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Projection of future wildfire emissions in western USA under climate change: contributions from changes in wildfire, fuel loading and fuel moisture

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Abstract. Numerous devastating air pollution events from wildfire smoke occurred in this century in the western USA, leading to severe environmental consequences. This study projects future fire emissions in this region under climate change with a focus on comparing the relative contributions from future changes in burned area, fuel loading and fuel moisture. The three properties were projected using an empirical fire model, a dynamical global vegetation model and meteorological conditions respectively. The regional climate change scenarios for the western USA were obtained by dynamical downscaling of global climate projections. The results show overall increasing wildfires and fuel loading and decreasing fuel moisture. As a result, fire emissions are projected to increase by ~50% from 2001–2010 to 2050–2059. The changes in wildfires and fuel loading contribute nearly 75% and 25% of the total fire emission increase, respectively, but the contribution from fuel moisture change is minimal. The findings suggest that the air pollution events caused by wildfire smoke could become much more serious in the western USA by the middle of this century, and that it would be essential to take the future changes in fuel conditions into account to improve the accuracy of fire emission projections.

Keywords: climate change, wildfire, emission, fuel loading, fuel moisture, vegetation modelling, dynamical climate downscaling, fire potential index, western United States.

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Introduction

In contrast to the declining trends of total burned area worldwide (Doerr and Santın 2016; Andela *et al.* 2017), wildfires in the United States have increased significantly in the past three decades (Westerling *et al.* 2006; Marlon *et al.* 2012; Abatzoglou and Kolden 2013; Dennison *et al.* 2014; Westerling 2016; Holden *et al.* 2018; Nauslar *et al.* 2018). More than 70 000 wildfires occur each year in the USA, burning out nearly 7 million acres on average since 2000 (CRS 2020). The western USA contributed most of the burned area despite having a smaller number of occurrences than the eastern USA.

Wildfires emit large amounts of pollutant particles and gases that can significantly affect air quality, human health, and climate (Crutzen *et al.* 1979; Andreae and Merlet 2001;

Liu 2004; Wiedinmyer *et al.* 2006; Jaffe *et al.* 2008; Heilman *et al.* 2014; Brey and Fischer 2016; Navarro *et al.* 2016; O'Neill *et al.* 2017; O'Dell *et al.* 2019; Zhao *et al.* 2019; Zou *et al.* 2019*a*; Guan *et al.* 2020; Xie *et al.* 2020). Fire emissions accounted for approximately one-third of the total emissions of fine particulate matter with a diameter of 2.5 μm or smaller ($PM_{2.5}$) in the USA (Urbanski *et al.* 2011). The fire emissions of ozone precursors such as volatile organic compounds (VOC) and NO_x can elevate tropospheric O_3 level (Jaffe *et al.* 2013). $PM_{2.5}$ and O_3 pose severe threats to human health (Liu *et al.* 2015*a*; Stowell *et al.* 2019) and are two of the air pollutants subject to the US Environmental Protection Agency's National Ambient Air Quality Standards (NAAQS). As atmospheric aerosols, smoke particles affect atmospheric radiations directly through scattering and absorbing solar radiation and indirectly through modifying cloud microphysics, which further affects climate (Liu 2005; Liu *et al.* 2014*a*).

Wildfire emissions are determined by burned area, fuel loading, consumption efficiency, and emission factors (Ottmar *et al.* 2008; Urbanski 2014). Many resources are available for estimating these parameters. Burned area measurements are available from ground reporting (e.g. the US National Interagency Fire Center historical fire statistics, https://www.nifc.gov) and satellite remote sensing such as the Global Fire Emissions Database (GFED) for global fire detections using MODIS/MIIS (Giglio *et al.* 2013) and the Monitoring Trends in Burn Severity (MTBS) for USA large fires using Landsat (Eidenshink *et al.* 2007). Fire models, which are necessary for projecting future fires, are also used to simulate burned areas based on statistical relationships (Spracklen *et al.* 2009; Yue *et al.* 2013) and vegetation models (Li *et al.* 2012, 2013; Yang *et al.* 2015). Fuel loading can be obtained by fuel systems such as the Fuel Characteristic Classification System (FCCS) (Ottmar *et al.* 2007) and LANDFIRE (Rollins 2009) and LiDAR measurements (Hudak *et al.* 2016; Bright *et al.* 2017), and simulated using dynamical global vegetation models (DGVMs) (Zhang *et al.* 2010). Vegetation models are necessary for projecting future fuel loading conditions. Tools such as CONSUME (Prichard *et al.* 2007) provide equations to calculate consumption efficiency based on fuel (type, moisture) and fire (type, intensity, and phase) properties. Fire emission factors are available from, for example, the First Order Fire Effects Model (FOFEM) (Reinhardt *et al.* 1997; Lutes 2020) based on field and laboratory measurements (Urbanski 2014; Prichard *et al.* 2020). Many datasets such as GFED (Giglio *et al.* 2013), the Fire INventory from NCAR (FINN) (Wiedinmyer *et al.* 2011), and the Fire Information Reconciled Emissions (CFIRE) inventory (Larkin *et al.* 2020) directly provide fire emissions. Fire emissions are also derived from other atmospheric measurements such as optical depth (Mirzaei *et al.* 2020) and fire radiative power (Ichoku *et al.* 2008).

Climate is one of the natural factors affecting wildfire and fuels (Littell *et al.* 2009; Abatzoglou and Williams 2016; Zhang and Wang 2016; Hostetler *et al.* 2018; Williams *et al.* 2019; Brown *et al.* 2020). Wetter weather conditions before a fire season often produce more-than-normal quantities of fuel to burn, whereas warmer and drier conditions during a fire season make it easier to ignite a fire and for the fire to spread. Also, drier fuels have larger consumption efficiency and therefore larger emissions. An urgent issue for climate and fire emission relationships is the impacts of climate change. Climate models have projected that the greenhouse effect could result in significant climate change (IPCC 2014), including overall warming and drying trends in the USA (Cayan *et al.* 2010; Gao *et al.* 2014), and that wildfires would increase accordingly (Brown *et al.* 2004; Balshi *et al.* 2009; Flannigan *et al.* 2009; Littell *et al.* 2009; Spracklen *et al.* 2009; Liu *et al.* 2013; Yue *et al.* 2013; Liu *et al.* 2016; Goss *et al.* 2020). Fire emissions and the air quality impacts are likely to increase accordingly (Spracklen *et al.* 2009; Yue *et al.* 2013; Ford *et al.* 2018).

Besides wildfires, vegetation is expected to change remarkably under changing climate (Bachelet *et al.* 2001; Keane *et al.* 2004; Cary *et al.* 2006; Corlett and Westcott 2013; Alexander *et al.* 2015; Sheehan *et al.* 2015; Shafer *et al.* 2015; Holsinger *et al.* 2019), which is another contributor to future changes in fire emissions (McKenzie *et al.* 2014). Vegetation species could migrate from one region to another and the biomass of a species could become larger due to a longer growth season. Both changes would lead to different fuel loading. In considering climate-induced vegetation changes, Yue *et al.* (2013) recognised the need for fire emission projection, though the changes were not included in calculating future fuel loading because a DGVM only produced a small vegetation change. Ford *et al.* (2018) projected wildfire and vegetation conditions using the Community Land Model (CLM) DGVM (Oleson *et al.* 2013) with fire and carbon emission schemes (Li *et al.* 2012, 2013). Because wildfire and vegetation were projected interactively, the relative contributions of the two properties to wildfire emissions were not clear. Also, the vegetation species were not converted to fuel types, making it difficult to apply the field and laboratory fuel measurements provided in forest management tools such as FCCS, CONSUME, and FOFEM.

Fuel moisture is an important factor for fuel consumption efficiency that is very sensitive to climate and projected to change remarkably under climate change in the USA and other world regions (Flannigan *et al.* 2016; Liu 2017). This could lead to changes in future consumption efficiency and fire emissions. However, the relative importance of this property in comparison with wildfire and fuel loading for future fire emissions is unclear.

The purpose of this study is to project future wildfire emissions in the western USA under changing climate and to understand the relative contributions from future changes in fire, fuel loading, and fuel moisture. Wildfires, fuel loading, and fuel moisture were projected using an empirical fire model developed based on the extreme value theory, a DGVM, and meteorological conditions respectively. Dynamical downscaling of global climate change projections was used to obtain regional climate change scenarios for the western USA. It was hypothesised that climate change due to the greenhouse effect would increase surface temperature, reduce relative humidity, and intensify drought; although these changes would increase fire frequency and therefore fire emissions, as predicted in many previous studies, they would also modify fuel loading and moisture conditions, which would change the magnitude of the fire emission increases. The results are expected to provide information for understanding the uncertainty in projecting future fire emissions only based on fire projections.

Methods

Regional climate downscaling

The methods and procedure to project future fire emissions are illustrated in Fig. 1. Two datasets of regional climate change scenarios, CESM-WRF (Community Earth System Model, Weather Research and Forecast) and HadCM-HRM (Hadley Centre Climate Model, Hadley Regional Model), were used. For the CESM-WRF dataset, we ran a regional meteorological model, the WRF model (Skamarock *et al.* 2008), with the boundary conditions provided by the Coupled Model Inter-comparison Project – phase 5 (CMIP5) global climate projected by the National Center for Atmospheric Research (NCAR)'s CESM version 1 (Hurrell *et al.* 2013; Monaghan *et al.* 2014) under the Representative Concentration Pathway (RCP) 8.5 emission scenario (Meinshausen *et al.* 2011; Taylor *et al.* 2012). The resolution was 12 km and the time periods were 2001–2010 for the present and 2050–2059 for the future. CESM-WRF scenario was used for projection of future wildfires.

The HadCM-HRM dataset was provided by the North American Regional Climate Change Assessment Program (NARCCAP) (Mearns *et al.* 2012). A regional meteorological model, the HRM3, was run with the boundary conditions provided by the CMIP3 global climate projected by the Hadley Centre Climate Model, version 3 (HadCM3) under the IPCC Special Report on Emission Scenarios (SRES) A2 (Nakićenović *et al.* 2000). The resolution was 50 km with the time periods of 1971–2000 for the present and 2041–2070 for the future. The HadCM-HRM scenario was used for projections of future fuel loading and moisture, which had been conducted at a time when only CMIP3 global climate projections were available.

Fire projection

Fire occurrence prediction models can be classified into two types of DGVMs and statistical models. Most DGVMs have incorporated fire modules that predict fire occurrence mainly based on vegetation conditions as well as weather and human factors (Venevsky *et al.* 2019). Statistical models build fire relationships with meteorological and other conditions based on data (Taylor *et al.* 2013; Plucinski *et al.* 2014; Phelps and Woolford 2021). Such relationships include logistic regression (Nadeem *et al.* 2020), logistic generalised additive models (Woolford *et al.* 2011), and machine learning methods (Van Beusekom *et al.* 2018).

The present and future wildfires were obtained in this study from modelling results of an empirical fire model (EFM), which includes generalised regression equations formed based on the extreme value theory (Liu *et al.* 2014*b*). The predictors are normalised Keetch–Byram Drought Index (KBDI) (Keetch and Byram 1968), appearing as a linear combination of three terms in powers of 1, 2, and 3, and normalised relative humidity (*RH*). KBDI measures wildfire potential determined by daily maximum temperature and precipitation and average annual precipitation. The value ranges of 0–200, 200–400, 400–600, and 600–800 indicate low, moderate, high, and extreme fire potential. KBDI was formed based on the fire and meteorological conditions in south-east USA. There are applications of this index in different world regions with reasonable relationships with fire activity. We recently found that KBDI was a better predictor than meteorological variables and some other fire/drought indices for seasonal and annual fires (Zhao and Liu 2021). Because the magnitude (average) varies from the south-east to

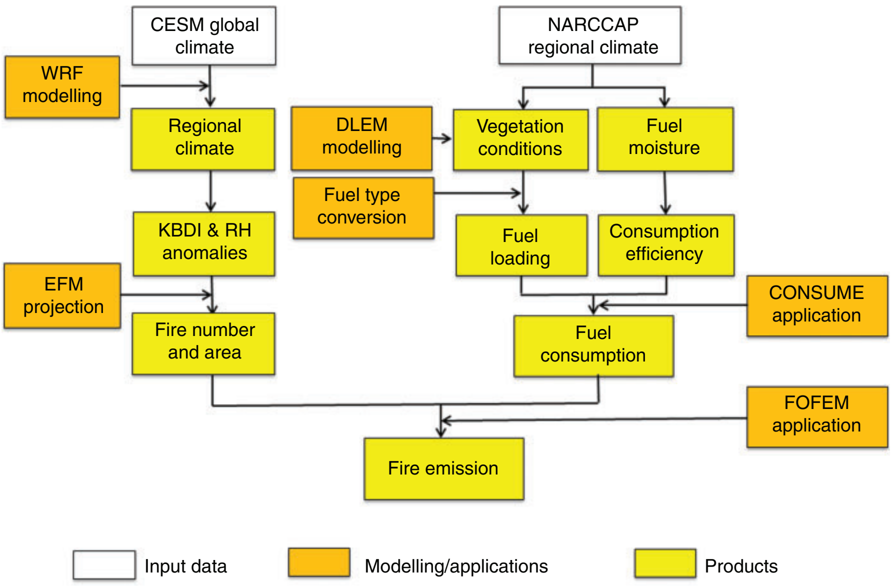

Fig. 1. Diagram of research methods. CONSUME is a tool for fuel consumption and emissions. CESM, Community Earth System Model; DLEM, Dynamical Land Ecosystem Model; EFM, Empirical Fire Model; FOFEM, First Order Fire Effects Model; KBDI, Keetch–Byram Drought Index; NARCCAP, North American Regional Climate Change Assessment Program; *RH*, relative humidity; WRF, Weather Research and Forecast.

another region, the anomalies make more sense than the absolute values for a specific region. For this reason, we used anomalies rather than absolute values in this study.

KBDI and *RH* at a location of a historical fire were first calculated. Their anomalies were obtained by subtracting these values from the corresponding multiple-year averages at this location. The KBDI anomaly was put into an anomaly category. The number of this KBDI anomaly was counted for all fires. The average of all *RH* anomalies with this KBDI anomaly category was obtained. Note that KBDI and *RH* could go different ways because they are proportional and inversely proportional to temperature respectively. However, they are mostly consistent at a long time scale, during which abnormal atmospheric circulations are a major driver for both properties. For example, KBDI above normal over a long period usually indicates a drought condition and is in favour to fire occurrence. *RH* usually goes below normal under drought condition. The statistical significance of the future changes in KBDI and *RH* was tested using t-statistic (same for fuel moisture and fuel loading is described below).

Wind is a meteorological variable often used in fire prediction. It was not included in this study for a couple of reasons. First, we compared KBDI with two other fire indices (Liu *et al.* 2014*b*), Fosberg Fire Weather Index, which includes temperature, humidity, and wind factors, and Large Fire Potential meteorological condition, which measures windy and dry (unsaturation degree) conditions. The KBDI had better relationships with large fires. Second, the EFM (including wind speed as a predictor) had lower fitting rate than the one without this parameter.

The variable to be predicted is the total number of fire occurrences in the western USA over a certain time period divided by the number of the KBDI at a specific anomaly level per grid point of the region. The EFM is composed of a set of equations, each for a fire size range and a KBDI anomaly level. The projected average fire number is the sum over all fire ranges and KBDI anomaly levels. Note that this model projects average fire number in the western USA without spatial resolution. A similar model but with regional resolution would hardly reach a significance level because of very limited number of historical fires for a certain fire size range and KBDI anomaly level. Also note that burned area was not predicted by the model. The present burned area for each of the fire size categories was obtained from measured data. The future burned area of each size category was obtained from the present burned area with a predicted increasing factor of the ratio of the future-to-present fire number for the category.

The historical fire data used for developing the model were the Federal Wildland Fire Occurrence Data (http://wildfire.cr.usgs.gov/firehistory/data.html), which contains fire records collected by USA federal land management agencies for fires that occurred during 1980–2013. This dataset was used to calculate fire emissions for the continental USA (Liu 2004). The historical daily meteorological data used to develop the model were obtained from the North American Regional Reanalysis (NARR) at a horizontal resolution of 32 km (Mesinger *et al.* 2006). The Chi-squared test for the linear regression models showed significance level of $P < 0.01$.

Fuel loading modelling

Forest fuels for a fire are all kinds of plant material, including grasses, shrubs, trees, dead leaves and branches, and duff. Dead fuels are divided into four 'timelag' categories: 1-h, 10-h, 100-h, and 1000-h fuels, corresponding to fuels of less than 0.25 inch, 0.25–1 inch, 1–3 inches, and 3–8 inches diameter respectively. Fuel loading is the amount of fuel present expressed quantitatively in terms of weight of fuel per unit area. We used the Dynamical Land Ecosystem Model (DLEM) (Tian *et al.* 2010) to simulate fuel loading. DLEM is a highly integrated process-based terrestrial ecosystem model that simulates daily carbon, water and nitrogen cycles driven by the changes in atmospheric chemistry, including ozone, nitrogen deposition, CO_2 concentration, climate, land-use and land-cover types and disturbances. Similar to most DGVMs cited in Introduction, DLEM includes multiple core components of biophysics, plant physiology, soil biogeochemistry, dynamic vegetation, and land-use. The DLEM carbon pools have four fuel types of litter and duff, herb/grass, shrub, and coarse woody debris. Although the number of fuel types is relatively small in compassion with many other DGVMs, there is a feature with DLEM that was especially useful for fire research of this study: the model had a module to convert simulated carbon pools to fuel types widely used for fire emission calculation.

The carbon pools were converted into the FCCS fuel load map types based on the approach used in Zhang *et al.* (2010): litter and duff in DLEM were comprised of 1- and 10-h dead fuels in FCCS; herb/grass in DLEM was equivalent to grass in FCCS; shrub in DLEM was equivalent to shrub in FCCS; and coarse woody debris in DLEM comprised 100-h and longer-lag fuels in FCCS. Fuel loading was estimated by accumulating biomass of all types of the FCCS fuels. It was assumed that distribution of fuelbeds would not change from present. Note that when projecting fuel loading using the DLEM, the model was run continuously from 1970 to 2070. However, the original NARCCAP downscaled data were not available for between 2000 and 2040. An algorithm was developed to fill this data gap (Liu *et al.* 2015*b*).

Fuel moisture calculation

Fuel moisture can be obtained from measurements and modelling using meteorological variables or vegetation models. In this study, we used the empirical algorithms from the National Fire Danger Rating System (NFDRS) (Cohen and Deeming 1985) to estimate fuel moisture based on meteorological conditions. The 1- and 1000-h fuel moistures in the continental USA based on multiple NARCCAP regional climate change scenarios were available (Liu 2017). The calculations of fuel moisture using the NFDRS scheme are similar between 1- and 10-h fuels and between 100- and 1000-h fuels. For this study, the results of 1000-h fuel moisture projected based on the HadCM3-HRM3 regional climate change scenario were used.

Fire emission calculation

Fire emission was calculated using:

$$E_k = A \times FL \times CE \times EF_k \tag{1}$$

where E_k is wildfire emissions of species k, A area burned, FL fuel loading, CE consumption efficiency, and EF_k emission factor of species k (Liu 2004).

CE was obtained based on equations provided in Consume 3.0 (Prichard *et al.* 2007). The values for coarse wood and ground fuels are dependent on 1000-h fuel moisture and duff moisture respectively. There is no general duff moisture model, so some fuel tools such as FARSITE (Finney 2004) use empirical relationships between duff moisture and dead fuel moisture. In this study, we converted the fitting line shown in Brown *et al.* (1985) to the following function:

$$FMC_{duff} = 175/20 \times (FMC_{1000} - 5) \quad (2)$$

where FMC_{duff} and FMC_{1000} are duff and 1000-h fuel moisture in % respectively.

EF_k was obtained from FOFEM 4.0 (Reinhardt *et al.* 1997). The values in FOFEM 4.0 are presented for various fuel types of the western USA. The newly released FOFEM 6.7 (Lutes 2020) updates fire emission factors based on, for example, Urbanski (2014) and Prichard *et al.* (2020), which are larger than the old values for some emission species such as $PM_{2.5}$. However, the updated values are presented in different fire phases rather than fuel types. Thus, EF_k in the old FOFEM version was used for this study.

The calculated present $PM_{2.5}$ emissions of fires for the western USA states were compared with two sources provided in Urbanski *et al.* (2011), the 2005 EPA National Emission Inventory (NEI) and the Wildland Fire Emission Inventory (WFEI). The EPA NEI used the same fire emission factors as this study. The WFEI was a high-resolution model for non-agricultural open biomass burning, with burned aeras from satellite remote sensing and emission factors from probability distribution functions developed based on multiple field measurements.

Results

Wildfires

Present wildfires

Nearly 3000 large wildfires occurred in western USA during 2001–2010 (Fig. 2), ~15, 30, 90, 500, 500, and 1900 with the sizes of >200, 100–200, 50–100, 10–50, 5–10, and 1–5 thousand acres respectively. The fires of >200 thousand acres were found mostly in the south-western half of western USA (Fig. 3). The fires of 10–50 thousand acres accounted for ~1 million acres each year, and those in other size ranges each accounted for ~0.5 million acres each year. The total annual burned area was ~3.5 million acres.

The fire number was ~400–500 in 2006 and 2007, 300–350 in each year of 2001–2004 and 2005, and 140 in 2004 (Fig. 4*a*). The burned area was around 7 million acres in each of 2002, 2006, and 2007 (Fig. 4*b*). Both monthly fire number and burned area were much larger in summer (June to August) than other seasons (largest in July), larger in fall than spring, and minimal in winter (Fig. 5).

Changes in meteorological conditions for wildfires

KBDI averaged over summer and fall seasons during 2001–2010 (Fig. 6*a*) varied from extreme potential in most of California

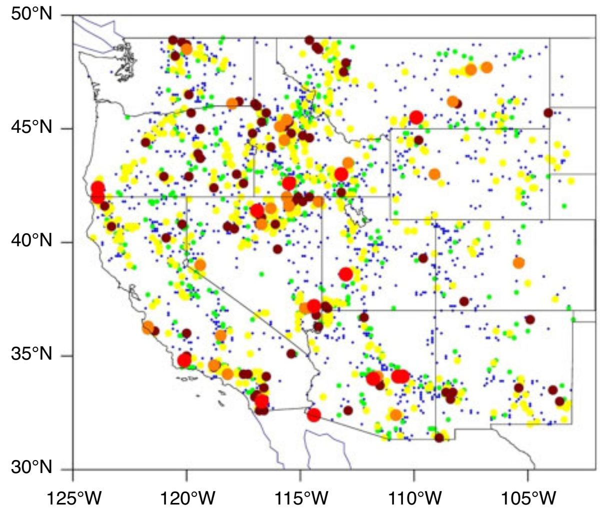

Fig. 3. Wildfires in western USA during 2001–2010. The fire size ranges (in acre) are >200 000 (red in the online version), 100 000–200 000 (orange in the online version), 50 000–100 000 (brown in the online version), 10 000–50 000 (yellow in the online version), 5000–10 000 (green in the online version), and 1000–5000 (blue in the online version).

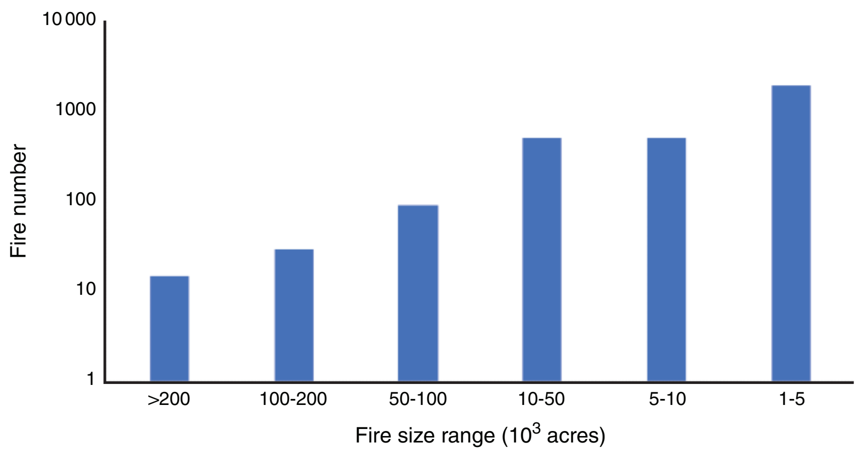

Fig. 2. Fire number in each fire size category.

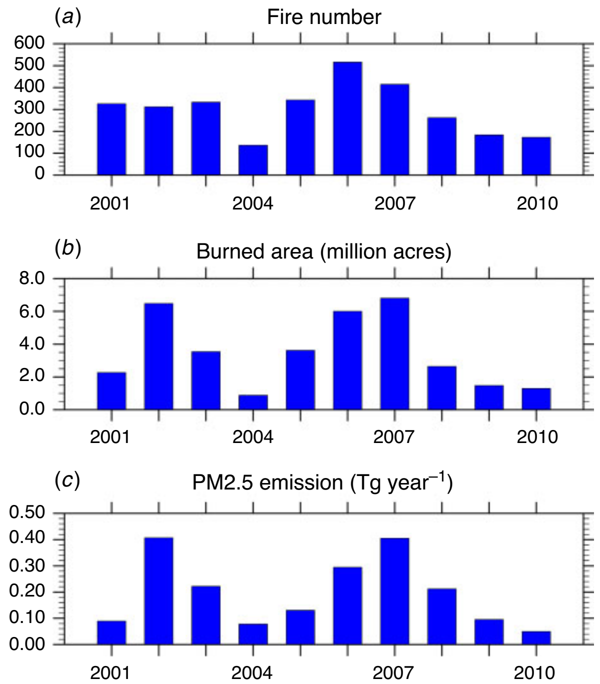

Fig. 4. Annual wildfires and emissions during the present period in western USA. (*a*) Fire number. (*b*) Burned area. (*c*) Particulate matter ≤2.5 µm ($PM_{2.5}$) emission.

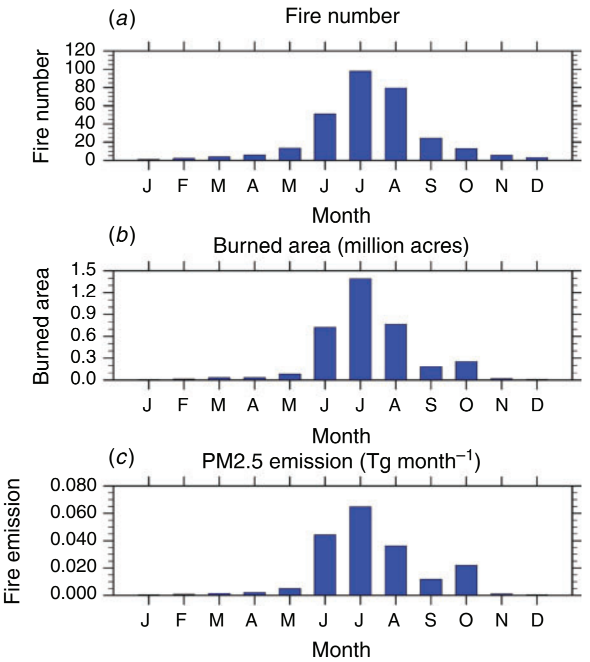

Fig. 5. Monthly wildfires and emissions in western USA averaged over 2001–2010. (*a*) Fire number. (*b*) Burned area. (*c*) Particulate matter ≤2.5 µm ($PM_{2.5}$) emission.

and south-western Nevada (KBDI >600), to high or moderate potential in some areas of the South-west, southern Great Plains, and North-west (200–600), to low potential in the Rocky Mountains and northern Great Plains (<200). By 2050–2059, KBDI is projected to increase across western USA (Fig. 6*b*). The increase is more remarkable in the areas where fire potential was relatively low during 2001–2010, by more than 100 in the northern Great Plains and 50–100 in many areas of the North-west, South-west, and southern Great Plains. The change is significant at $P < 0.01$.

RH averaged over summer and fall seasons during 2001–2010 (Fig. 7*a*) was lower than 50% in most of California, the Great Basin, and the South-west, and lowest in the California–Nevada border area (less than 30%). *RH* was greater than 60% in the northern Pacific Coast, Rocky Mountains, and northern Great Plains. *RH* is likely to decrease by 2050–2059 in most of the western USA. The change is significant at $P < 0.01$. The decrease is more remarkable in some areas where *RH* was higher during 2001–2010, such as the Rocky Mountains. In contrast, *RH* would increase in the relatively dry areas during 2001–2010, including California and the Great Basin. The future changes in KBDI and *RH* indicate that climate change likely increases the dryness in most of western USA, mainly in the present relatively wet areas.

Changes in wildfires

Wildfires are projected to increase for all fire size ranges. The total number of wildfires in western USA during 2001–2010 obtained using the fire model based on the KBDI and *RH* values is ~2460, which is 18% lower than the observed fire number. The annual burned area corresponding to the predicted fire number is ~2.6 million acres, which is 26% lower than the observed area.

The model projects an increase in fire number by ~12% from the present period to the future period of 2050–2059, due to the overall increasing KBDI and decreasing *RH*. The increasing rate of fire number is larger for the fire ranges with larger fire sizes, leading to a much larger increasing rate for burned area than fire number. Burned area is projected to increase by 32%.

Fuel loading

The simulated fuel loading during 1971–2000 using DLEM was more than 5 kg m^{-2} (20 tons $acre^{-1}$) in the northern Pacific coast, southern Rocky Mountains, and some other mountain areas (Fig. 8). Fuel loading is projected to increase in these areas by 2041–2070 by up to 0.5 kg m^{-2} (2 tons $acre^{-1}$). The increase is significant at $P < 0.01$. However, fuel loading is projected to decrease by up to 0.5 kg m^{-2} (2 tons $acre^{-1}$) in the Great Plains, southern South-west, and far northern Rocky Mountains. Wood biomass and live herb would increase while litter and duff would decrease.

Fuel moisture

The spatial patterns of present FMC_{1000} and future change (Fig. 9) are similar to those of *RH*. The spatial correlation coefficient between the two fields is 0.76 ($P < 0.01$). Present FMC_{1000} increases from below 6% in California and Nevada to 10% in South-west and southern Great Plains, 14% in the northern Great Plains, and more than 20% in some northern Pacific Coast and Rocky Mountains. FMC_{1000} is projected to decrease overall, by 1% in most of the Rocky Mountains and

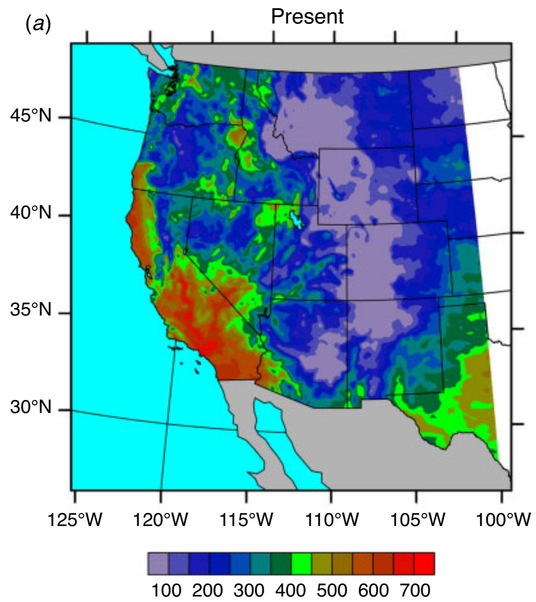

Fig. 6. Keetch–Byram Drought Index averaged over summer and fall seasons. (*a*) 2001–2010. (*b*) Difference between 2050–2059 and 2001–2010.

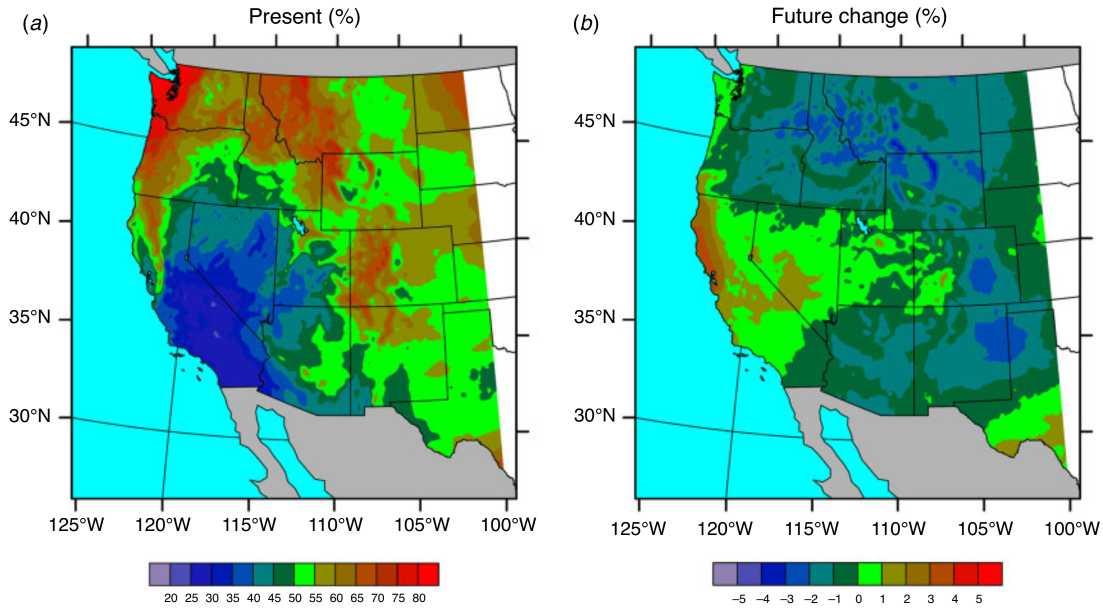

Fig. 7. Relative humidity averaged over summer and fall seasons. (*a*) 2001–2010. (*b*) Difference between 2050–2059 and 2001–2010.

Great Plains. It would increase slightly in California and eastern Oregon. The change is significant at $P < 0.01$.

Fire emissions

The annual $PM_{2.5}$ emission from wildfires in western USA (calculated based on the observed burned area during 2001–2010) and the simulated fuel loading and fuel moisture during 1971–2000 was 0.189 Tg. The annual variation of $PM_{2.5}$ emission (Fig. 4*c*) is similar to that of burned area (Fig. 4*b*). The calculated $PM_{2.5}$ emission of 2005 was 0.123 Tg, which was slightly larger than the 2005 EPA NEI of fire mission (0.117 Tg), but 16% lower than the WFEI (0.147 Tg) for the western states (Urbanski *et al.* 2011).

Wildfire annual $PM_{2.5}$ emission projected (based on the projected burned area during 2050–2059) and fuel loading and fuel moisture during 2041–2070 is 0.283 Tg, an increase of

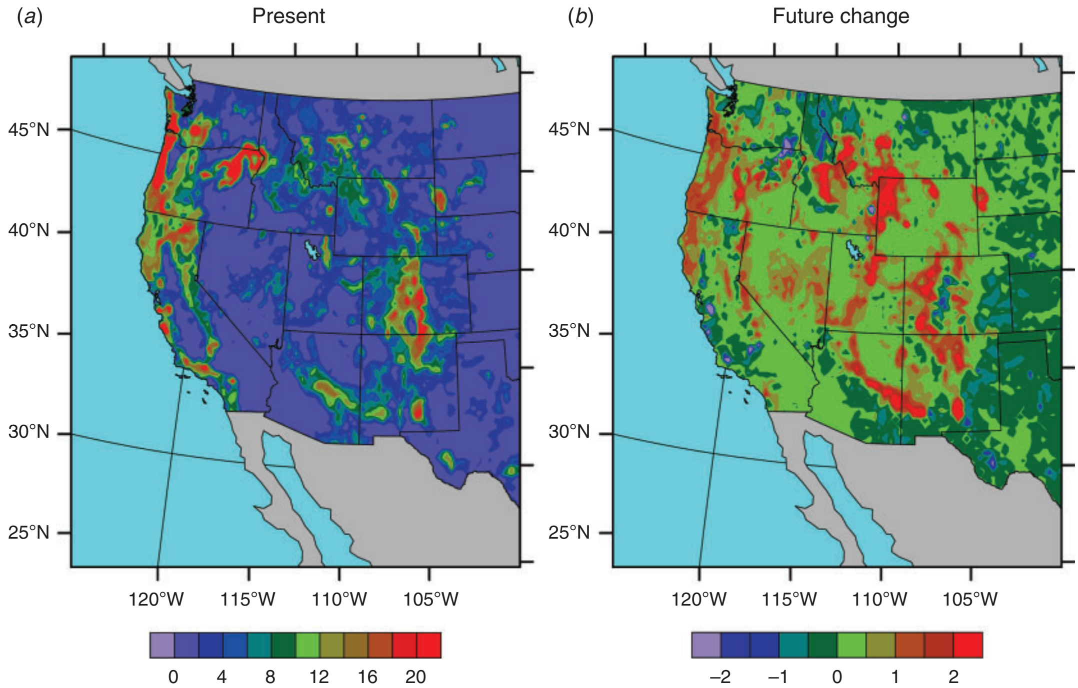

Fig. 8. Fuel loading averaged over summer and fall seasons. (*a*) 1971–2000. (*b*) Difference between 2041–2070 and 1971–2000.

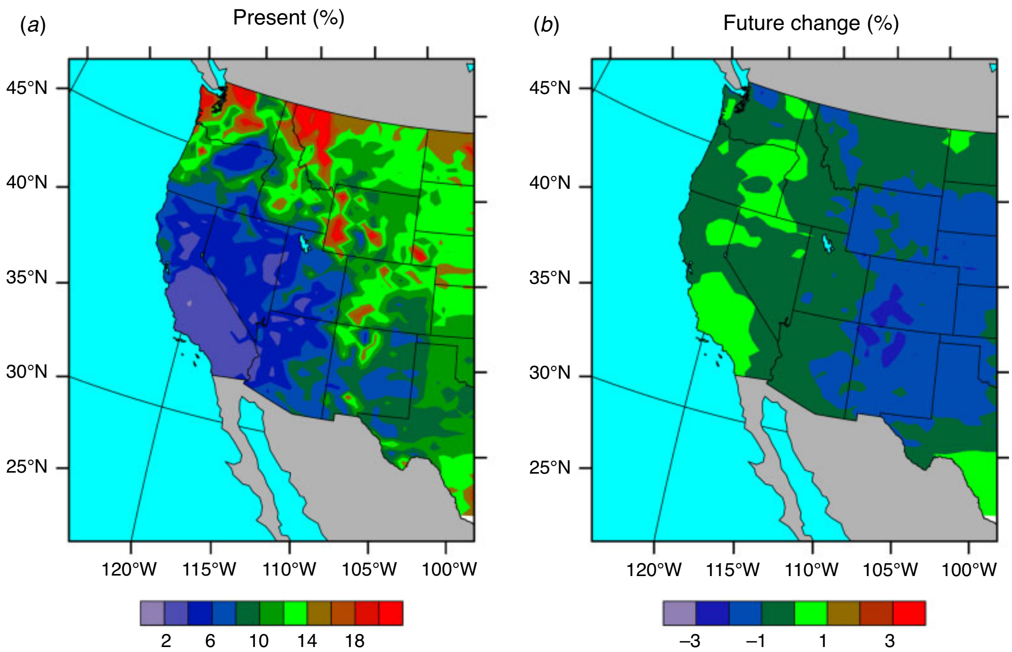

Fig. 9. Fuel moisture averaged over summer and fall seasons (%). (*a*) 1971–2000. (*b*) Difference between 2041–2070 and 1971–2000.

49.2% from the present period (Fig. 10). The projected increase in burned area, increase in fuel loading, and decrease in fuel moisture would lead to increases of $PM_{2.5}$ emission by 34.07%, 10.54%, and 1.07%, respectively, from 2001–2010 to 2050–2059. Thus, the changes in the three properties contribute to ~74.6%, 23.1%, and 2.3% of total fire emission increase. Note that the sum of the three increasing rates is slightly smaller than the total increasing rate. The projections of other fire emission species could be obtained through comparing emission factors between $PM_{2.5}$ and other species.

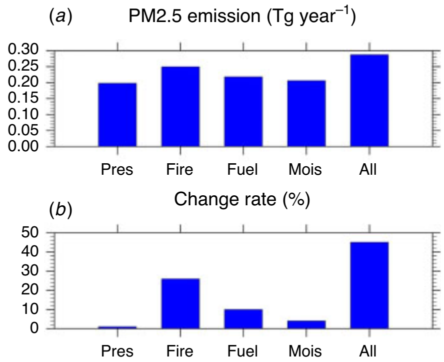

Fig. 10. Annual particulate matter ≤2.5 μm ($PM_{2.5}$) emission from wildfire. (*a*) Emission (*E*, Tg year^{-1}). Pres, present *E* using present burned area (*A*) (observation), fuel loading (*FL*), and fuel moisture (*FMC*); Fire, future *E* using future *A* and present *FL* and *FMC*; Fuel, future *E* using future *FL* and present *A* and *FMC*; Mois, future *E* using future *FMC* and present *A* and *FL*; All, future *E* using future *A*, *FL*, and *FMC*. (*b*) Increasing ratio (%), the difference in *E* between Pres, Fire, Fuel, Mois, or All and Pres divided by *E* of Pres.

Discussion

Increasing trends in future fire emissions

We projected an increase in fire emission of $PM_{2.5}$ by ~50% in western USA from 2001–2010 to 2050–2059. This trend is the same as those from previous projections (Spracklen *et al.* 2009; Yue *et al.* 2013; Ford *et al.* 2018), despite the fact that it is difficult to compare the magnitude of increase among the projections. One of the reasons for the difficulty is the difference in emission species: we projected future $PM_{2.5}$ emission from wildfire, while others projected organic carbon and element carbon emissions from wildfire. A direct application of projected fire emissions is to provide fire emission inputs for simulation of spatial distributions and temporal variations of smoke using atmospheric transport and chemical models for evaluating the air quality, human health, and climate impacts of future wildfires. Such applications have been made with each of the three previous studies. We also applied our projected future fire emissions to project future $PM_{2.5}$ and O_3 in western USA using a regional air quality model (Yang *et al.*, 2021, unpubl. data). The results show substantial increases in air pollutions in the future due to the increasing fire emissions, which would lead to increased exceedance of air quality standards in western USA.

The compositional analysis is a useful tool for fire study (Weise *et al.* 2020). We used this tool in a recent study (Zhao *et al.* 2020), but did not for this study because of two considerations. First, unlike Zhao *et al.* (2020), for time series analysis, this study predicted total fire number without spatial and temporal resolutions. Second, the predicted fires were increased for all size categories, suggesting that the impacts of fire number dependence on size category would not change the increasing trends of the total fires of all categories.

The role of future vegetation changes

A new understanding of the impacts of wildfire on air pollutant emissions obtained from this study is the importance of future change in fuel loading. The change in fuel loading would contribute as much as one-third of the change in burned area to the total fire emissions. Thus, projection of future fuel loading is critical for accurate projection of future fire emissions. Fuel moisture was found to have a minimal contribution to future change in fire emissions. CONSUME (a tool for fuel consumption and emissions) used in this study connects fuel consumption efficiency with fuel moisture only for coarse woody and ground fuels, which may underestimate the roles of moisture in reducing consumption of other types of fuels. Studies using different fuel moisture-consumption relationships are needed to improve our understanding of the importance of fuel moisture to future fire emissions.

The DLEM simulations conducted in the study only considered biomass changes under changing climate. Vegetation types of a specific region could also change under changing climate, which should be considered in future projection of fuel loading. Some other impacts of climate change were also missed in this study, for example, possibly longer growing seasons under warmer conditions. These impacts could modify the decomposition rates of falling fuels.

Atmospheric models have been used to project the spatial distributions and temporal variations of fire emissions. Earth system models include coupled atmospheric and vegetation components with fire processes (Liu 2018). The recent development added capacity to CESM in simulating fire-smoke-atmospheric interactions (Zou *et al.* 2019*b*). Thus, they can be used to project not only changes in wildfire, fuel, and emissions under changing climate but also atmospheric concentrations of smoke pollutants.

Uncertainties

There are several sources for uncertainties with the results obtained from this study. Different time and length of present and future periods and IPCC emission scenarios were used between wildfire and fuel projections. The periods were 2001–2010 and 2050–2059 for wildfire and emission projections and 1971–2000 and 2041–2070 for fuels. The magnitude of the changes in fuels could be smaller if the periods for wildfire projection had been used for fuel loading projection. On the other hand, the large emission scenario of PRC8.5 was used for wildfire projection but the moderate emission scenario of A2 was used for fuel loading projection. The magnitude of the projected changes in fuels could be larger if the RCP8.5 emission scenario had been used for fuel loading projection. In addition, the present and future periods for wildfire projection in this study were only for 10 years. Wildfires vary noticeably at not only annual but also decadal scale. Wildfires in western USA were relatively less active during the first half of the past four decades but increased remarkably in the second half. A better representation of present fire conditions would require a period for three decades or longer.

The annual burned area corresponding to the predicted fire number is ~2.6 million acres, which is 26% lower than the observed area. The fire model was developed using the observed fire data during 1980–2013. Fires were less active during 1980–1999 than 2000–2013. Thus, the fire model developed using the fire data may underrepresent fire activity during the active period of 2001–2010.

The treatment of fuels and fuel loading was relatively weak in this study. This effort to compare the relative contributions from changes in fuel loading, fire, and fuel moisture with fire emissions in the future was among the early attempts in the fire research community. Improvements, especially in fuel loading modelling, are needed in the future.

The fire prediction did not consider the impacts of burned areas on subsequent fires. The USA has ~800 million acres each of forested land and rangeland. The annual burned areas by wildfires are ~6 million acres on average. Grass regenerates very fast. Thus, the impacts of omission of burned areas of a year on prediction of fires in subsequent years are expected to be minimal for rangeland fires. However, assuming tree generation takes a decade to reach a size with enough fuel for burning (a very arbitrary estimate), and that two-thirds of wildfires occur on forested lands, the prediction of forest fires would be biased by up to about +5% (4 million burned areas each year per 800 million acre forested land × 10 years).

Fire management

DGVMs have increased the capacity of fire modelling. They have become a core component of climate system models. In the meantime, many forest fire management tools, for example, LANDFIRE (Rollins 2009) and the First Order Fire Effects Model (FOFEM) (Reinhardt *et al.* 1997), have been expanded and updated to include the most recent research results. Integration of these tools with the DLEM and other DGVMs and ESMs will help fuel modelling and management.

Conclusions

Projections of future wildfire emissions in western USA have been based on both projected fire and fuel conditions under climate change. The results indicated that fire emissions would increase by ~50% from 2001–2010 to 2050–2059 due to the future changes in wildfires and fuels. Thus, wildfire impacts on air quality and human health would become much more serious in western USA by the middle of this century. The results also showed that the changes in future fuel loading would contribute substantially to future fire emission increase. Thus, it is essential to include fuel loading projection in future efforts to improve projection of fire emissions under climate change. Also, integration of recently improved fuel mapping tools with DGVMs and ESMs will help fuel modelling and management.

Data availability statement

Data are available upon request. Please contact Dr Yongqiang Liu at yongqiang.liu@usda.gov for fire and fuel data, and Dr Joshua Fu at jsfu@utk.edu for climate change scenario data.

Conflicts of interest

The authors declare no conflicts of interest.

Declaration of funding

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