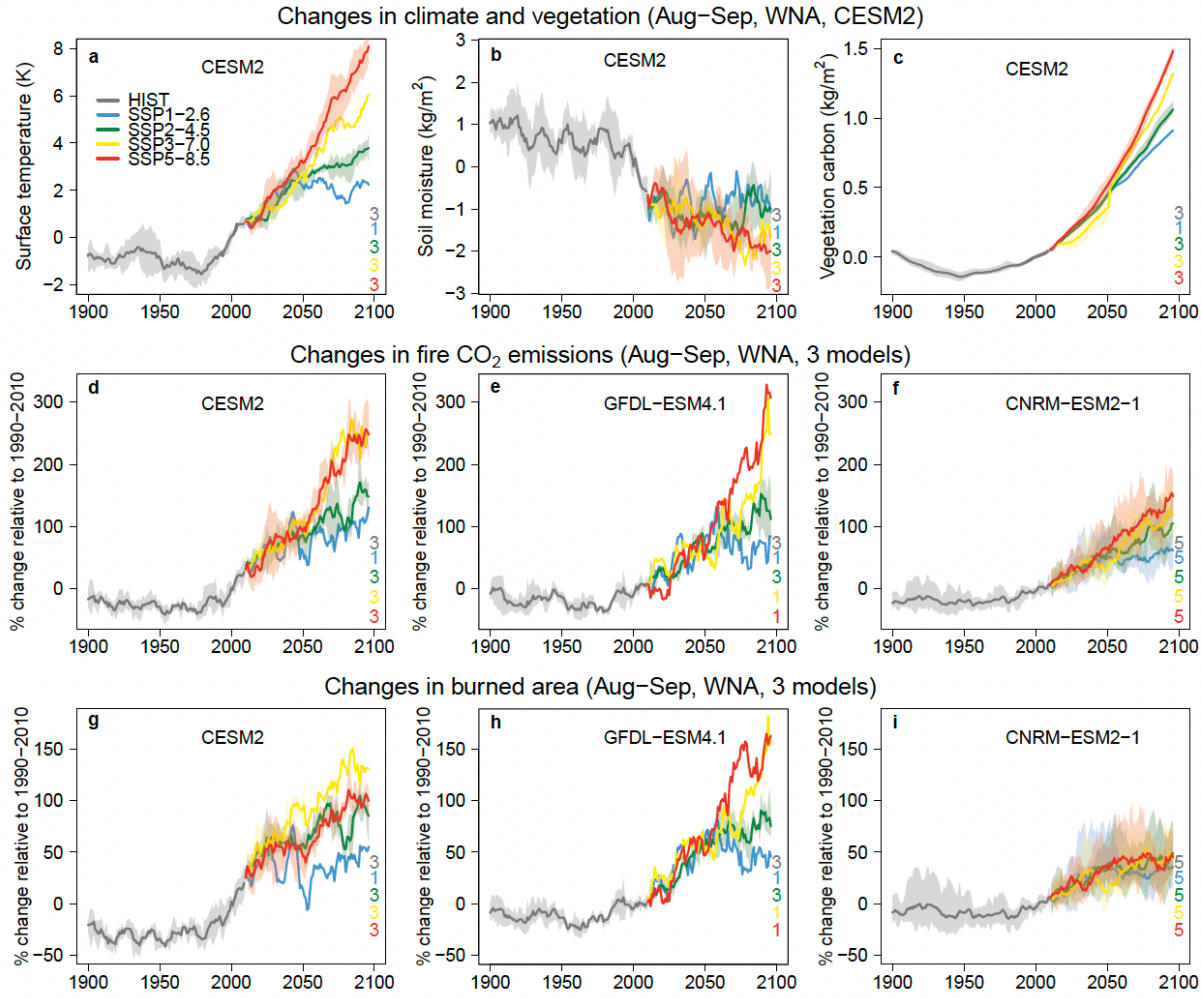


**Figure 4. Changes in climate and fires during August–September in the 21st century.** Changes in 10-year running average of surface temperature (a), soil moisture in top 10 cm (b), and carbon mass in vegetation (c) relative to the 1990–2010 averages in August–September over western North America from CESM2 historical simulations (gray) and future projections (colors) under four SSPs (Table S1). (d-f) same as (a) but for total fire emissions of $CO_2$ (in percent) and (g-i) burned area (in percent) from three CMIP6 Earth System models: CESM2 (left), GFDL-ESM4.1 (middle) and CNRM-ESM2-1 (right). Thick lines represent the multi-ensemble mean, with shading illustrating the spread of available ensemble members (numbers denoted at the bottom-right corner of each graph).

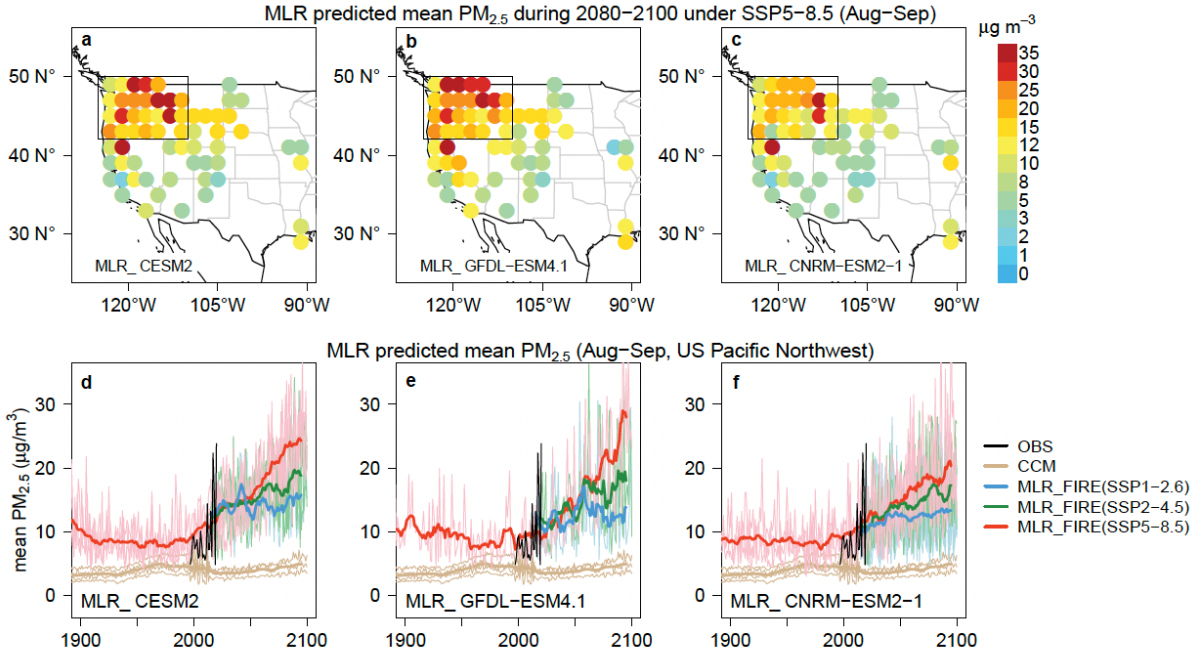


**Figure 5. Projected changes in August–September mean $PM_{2.5}$ due to increasing fire emissions. (a-c)** The August–September mean $PM_{2.5}$ in 2080–2100 at western US sites (averaged over a 2°×2° grid) predicted by MLR driven by fires from three CMIP6 models under SSP5-8.5. Only grids with MLR correlation $r^2$>0.5 are shown. (d-f) Temporal evolution of August–September mean $PM_{2.5}$ averaged over US Pacific Northwest sites (box on map) during 1900–2100 from the chemistry-climate model simulations with prescribed fire emissions (tan lines) versus from the MLR model predictions considering the impacts of future climate change on fire emissions under SSP1-2.6 (blue lines), SSP2-4.5 (green lines), and SSP5-8.5 (red lines). Thick lines represent 10-year running multi-ensemble averages and thin lines represent averages for individual years from each ensemble member of each model (3 for CESM2, 1 for GFDL-ESM4.1, and 5 for CNRM-ESM2-1). The August–September interannual time series from observations (black lines) is also shown for comparison.

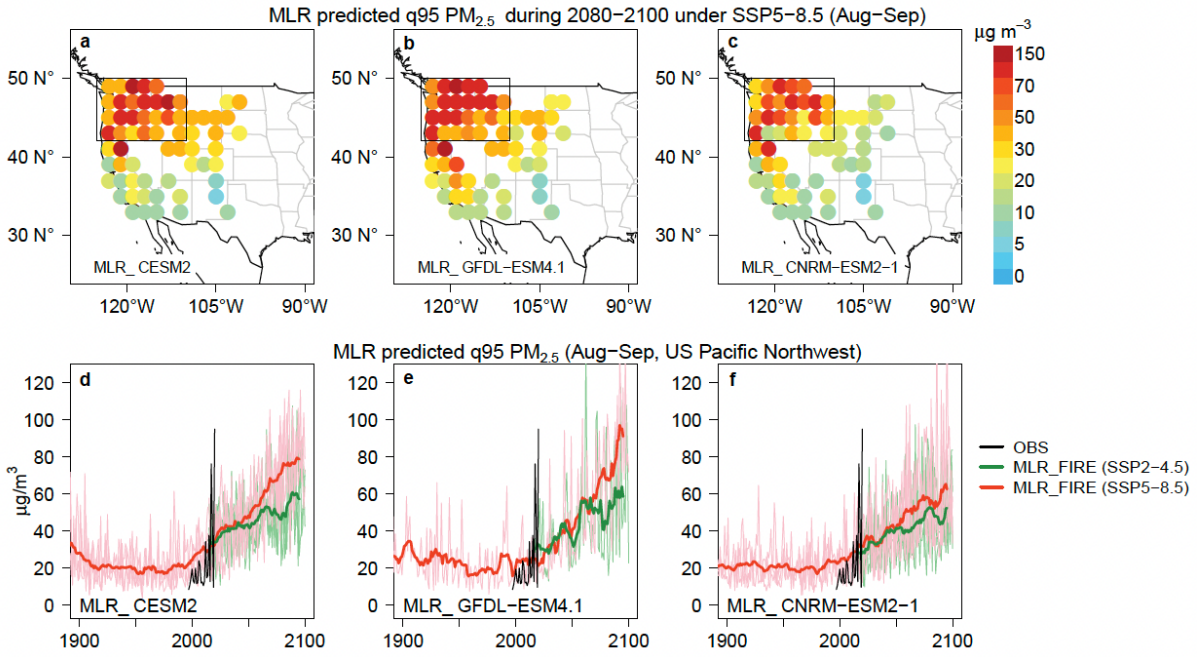


**Figure 6. Projected changes in $PM_{2.5}$ extremes in August–September due to increasing fires.** (a-c) The 95$^{th}$ percentile of daily $PM_{2.5}$ (q95) during August–September in 2080–2100 at western US sites (computed over a 2 °×2° grid) predicted by MLR driven by fires from three CMIP6 models under SSP5-8.5. Only grids with MLR correlation $r^2$>0.5 are shown. (d-f) Temporal evolution of the q95 $PM_{2.5}$ in August–September averaged over US Pacific Northwest sites (box on map) from the MLR model projections under SSP2-4.5 (green) and SSP5-8.5 (red). Thick lines represent 10-year running multi-ensemble averages and thin lines represent averages for individual from each ensemble member of each model (Table S1). The August–September interannual time series from observations (black lines) is also shown for comparison.

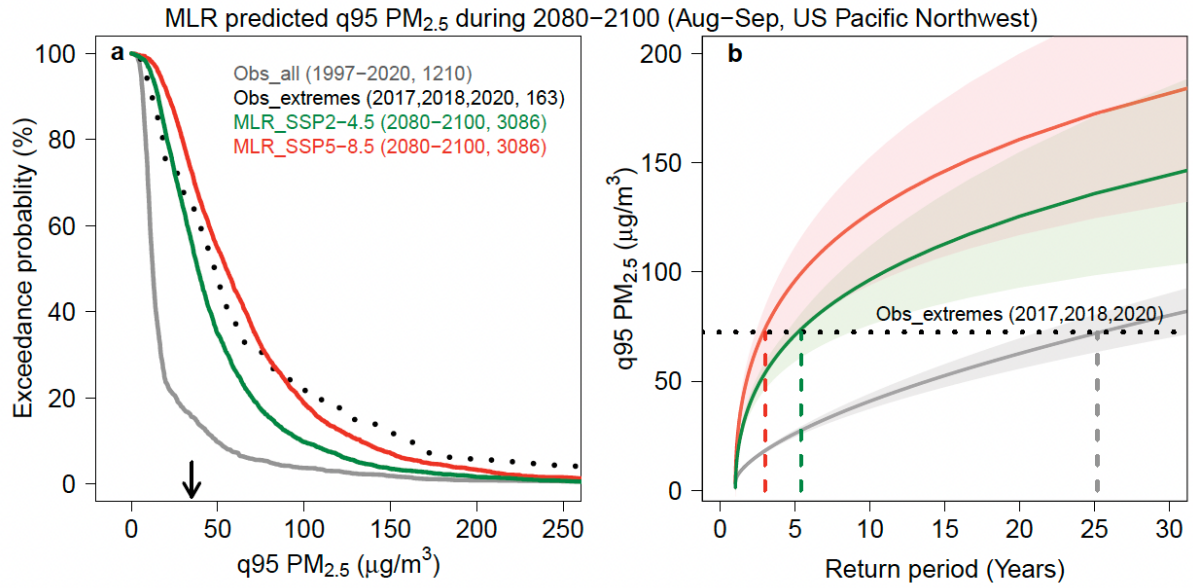


**Figure 7. Likelihood of historical pollution extremes in a warming climate.** Exceedance probability of the 95$^{th}$ percentile of daily $PM_{2.5}$ at US Pacific Northwest sites during August–September: from observations during 1988–2020 (gray solid line) and during the 2017, 2018 and 2020 extreme fire seasons (black dotted line), from the MLR $PM_{2.5}$ predictions driven by fires in three CMIP6 models during 2080–2100 under SSP2-4.5 (green) and SSP5-8.5 (red). The arrow denotes the 35 $\mu g/m^3$ US National Ambient Air Quality Standard for 24-h average $PM_{2.5}$. Numbers in brackets represent sample size for calculating the exceedance probability; (b) return period of the 95$^{th}$ percentile of daily $PM_{2.5}$ at US Pacific Northwest sites in August–September fitted using generalized extreme value distribution: from observations during 1997–2020 (black solid line), and from the MLR $PM_{2.5}$ predictions driven by fires in three CMIP6 models during 2080–2100 under SSP2-4.5 (green) and SSP5-8.5 (red). The 95$^{th}$ percentile of daily $PM_{2.5}$ in August–September of 2017, 2018 and 2020 is marked as the horizontal dotted line. Shading for observations represents the 95% confidence intervals of estimated $PM_{2.5}$ levels for different return periods. Shading for MLR projections represents the maximum and minimum of estimated $PM_{2.5}$ levels for different return periods from different model ensembles. Intercepts between the horizontal black dotted line and the fitted solid lines represent the return periods for the observed 2017–2020 extremes in present and future climates.

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## Supplementary Information for

# Tripling of Western US Particulate Pollution from Wildfires in a Warming Climate

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**This PDF file includes:**

**Supplementary Information Text**

**Appendix S1. Cross validation of the MLR model**

For each grid d with n years of available observations, we train the model using n-1 years of data and predict over the remaining year. The resulting leave-one-out cross validation results for both the mean $PM_{2.5}$ ($r^2$=0.56–0.61, root mean square error, RMSE =4.0–5.6 μg/m$^3$) and the 95th percentile $PM_{2.5}$ ($r^2$=0.51–0.66, RMSE=11.3–14.1 μg/m$^3$) in August–September averaged over western US grids are statistically significant ($p$<0.05). The results are close to the standard model fit ($r^2$=0.76–0.82, RMSE=2.3–7.7 μg/m$^3$), indicating robustness of the MLR model.

**Appendix S2. Meteorological dataset**

Monthly mean surface temperature, precipitation and relative humidity are obtained from the European Centre for Medium-Range Weather Forecasts Reanalysis version 5 (ERA5) (94). The relative humidity is calculated from the dew point temperature in ERA5 as

$RH = 100\% \times \frac{e_s(T_d)}{e_s(T)}$ ,

where $T_d$ is the dewpoint temperature and $T$ is the temperature, and $e_s$ is the saturation vapor pressure, which can be empirically calculated using Bolton's method (111) in the form of

$e_s(T) = 0.6112 \exp\left(\frac{17.67T}{T+243.5}\right)$ ,

Air stagnation in the U.S. National Centers for Environmental Information dataset is defined as days when there is no precipitation, sea level geostrophic winds are lower than 8 m/s (or <10 m/s when there is a surface to 850 mb temperature inversion), and 500 mb wind speeds are lower than 13 m/s (112). Air stagnation in the CMIP6 models is defined as days with precipitation smaller than 1 mm, surface wind speed lower than 3.2 m/s and 500 mb wind speeds lower than 13 m/s (113).

**Appendix S3. Fire modules in the three CMIP6 models**

The fire module in CESM2 includes four components: non-peat fires outside croplands and tropical closed forests, agricultural fires in croplands, deforestation and degradation fires in the tropical closed forests, and peat fires (42, 45, 51). The burned area fraction is determined by climate and weather conditions, vegetation composition and structure, and human activities. Among them, human influence is represented by anthropogenic ignitions (increase with population density), fire suppression (increase with population density and gross domestic product per capita human), agricultural waste burning, and deforestation rate. After the calculation of burned area fraction, fire impacts are estimated, including fire emissions due to biomass and peat burning as well as plant-tissue mortality, which lead to adjustment of terrestrial ecosystem structure and functioning. We use the coupled simulations from CESM2-WACCM, a version of CESM2 with the same land model but with comprehensive chemistry extending to 130 km vertically (57, 114).

The fire module in GFDL-ESM4.1 is developed within a global dynamic vegetation and land surface model that comprises two sub-models for simulating agricultural and non-agricultural fires (43, 47, 97). The area burned for agricultural fires on cropland and pasture at each grid cell is forced with satellite observations of fire seasonality and frequency, depending on grid-scale crop and pasture area but not environmental changes. Simulation of non-agricultural fires follows the process-based fire model in CESM2, which predicts area burned at each grid cell as a product of the number of fires and burned area per fire, depending on grid-scale fuel availability, fuel moisture, and ignition source. Human fire suppression is represented as a function of population density. An enhanced fire rate of spread is introduced to better represent crown fires with high intensity. Non-agricultural fires are simulated on a daily basis, allowing multiday burning with a maximum duration of 30 days. $CO_2$

emissions from fires are estimated by applying combustion completeness factors for different vegetation types on the aboveground biomass within the burned area.

CNRM-ESM2-1 represents natural wildfires over forests and grasslands in a land model that uses prescribed land use and land cover change files (50, 99). The grid cell fire fraction calculation was adapted to a daily timestep and depends on availability of fuel and fuel moisture, approximated by soil moisture and temperature. Fire fraction is set to zero when the surface litter carbon content is below 200 $gC/m^2$ and when soil temperature is lower than 0°C. It is also set to zero when more than 20% of the grid cell is covered by croplands. Except for this limitation on cropland, human fire suppression is not represented. Fire-induced emissions and fire effects on living and dead biomass are Plant Functional Type-dependent.

**Supplementary Figures S1 to S14:**

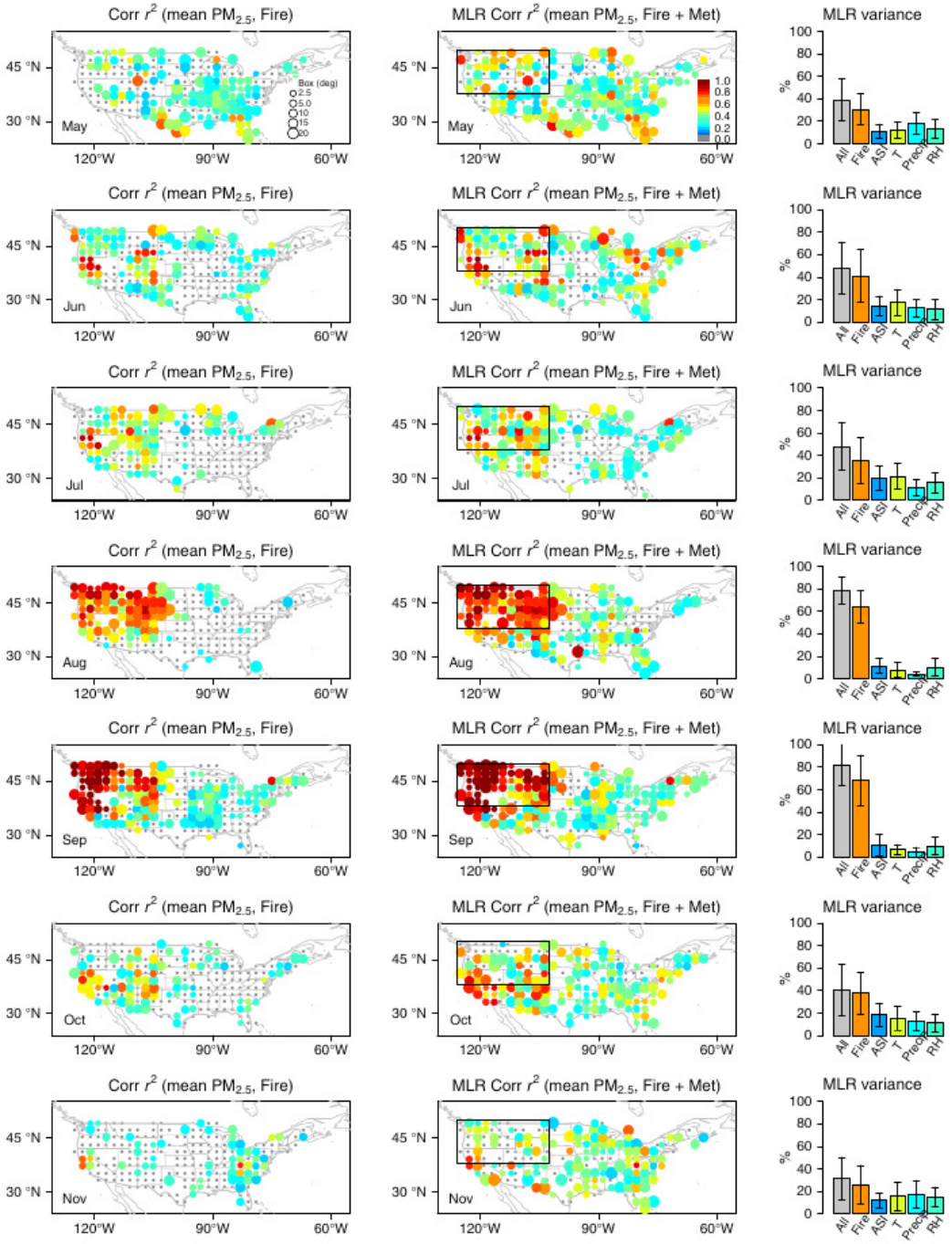



**Figure S1.** Observed correlations between fires and surface $PM_{2.5}$ air quality. Correlation $r^2$ of mean $PM_{2.5}$ averaged over each 2°x2° grid with regional total $CO_2$ emissions from fires in May–November during 1997–2020, derived from simple linear regression (left panels) and multiple linear regression (middle panels) with consideration of meteorological variables, and the variance explained over the western US (black box on maps) by each predicting variable (right panels). The $r^2$ values are color-coded for sites with significant correlations, with gray indicating sites with insignificant correlations ($p$

> 0.05). The width of the box (in degrees), within which regional total fire emissions are best correlated with $PM_{2.5}$ at that site, is given in the right corner in the top panel.

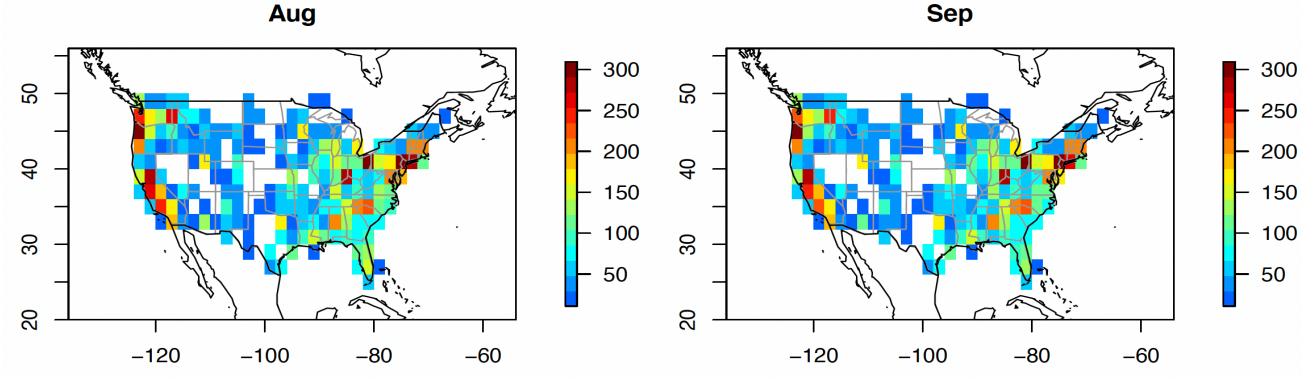



**Figure S2.** Sample sizes of surface $PM_{2.5}$ observations. Number of samples for calculating monthly means and q95 $PM_{2.5}$ at each 2°×2° grid in August and September averaged over 1997–2020.

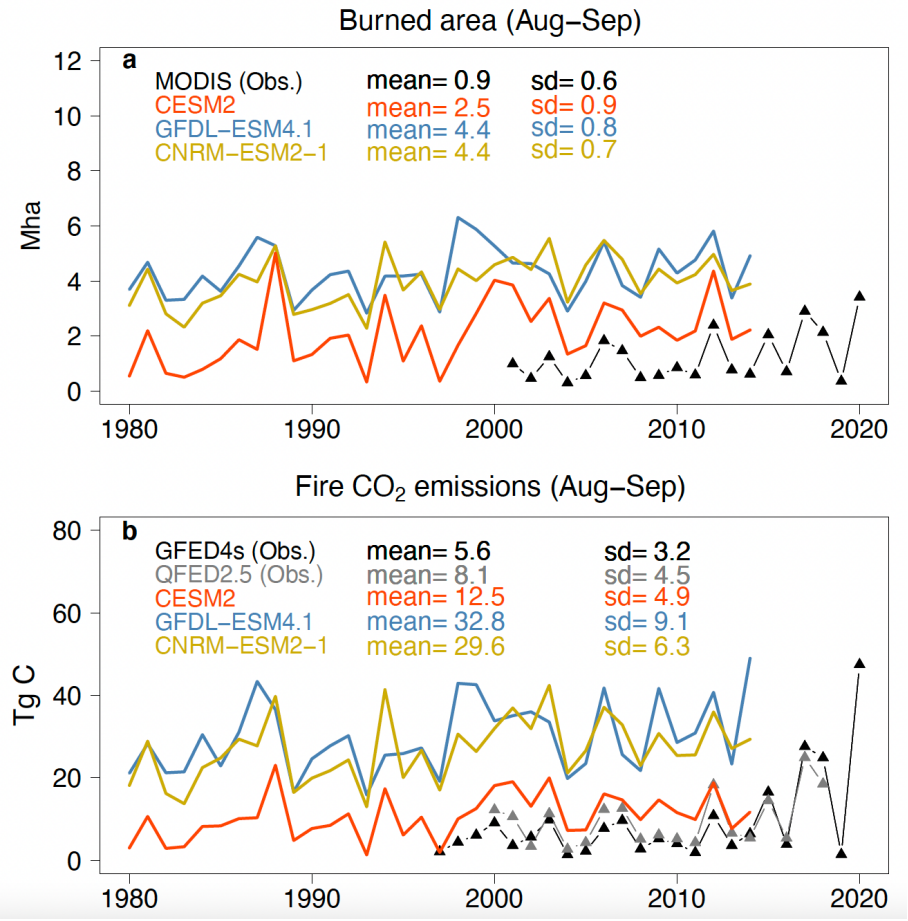



**Figure S3.** Evaluating model simulations of fires over western North America. (a) The August–September total burned area over western North America (black box in Fig. S4) from 1980 to 2020 from MODIS satellite observations (black) and from three CMIP6 land-only experiments (solid lines). (b) same as (a) but for fire $CO_2$ emissions from two satellite observation-based inventories (black for GFED4s; gray for QFED2.5) and from three CMIP6 land-only experiments (solid lines). Means and standard deviations (sd) during 2000–2014 are reported.

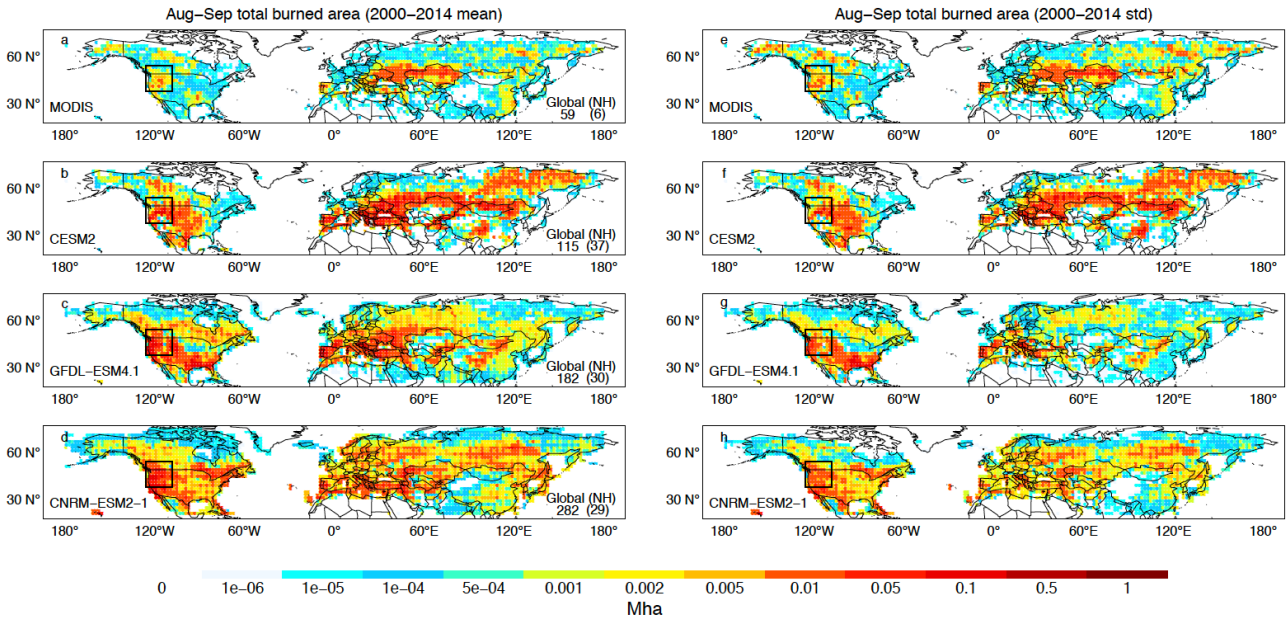



**Figure S4.** Spatial distribution of burned area from observations and land-only simulations. Mean (left panels) and standard deviation (right panels) of the August–September total burned area during 2000–2014 from MODIS satellite observations and from three CMIP6 land-only simulations. Black box represents western North America where fire $CO_2$ emissions are integrated for analysis in Figs. 2-4. Global and Northern Hemisphere total burned area (Mha) are reported at the right corner.

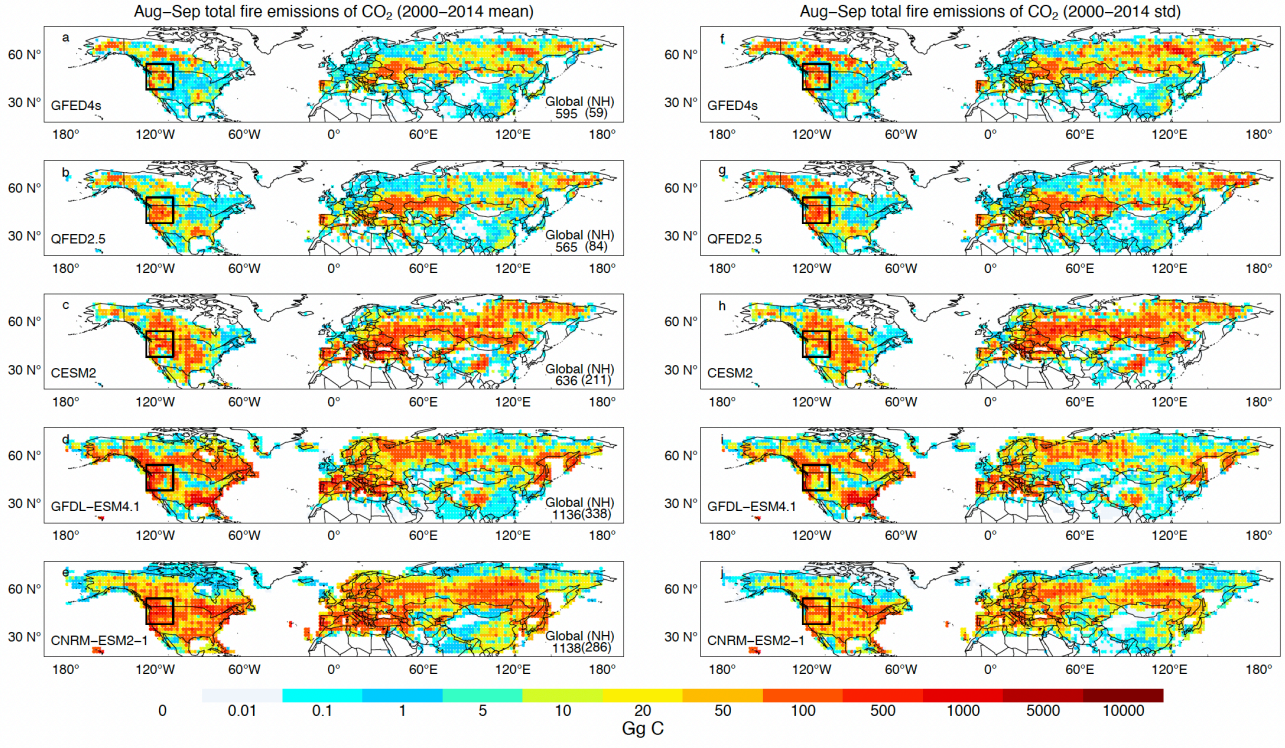



**Figure S5.** Spatial distribution of fire emissions of $CO_2$ from observations and land-only simulations. Mean (left panels) and standard deviation (right panels) of the August–September total $CO_2$ emission from fires during 2000–2014 from two satellite observation-based emission inventories (GFED4s and QFED2.5) and from land-only experiments of three CMIP6 fire models driven by observation-based meteorological forcings. Black box represents western North America where fire $CO_2$ emissions are integrated for analysis in Figs. 2-4. Global and Northern Hemisphere total fire $CO_2$ emissions from fires (TgC) are reported at the right corner.

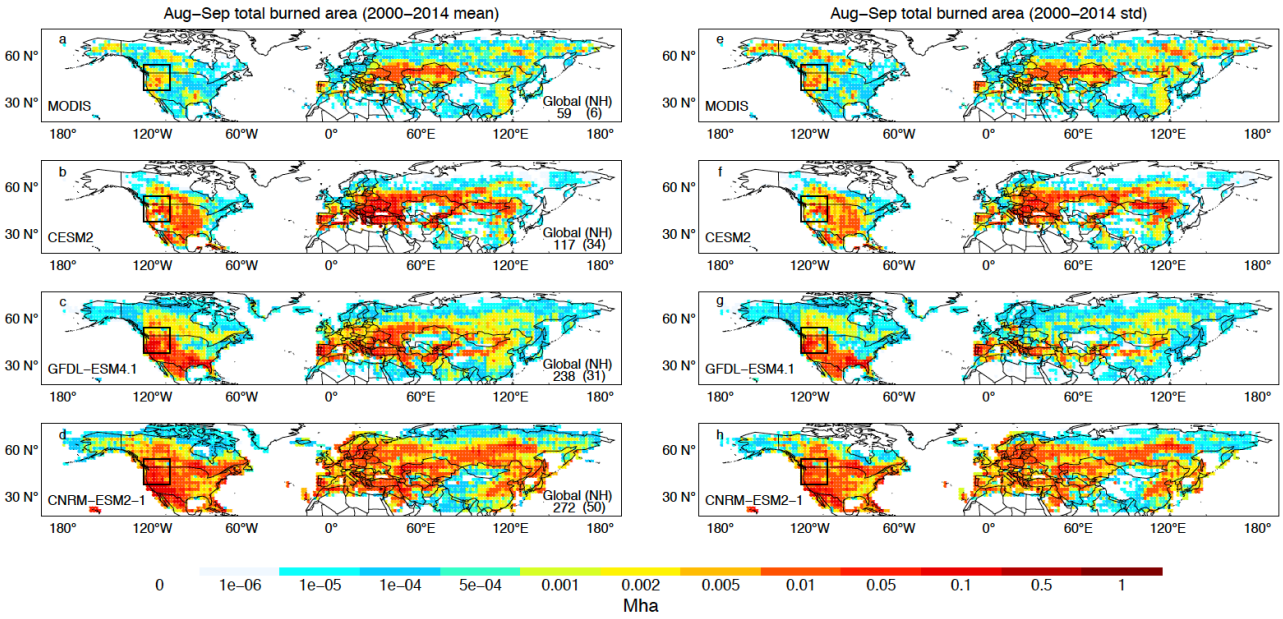



**Figure S6.** Same as Fig. S4, but with model results from the CMIP6 coupled model simulations.

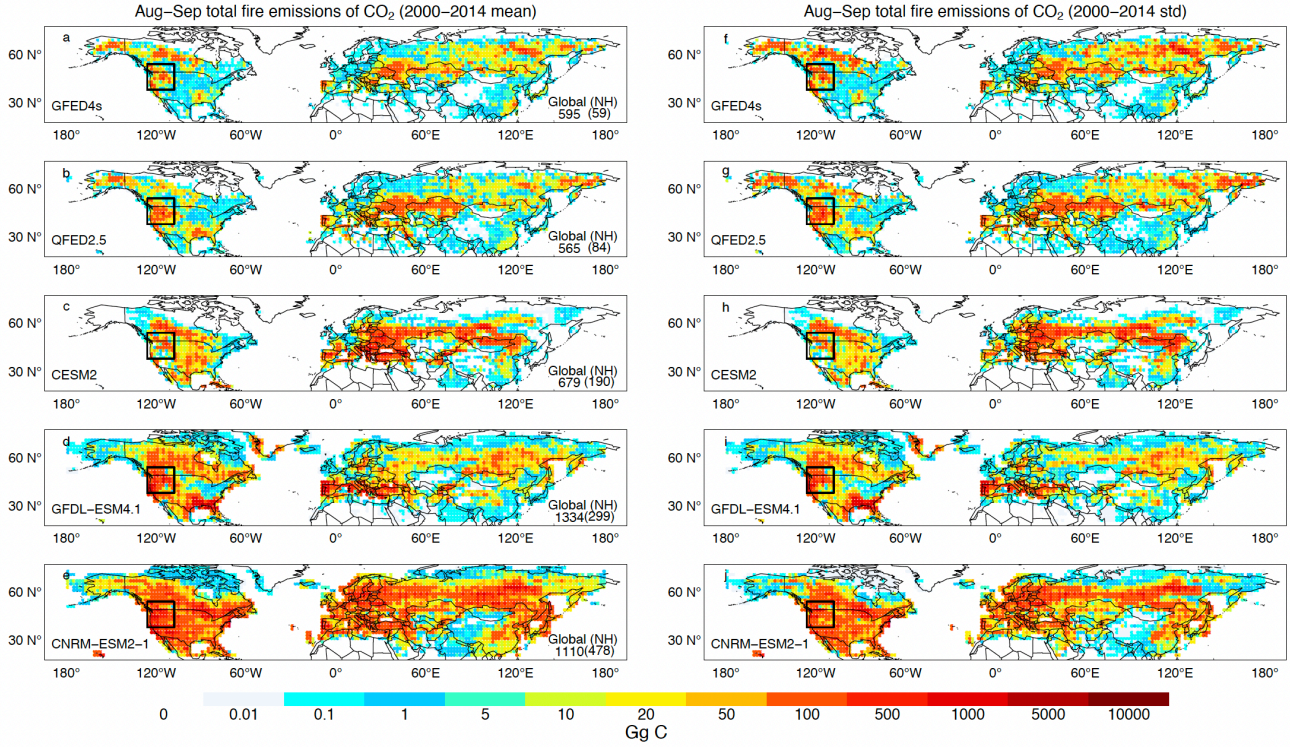



**Figure S7.** Same as Fig. S5, but with model results from the CMIP6 coupled model simulations.

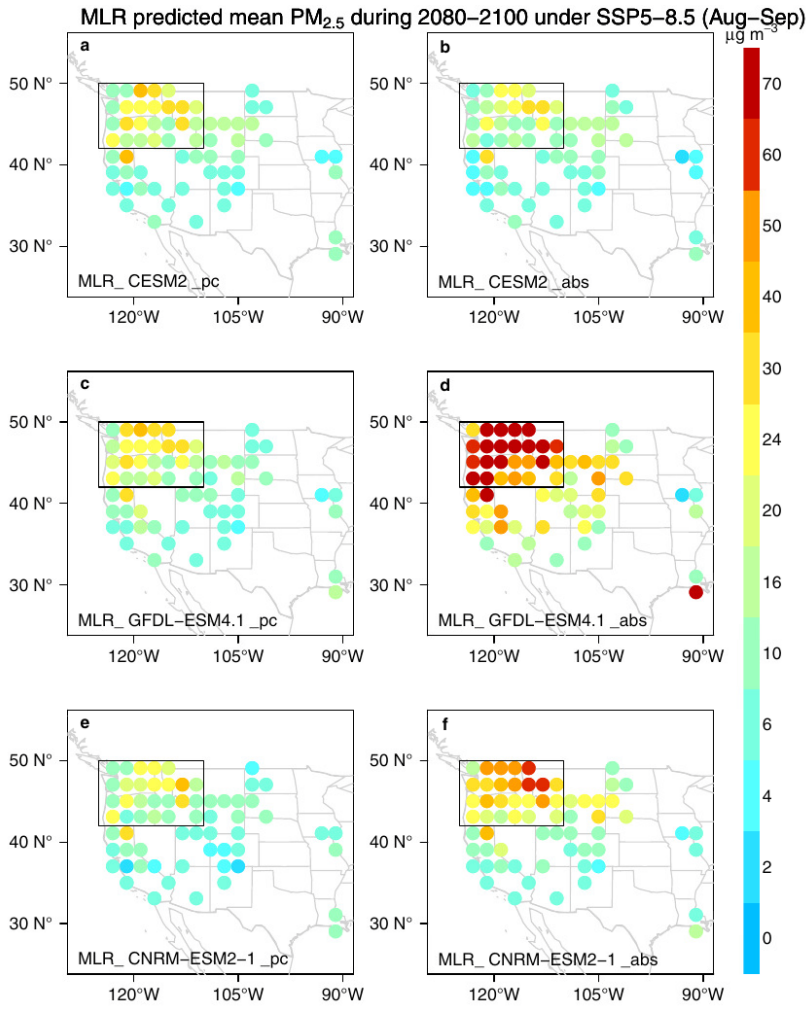



**Figure S8.** Uncertainties in MLR $PM_{2.5}$ predictions based on percentage versus absolute change of fires. (Left panels) August–September mean $PM_{2.5}$ in the late 21st century (2080–2100) at western US sites (averaged over a 2 °×2° grid) predicted by MLR driven by the percentage change of fire $CO_2$ emissions under SSP5-8.5 relative to the respective 1990–2010 average from each CMIP6 fire model. (Right panels) same as the left panels but driven by the absolute changes in each model. Only grids with MLR correlation $r^2$>0.5 are shown.

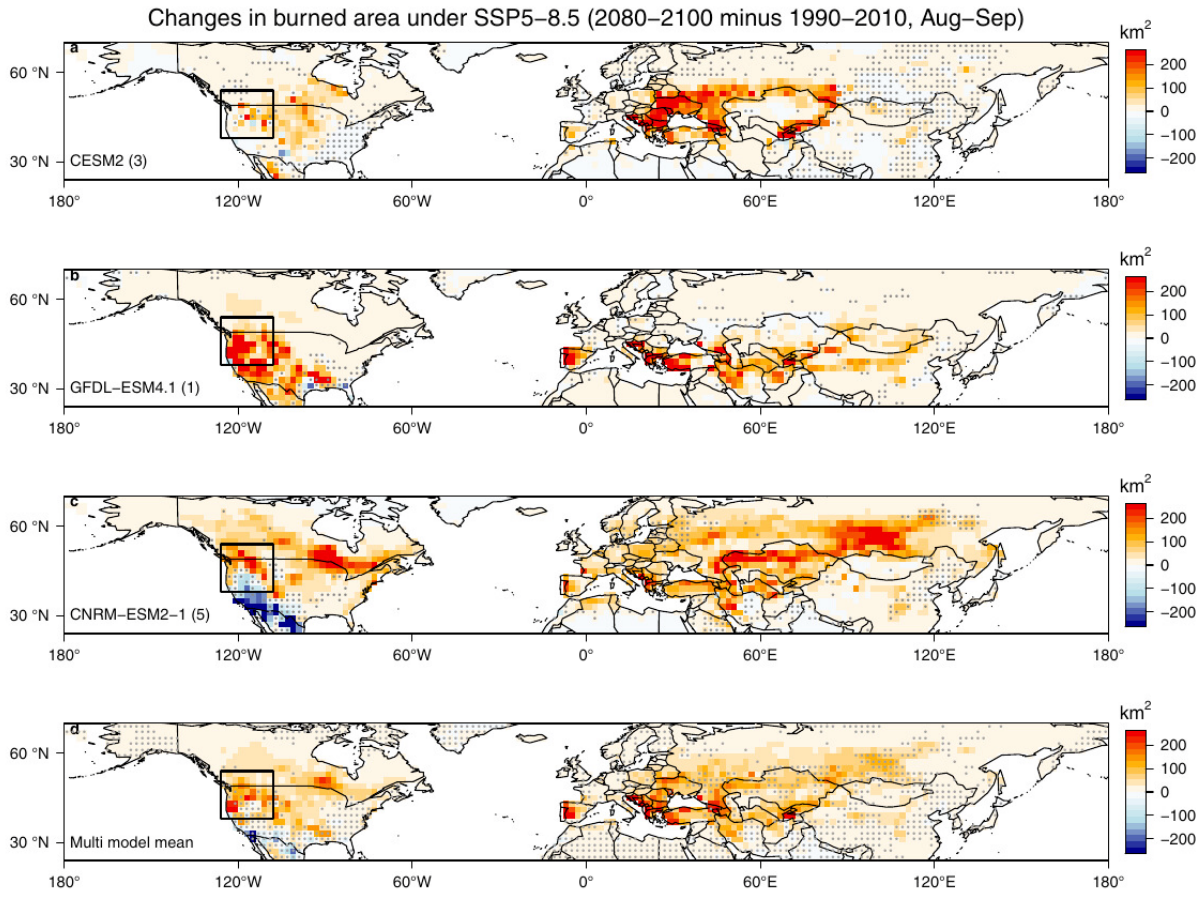



**Figure S9.** Changes in burned area over northern mid-latitudes by three CMIP6 Earth system models. Changes in the August–September total burned area during the late 21st century (2080–2100) compared to present day (1990–2010) under SSP5-8.5 simulated by three CMIP6 models. Number of ensembles for each model is shown in the parentheses at the bottom-left corner. The black box represents western North America. Stippling indicates grids where the changes are not statistically significant at 95% confidence level from >50% of the available ensembles. For multi model mean, the results are first averaged across the available ensemble members from each model (3 for CESM2, 1 for GFDL-ESM4.1 and 5 for CNRM-ESM2-1), and then averaged across the models. Stippling indicates grids with less than two models show statistically significant ($p < 0.05$) changes or the three models do not agree in sign. For each model, a change is defined significant if >50% of the ensemble changes are statistically significant ($p < 0.05$).

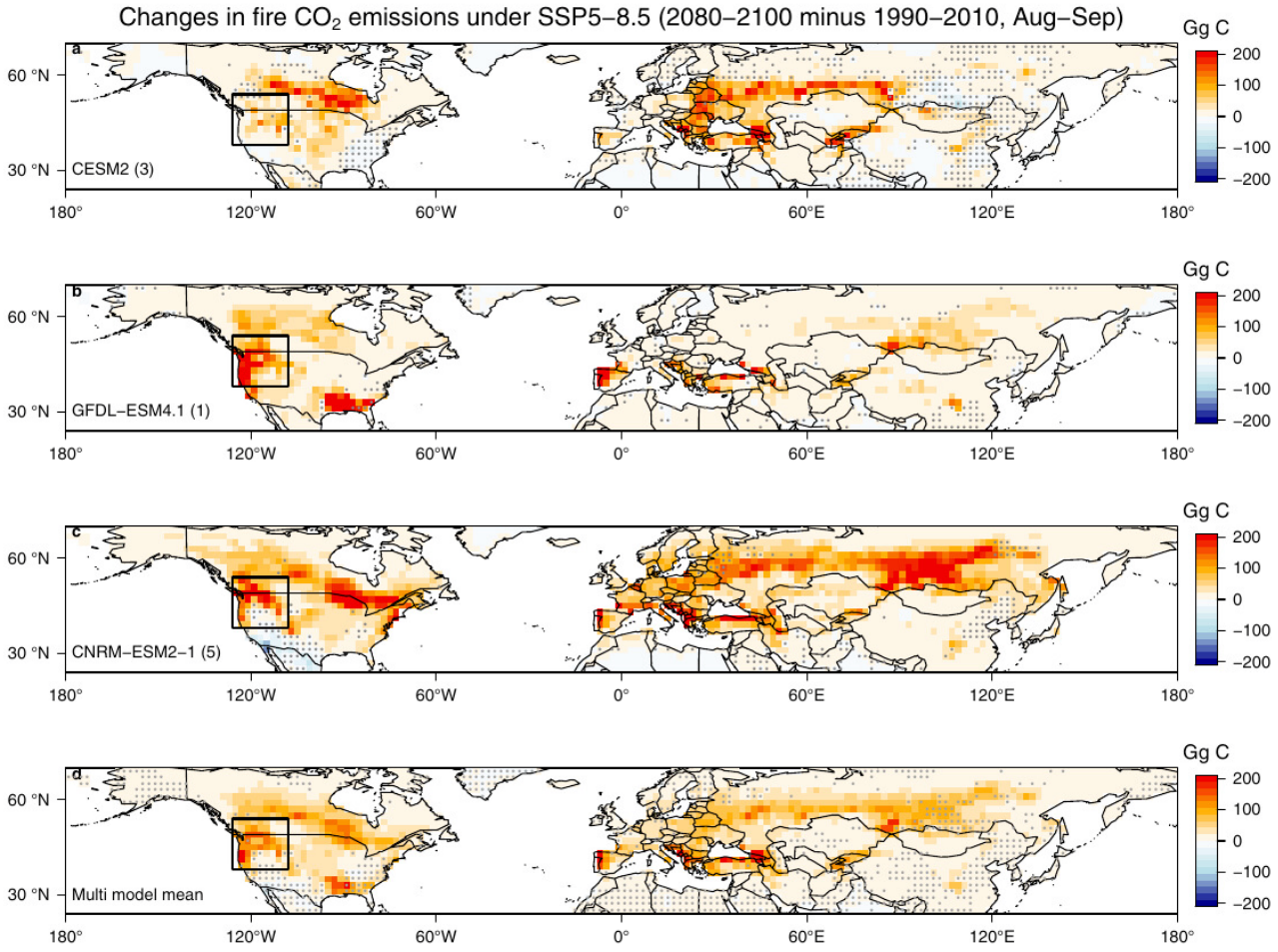



**Figure S10.** Same as Fig. S9, but for fire $CO_2$ emissions.

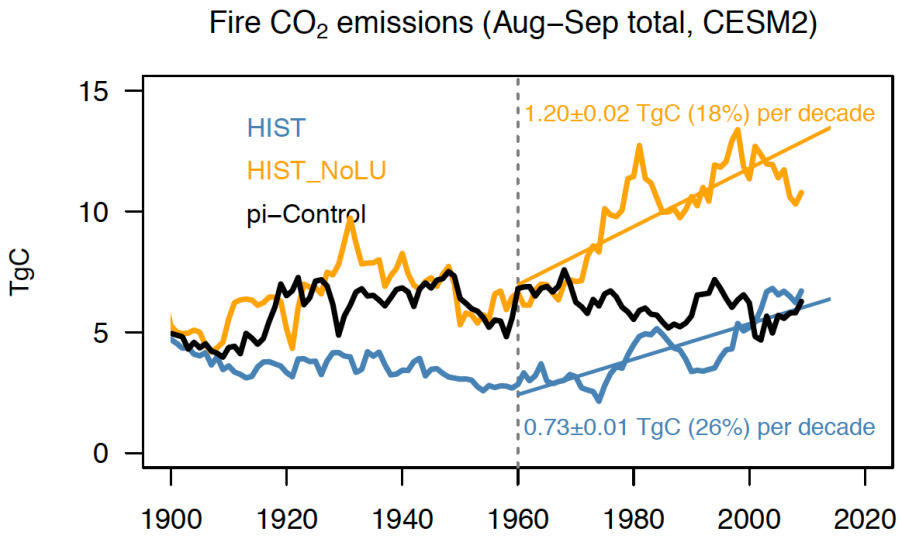



**Figure S11.** Historical evolution of fires over western North America. Temporal evolution of August–September total fire $CO_2$ emissions (10-year running average) over western North America during 1900–2014 from CESM2 pre-industrial control simulation (pi-Control, black), coupled simulation with all forcings and historical land use and population density (HIST, blue), and coupled simulation with all forcings but with land use and population density held constant at 1850 level (HIST_NoLU, orange). Linear trends (in absolute and percentage relative to 1960 level) during 1960–2014 as well as the 95% confidence limits are reported.

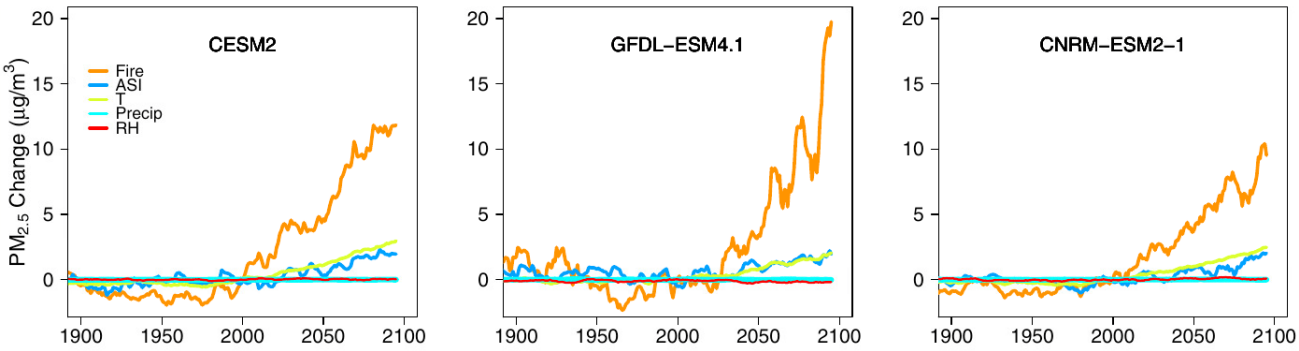



**Figure S12.** Projected changes in August–September mean $PM_{2.5}$ from each predicting variable. The MLR predicted 10-yr running average of changes in August–September mean $PM_{2.5}$ averaged over the US Pacific Northwest (black box in Fig. 5) based on the CMIP6 Earth system model projections of each predicting variable: fire $CO_2$ emissions (orange), air stagnation index (blue), surface temperature (green), precipitation (cyan) and relative humidity (red).

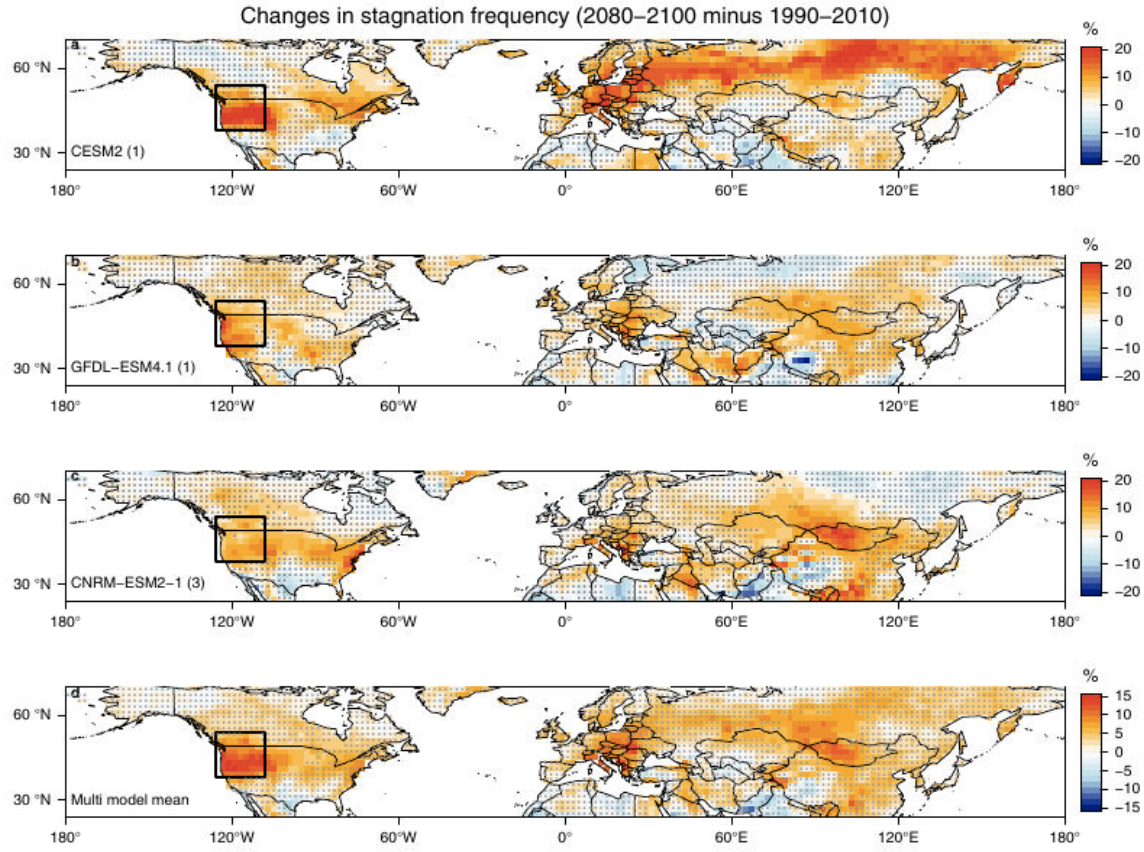
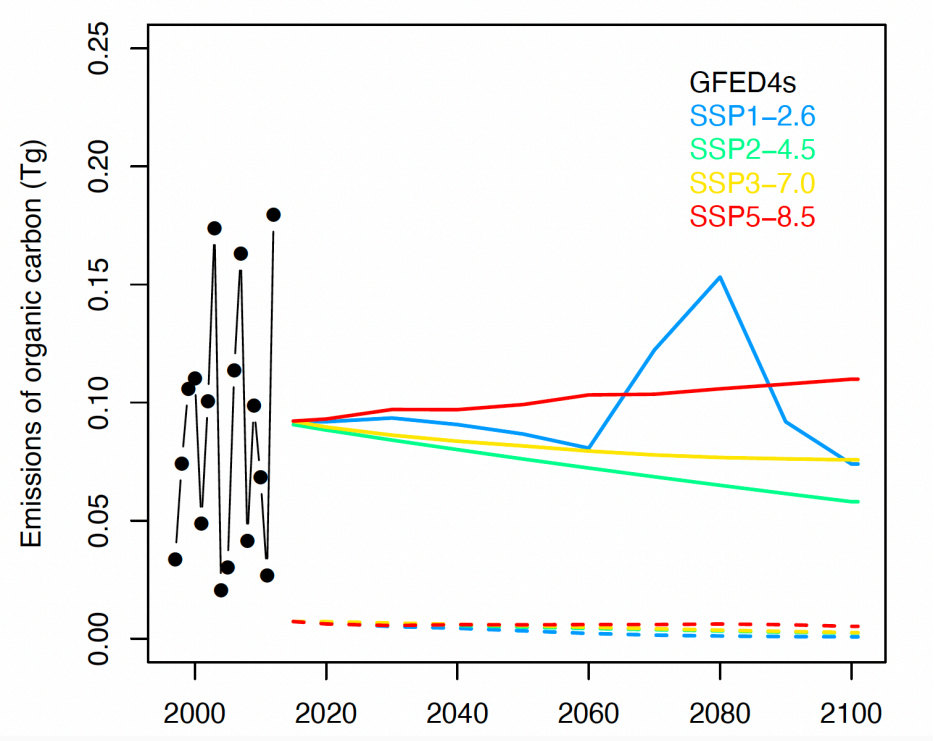



**Figure S13.** Same as Fig. S9, but for air stagnation frequency.




71

72 **Figure S14.** Prescribed organic carbon emissions used for chemistry-climate model $PM_{2.5}$
73 predictions. Shown are August–September total organic carbon emissions over western North
74 America from biomass burning (color-coded solid lines) and anthropogenic sources (color-coded
75 dashed lines) during 2015–2100 under four SSPs. Prescribed fire emissions from GFED4s for
76 historical simulations (before 2014; black) are also shown.

77

78 **Supplementary Tables 1 and 2**

79 **Table S1** List of CMIP6 fire models, and number of ensembles from each experiment.

| Models | Land-only | Coupled Historical | Coupled SSP1-2.6 | Coupled SSP2-4.5 | Coupled SSP3-7.0 | Coupled SSP5-8.5 |
|---|---|---|---|---|---|---|
| | 1850–2014 | | 2015–2100 | | | |
| CESM2 (1.25°×0.94°) | 1 | 3 | 1 | 3 | 3 | 3 |
| GFDL-ESM4.1 (1.25°×1°) | 1 | 3 | 1 | 3 | 1 | 1 |
| CNRM-ESM2-1 (1.4°×1.4°) | 1 | 5 | 5 | 5 | 5 | 5 |

80

**Table S2** Multi-ensemble means of changes in fire $CO_2$ emissions (in percent relative to 1990–2010) over western North America and the MLR-predicted $PM_{2.5}$ (μg/m$^3$; percentage changes in parenthesis) averaged over US Pacific Northwest sites by late 21$^{st}$ century (2080–2100).

| Models | SSP1-2.6 | SSP2-4.5 | SSP3-7.0 | SSP5-8.5 |
|---|---|---|---|---|
| | Fire $CO_2$ emissions, August–September | | | |
| CESM2 | +113% | +145% | +254% | +242% |
| GFDL-ESM4.1 | +70% | +121% | +202% | +262% |
| CNRM-ESM2-1 | +60% | +100% | +110% | +133% |
| | Mean $PM_{2.5}$ (US Pacific Northwest), August–September | | | |
| MLR (CESM2) | 15.4 (+62%) | 18.4 (+93%) | 22.7 (+138%) | 23.9 (+150%) |
| MLR (GFDL-ESM4.1) | 12.7 (+34%) | 17.8 (+87%) | 22.4 (+135%) | 24.8 (+160%) |
| MLR (CNRM-ESM2-1) | 13.2 (+39%) | 16.6 (+74%) | 18.9 (+99%) | 18.9 (+99%) |
| | q95 $PM_{2.5}$ (US Pacific Northwest), August–September | | | |
| MLR (CESM2) | 46.4 (+91%) | 55.8 (+129%) | 73.0 (+201%) | 76.9 (+217%) |
| MLR (GFDL-ESM4.1) | 39.1 (+61%) | 57.2 (+136%) | 73.6 (+203%) | 81.6 (+236%) |
| MLR (CNRM-ESM2-1) | 38.1 (+57%) | 50.4 (+108%) | 56.4 (+132%) | 58.0 (+139%) |

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