"Fires of Unusual Size: Future of Extreme and Emerging Wildfires in a Warming United States (2020-2060)"

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Abstract

Observed increases in wildfire activity across the contiguous United States, which have occurred amid a warming climate and expanding residential footprint within flammable landscapes, illustrate the urgency of understanding near-future changes in fire regimes. Here, we use a statistical model including future projections of both human population distribution and atmospheric conditions from climate models to predict the number, size, and cumulative area burned by wildfires. We find an overall increase in both the number of fires (+56%) and total burned area (+60%) during 2020-2060 relative to a 1984-2019 baseline, as well as ubiquitous increases in area burned (+63%) by the largest fires. Additionally, we predict the emergence of observationally unprecedented fire frequency in eastern U.S. locations where wildfire was rare historically (+71%), and unprecedented increases in the size of the largest fires in the Western U.S. where fires were historically common—underscoring the need to prepare for more frequent and severe fire even in communities unaccustomed to them.

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Key Points:

- Large fire occurrence across the U.S. will increase by 56% between 2020-2060

- Annual burned area will increase by 60% overall and by 63% for the most extreme fires

- Increasingly extreme fires occur in U.S. West, with more numerous fire events in historically fire sparse Eastern U.S.

Abstract

Observed increases in wildfire activity across the contiguous United States, which have occurred amid a warming climate and expanding residential footprint within flammable landscapes, illustrate the urgency of understanding near-future changes in fire regimes. Here, we use a statistical model including future projections of both human population distribution and atmospheric conditions from climate models to predict the number, size, and cumulative area burned by wildfires. We find an overall increase in both the number of fires (+56%) and total burned area (+60%) during 2020-2060 relative to a 1984-2019 baseline, as well as ubiquitous increases in area burned (+63%) by the largest fires. Additionally, we predict the emergence of observationally unprecedented fire frequency in eastern U.S. locations where wildfire was rare historically (+71%), and unprecedented increases in the size of the largest fires in the Western U.S. where fires were historically common—underscoring the need to prepare for more frequent and severe fire even in communities unaccustomed to them.

Plain Language Summary

In this work we find that the future of fire in the U.S. will likely be characterized by more frequent and larger fires in most regions due to the changing climate and more people starting fires in new places. There will be more fires in the Eastern U.S. which have not experienced many fires in the recent past and the Western U.S. will see more fires that are even larger than the largest fires. These changes have major implications for ecosystem and fire management, disaster response and mitigation, and public policy.

1. Introduction

Over the past forty years, burned area in the United States (U.S.) has increased four-fold—at a rate of approximately 173,000 acres per year across the U.S. (Burke et al., n.d.). Numerous studies have focused on the western U.S. fire-climate relationships (Abatzoglou & Kolden, 2013; Dennison et al., 2014; Littell et al., 2009), projecting future burned area (Kitzberger et al., 2017; Littell et al., 2018; Liu & Wimberly, 2016; Spracklen et al., 2009), and large/extreme fires (Stavros et al., 2014), but few studies have examined these trends at a national-scale (Anderegg et al., 2022; Barbero, Abatzoglou, Larkin, et al., 2015; Barbero et al., 2014; Gao et al., 2021; Podschwit et al., 2018) or focused on areas with lower fire activity in the latter half of the 20th century like the Great Plains (Donovan et al., 2017) and eastern U.S. (Barbero, Abatzoglou, Kolden, et al., 2015; Prestemon et al., 2016), where there is also evidence of fire being responsive to warming and drying (Abatzoglou & Williams, 2016; Iglesias et al., 2022; A. P. Williams et al., 2015).

While climate variability and change explain a majority of area burned in many regions (Abatzoglou & Williams, 2016), human activity influences area burned through ignitions, suppression efforts, and land use/land cover change (LULC) (Chelsea Nagy et al., 2018; Mietkiewicz et al., 2020; Radeloff et al., 2018). These impacts become even more complex through non-linear interactions with environmental drivers (Abatzoglou et al., 2018; Cattau et al., 2020; Hawbaker et al., 2013; Syphard et al., 2017). Moreover, due to the ever-expanding "Wildland Urban Interface" (Radeloff et al., 2018), more homes and people are now located in fire-prone areas (Iglesias et al., 2021) than ever before. Because humans are responsible for igniting four times as many large wildfires as lightning across the U.S., and are today the primary source of large wildfires in both the eastern and the West Coast regions of the U.S.

despite human ignited fires being of lower intensity and smaller in size relative to lightning fires (Balch et al., 2017; Chelsea Nagy et al., 2018). It is important to account for these direct anthropogenic effects—especially the spatial distribution of people across the landscape—when considering future fire patterns.

Although large fires account for only a small percentage of the total number of fires, they comprise the majority of total burned area across the U.S. (Barbero et al., 2014; Stavros et al., 2014), and their capacity to exceed or escape suppression often makes them the most dangerous and costly wildfires to manage (J. Williams, 2013). Since large fires pose a significant threat to ecosystems, fire and ecosystem managers need to be better informed about where fires are expected to become more frequent, and how large the largest fires will become. To date, most future fire research that predicts annual burned area or probability of fire has excluded large regions of the U.S. defined as non-burnable by the presence of agriculture and barren land cover types, e.g., the Great Plains (Barbero et al., 2014; Stavros et al., 2014). These studies also lack explicit consideration of anthropogenic forces that lead to increased ignitions, peaking around a population density of approximately 10 people/km^2 (Pechony & Shindell, 2010), and changes in fuel.

In this study, we predict future fire events and sizes from 2020 to 2060 in the contiguous U.S. using Bayesian statistical models trained on historical fire, climate, and population data (Joseph et al., 2019). Historical fire events were obtained from the Monitoring Trends and Burn Severity (MTBS) program and were filtered to include only wildfire events >1000 acres (405 ha) and exclude prescribed and agricultural fires across the contiguous U.S., with no land types being excluded (e.g., agricultural land) (Eidenshink et al., 2007). We then use our models to estimate spatiotemporal trends in fires driven by projected future climate from eight global climate models (GCM) under the RCP 4.5 scenario, an intermediate emission scenario, along with projected population data under a population growth scenario where social, economic and technological trends do not shift significantly from historical patterns (SSP2: Shared Socioeconomic Pathway 2). Predicting the largest fire to ever occur in every ecoregion is extremely difficult, so it is common to use a fire size (ha, acres) threshold to capture a range of the largest fires (9,10), but this method often leads to the elimination of many ecoregions that only experience smaller fire sizes which are significant for a given ecoregion. Thus, we utilize a percentile threshold as done in Nagy et al. (2019) which identifies large fires proportionally as the largest 10% or 90th percentile of fires occurring within each EPA Level III U.S. ecoregion.

Our modeling approach in this study represents a substantial advance in three distinct ways. First, while most existing models are regional in scope and rely on simple linear regression models of climate and fire (Kitzberger et al., 2017; Littell et al., 2018), our model incorporates spatially varying non-linear effects of climate and population at a national-scale. Second, our Bayesian approach explicitly propagates uncertainty for derived parameters and when we integrate over the uncertainty in the predicted number of fires and the burned area we obtain the predicted maximum fire size per ecoregion (Joseph et al., 2019). Third, our use of the EPA hierarchical nesting of ecoregions across Level I, II, and III allows for the sharing of information among climatologically similar ecoregions (since level III ecoregions in a level II ecoregion are often adjacent). This nested approach therefore allows for the consideration of non-stationarity in relationships between climate and fire behavior for ecoregions that may shift in a warming climate.

Our key research questions are: 1) How much are large fires expected to increase over the next 40 years?; 2) Where will the most extreme fires occur in the future; and 3) Where will we see the emergence of fires (i.e., in areas where it has not been recently prominent)? The results presented are the ensemble average of the eight GCM's results, with individual model results presented in the Supplementary Information.

2. Materials and Methods

2.1 Bayesian statistical models to predict fire regimes

We used the models developed by Joseph et al. (2019) to predict wildfire extremes across the contiguous United States. Joseph et al. (2019) combined a 30-yr wildfire record with meteorological and housing data in spatiotemporal Bayesian statistical models, with spatially varying nonlinear effects to predict wildfires. Joseph et al. (2019) built one model to describe the total number of fires occurring and another describing the size of each wildfire. They constructed four models to model fire occurrence and compared the various models' predictive performance based on test-set log likelihood and posterior predictive checks for the proportion of zeros, maximum count, and total count. The models differed in the distributions used in the likelihood, with the zero-inflated negative binomial model having the best performance. They developed five models for fire size, each with a different distribution of fire size or burned area for a given fire event, and evaluated each model in terms of test set log likelihood and posterior predictive checks for fire size extremes. The lognormal model for the burned area provided the best performance. The model was trained on data from 1984-2009 withholding the period from 2010 to 2016 to evaluate predictive performance. By allowing the non-linear effects of weather and housing density to vary across space, this model achieved good predictive accuracy for fire extremes at a regional scale over the six-year prediction window. Further model details are located in the Supplementary Information.

2.2 Model Implementation

Further model details can be found in the Supplementary Information as well as published in Joseph et al. (2019). A Hamiltonian Monte Carlo method was used to sample from the posterior distributions of count and burned area models. The models were fitted using the No-U-Turn Sampler (Hoffman & Gelman, 2014). Models were fitted in the Stan probabilistic programming language using the rstan package (Carpenter et al., 2017; Stan Development Team, 2018). Four chains of 1000 iterations each were run, with the first 500 iterations discarded as warmup. After obtaining the output for each GCM the results were averaged to produce the ensemble mean which is presented in the main text and individual model results are provided in the Supplementary Information. Trends were fit with a linear regression model, where residuals and p values were used to assess fit and significance.

3. National Fire, Climate, and Population Data Utilized

3.1 Model Training Data

Wildfire event data for the contiguous United States was obtained from the Monitoring Trends and Burn Severity (MTBS) program (Eidenshink et al., 2007). MTBS data contains spatiotemporal information on the extent of large wildfire events from 1984-2019. Each event has a unique ID, start date, location information, and final fire size. They define large fires as a fire 1000 acres (~405 ha) or greater in the western United States and a fire 500 acres (~202 ha) or larger in the eastern United States. To maintain a consistent analysis across the U.S. we analyzed only fires greater than 1000 acres, leaving 12,219 fire events.

The models were driven by meteorological variables from gridMET (Abatzoglou, 2013), a gridded product that blends monthly high-spatial resolution (~4-km) climate data from the Parameter-elevation Relationships on Independent Slopes Model (Daly et al., 2008) with temporal attributes from the National Land Data Assimilation System (NLDAS2) regional reanalysis using climatologically aided interpolation to produce daily surface meteorological variables. Daily total precipitation, minimum relative humidity, mean wind speed, and maximum air temperature were averaged monthly from 1984-2019 at the Environmental Protection Agency level 3 (L3) ecoregion, 84 across the contiguous US (Omernik & Griffith, 2014). We calculated the cumulative monthly precipitation over the previous 12 months for each ecoregion-month combination.

Population density was used as a proxy for the spread in ignitions caused by humans (Radeloff et al., 2018). Population density estimates were obtained from the Integrated Climate and Land Use Scenarios (ICLUS, https://www.epa.gov/gcx/iclus-fourth-national-climate-assessment) Version 2.1 Fourth National Climate Assessment which reports population data for the conterminous US based on 2010 U.S. decennial census data.

3.2 Future Model Input Data

We are utilizing the Multivariate Adaptive Constructed Analogs (MACA) dataset consisting of 20 Coupled Model Inter-comparison Project (CMIP5) GCMs that provided daily output of the requisite variables for future experiments under the RCP4.5 scenario (Abatzoglou & Brown, 2012). There are two MACA datasets, we are using the product where the GCM model output is statistically downscaled by bias correcting the GCM outputs with training data from gridMET for 1979-2012 (MACAv2-METDATA). This allows for the continuity of analysis between Joseph et al. (2019) and this project. From the MACA dataset we obtained monthly values of precipitation, minimum relative humidity, maximum air temperature, and mean wind speed. We then calculated the average of each climate variable at the L3 ecoregion scale for each month in 2020-2060. From the monthly ecoregion precipitation we calculated the previous 12-month precipitation total for each ecoregion.

Of the 20 models available in the MACA dataset we chose 8 models based on the reported selection process for the USDA Forest Service to identify the best scenarios, climate models, and climate projections that could be applied at the scale of the conterminous United States (Joyce & Coulson, 2020). They ranked the models by the historical model performance which was based on 42 & 18 variable metrics (Rupp, 2016; Rupp et al., 2013). We used 8 out of the top 10 models ranked by both metrics, the other two models were missing the minimum relative humidity needed to run the model. We decided to only use the RCP 4.5 emission scenario because the choice of scenario has a very limited impact on climate projections by the mid-century, our cutoff period (Rangwala et al., 2021), and RCP 4.5 is considered a more likely scenario when compared to RCP 8.5 given our current commitments and observed trajectory (Burgess et al., 2020; *Hamburg Climate Futures Outlook*, n.d.; Hausfather & Peters, 2020).

Decadal projections of population up to 2100 were obtained from the ICLUS dataset based on 2010 Census population data along with fertility, mortality, and immigration rates from the Wittgenstein Center (http://www.wittgensteincentre.org/en/index.htm). These projections are consistent with the demographic assumptions of the Shared Socioeconomic Pathways (SSPs). We used the population projections from SSP2, known as the “middle-of-the-road” projection, where social, economic and technological trends do not differ greatly from the historical patterns. ICLUS v2 population is reported at geographical units resulting in 2256 units comprising Metropolitan and Micropolitan Statistical Areas and stand-alone rural counties. We used linear interpolation to estimate population density at the monthly time step per geographical unit and then aggregate across the geographical units to obtain an ecoregion scale mean monthly population density estimate for 2020-2060.

4. Results

4.1 Large fire occurrence will increase 56% over the next four decades

We predict that new patterns of projected fire events across the continental U.S. will emerge through 2020-2060 (Figure 1B-I). For results presented throughout this paper, CI refers to the 95% Confidence Interval. From the Monitoring Trends in Burn Severity (MTBS) dataset from 1984-2019 there were 12,219 large fires (> 1,000 acres or 404 ha) or an average of 339 fires per year. In contrast, we predict a total of 21,132 (CI:16,701; 25,536) large fires or 528 fires per year (CI:441; 673) for 2020-2060 (Figure 2A), which is a 56% average increase in the number of fires per year. The model predicts an increasing number of fires in nearly all ecoregions, with some ecoregions projected to increase substantially more than others (Figure 1A), which is consistent with previous research (Anderegg et al., 2022; Gao et al., 2021; Moritz et al., 2012). From 1984-2019, eight ecoregions had zero large fire events, while not a single model predicted an ecoregion experiencing less than one fire event in the next 40 years (mean=1.5 fires for those ecoregions). Across the U.S. the median number of large fires predicted per ecoregion was 125 and the mean was 251 fires. Places that had the largest number of fires in the recent past are projected to have the largest number of fires in the future. These ecoregions include the cold deserts of Utah, Nevada and the southern regions of Idaho and Oregon; Northwestern Great Plains centered on the border of Wyoming, Montana and the Dakotas; California Coastal Mountains and foothills; Arizona/New Mexico Mountains (Figure 3A), and much of the Western Cordillera which encompasses the Sierra Nevada as well as the Rockies. For much of the intermountain west including the cold deserts of the Great Basin the fire activity has increased partly due to the presence of invasive annual grass (Bromus tectorum L.) (Balch et al., 2013; Bradley et al., 2018). There is evidence of invasives altering fire regimes in ecoregions across the U.S. including the desert southwest, eastern temperate deciduous forests and southern pine savannah (Fusco et al., 2019). For much of the Southwest and the Great Basin fuel availability is one of the factors limiting fires in these arid environments, with the abundance of precipitation in the previous year determining the current-year fire season (Abatzoglou & Kolden, 2013; Mckenzie & Littell, 2016).

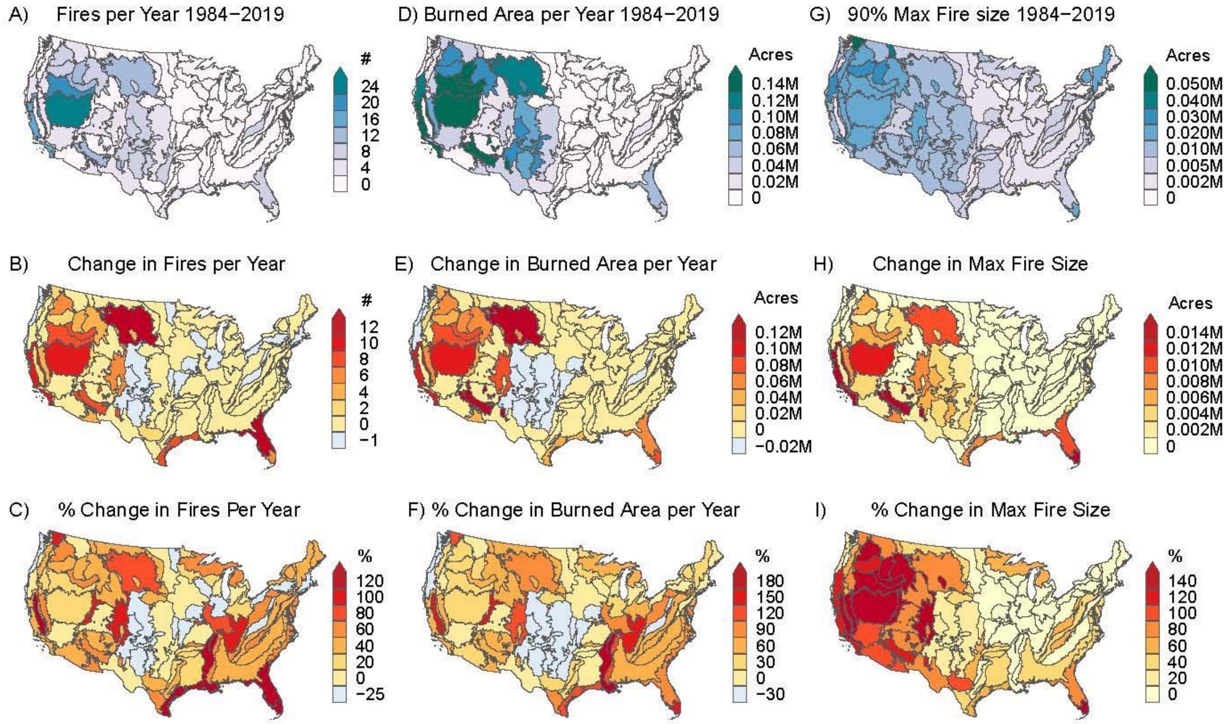

Figure 1. Baseline and change in wildfires, 1984-2019 vs. 2020-2060. A) Number of large fires per year per ecoregion from the 1984-2019 Monitoring Trends in Burn Severity (MTBS), B) Change in the number of fires per year per ecoregion comparing predicted 2020-2060 values to modeled 1990-2019 values, C) Percent change in the number of fires per year per ecoregion predicted 2020-2060 vs. modeled 1990-2019, D) Burned area per year (acres) per ecoregion from 1984-2019 (MTBS), E) Change in the burned area per year per ecoregion, predicted 2020-2060 vs. modeled 1990-2019, F) Percent change in the burned area per year per ecoregion, predicted 2020-2060 vs. modeled 1990-2019 , G) 90% maximum fire size (acres) per ecoregion from 1984-2019 (MTBS), H) Change (acres) in the 90% maximum fire size, predicted 2020-2060 vs. modeled 1990-2019, I) Percent change in the 90% maximum fire size (acres) per ecoregion, predicted 2020-2060 vs. modeled 1990-2019.

Our model predicts that the Northwestern Great Plains ecoregion will have the largest increase in the number of fire events, with a mean increase of 14.5 fires per year over 2020-2060. The ecoregions that ranked 2nd to 5th by average annual increase per year over the future period were: Southern Coastal Plain (13) with an increasing trend of 3.8 fires per decade from 1990-2060 (Figure 3C); California Coastal Sage (11); Central Basin and Range (10.8) with an increasing trend of 3.1 fires per decade from 1990-2060 (Figure 3B); Arizona/New Mexico Mountains (Figure 3A) (10); Snake River Plain (9.2). There were 26 regions that had no change or slightly negative change in fires per year (Figure 1B). Our model predicts that recent trends in large fire occurrences in a warming climate will greatly increase. The Arizona/New Mexico Mountains and Sierra/Klamath/Cascade Mountains ecoregions experienced increases of 0.6 fires per year from 1984-2011, and here we predict that this will increase to 12.5 fires per year from 2020-2060. No significant trends were observed for the Basin and Range ecoregions in the recent past (Dennison et al., 2014), but we project them to increase to 35.8 fires per year from 2020-

2060. The Great Plains have seen an increase from only 33 fires per year from 1985-1995 up to 117 fires per year from 2005-2014 (Donovan et al., 2017), and has doubled to quadrupled from 2014-2018 (Iglesias et al., 2022). Similarly, our model predicts the largest increase in the number of fires at 30.9 fires per year to occur in the Northwestern Great Plains. Even under lower emission scenarios, like the RCP 4.5, in the future the fire frequency and size are still projected to increase dramatically in regions like the Northern Great Plains, as well as the central and southeastern U.S. (Anderegg et al., 2022).

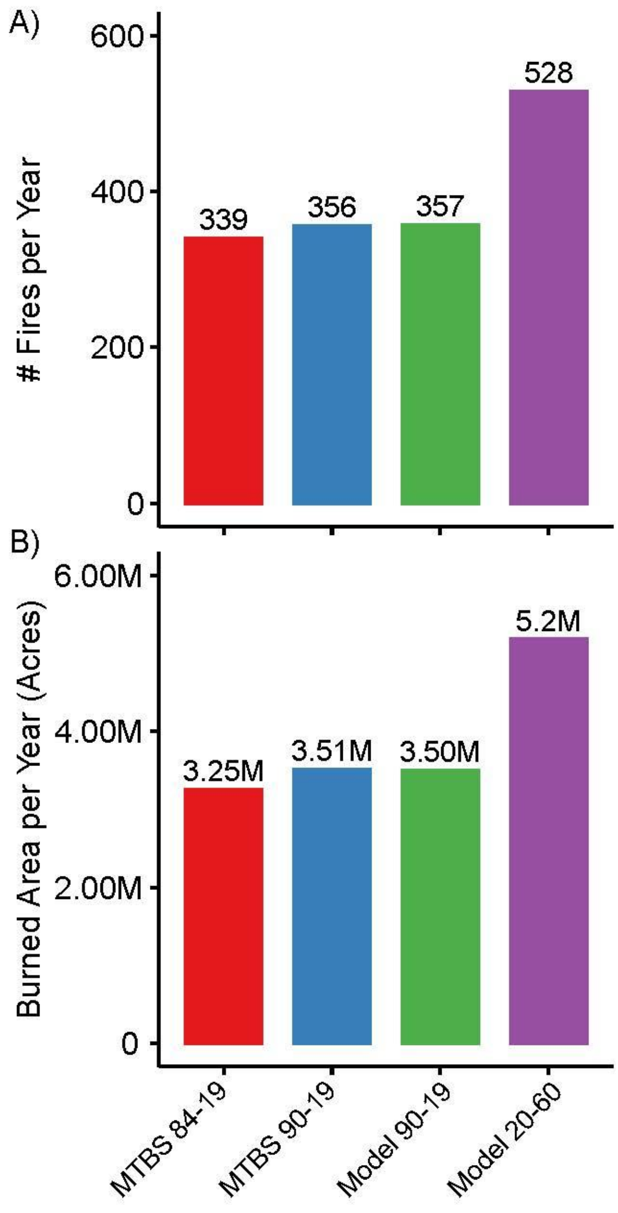

Figure 2. Observed and modeled average number of fires and burned area per year for the continental United States. A) Average number of fires per year across the continental U.S. from the: 1984-2019 Monitoring Trends in Burn Severity (MTBS) in red, 1990-2019 MTBS in blue, modeled past 1990-2019 in green, and modeled future 2020-2060 in purple. B) Average burned area per year across the continental U.S. from the: 1984-2019 Monitoring Trends in Burn

Severity (MTBS) in red, 1990-2019 MTBS in blue, modeled past 1990-2019 in green, and modeled future 2020-2060 in purple.

Many ecoregions had little to no fire activity per year from 1984-2019 (Figure 1A). In these regions, even a modest positive increase in fires per year (Figure 1B) resulted in substantial relative increases in fire occurrence from 2020-2060 (Figure 1C). The largest relative change in the number of fires per year is predicted in the Mississippi Alluvial Plain (233%), the area surrounding the Mississippi River (Figure 1C & 3E), as well as the Southeast Coastal Plains, and Southeastern Plains in parts of western Kentucky and Tennessee. While we found the largest relative increase in fire events to occur in the Mississippi Alluvial Plain, others projected the highest relative increase in fire probabilities across the U.S. to occur in the Upper Great Lakes (Minnesota, Wisconsin, Michigan) (Gao et al., 2021), which are among the ecoregions we find an emergence of fire in the future compared to the satellite record of fire. Eleven ecoregions are predicted to have fewer fires per year in the future. These regions are predicted to have a decrease in fires per year and therefore a negative percent change in the future: Coast Range (-25%) encompassing the coasts of California, Oregon and Washington; Central Appalachians (-10%) and a decreasing trend of -0.3 fires per decade form 1990-2060 (Figure 3D); and the Southwestern Tablelands (-1.5%) in northeastern New Mexico. Some of the regions that are predicted to have the largest number of fires in the future but also have historically experienced many fires will still see moderate relative increases, with a 44.8% increase in Cold Deserts and a 65.6% increase in the Central Semi-Arid Prairies (Figure 1C).

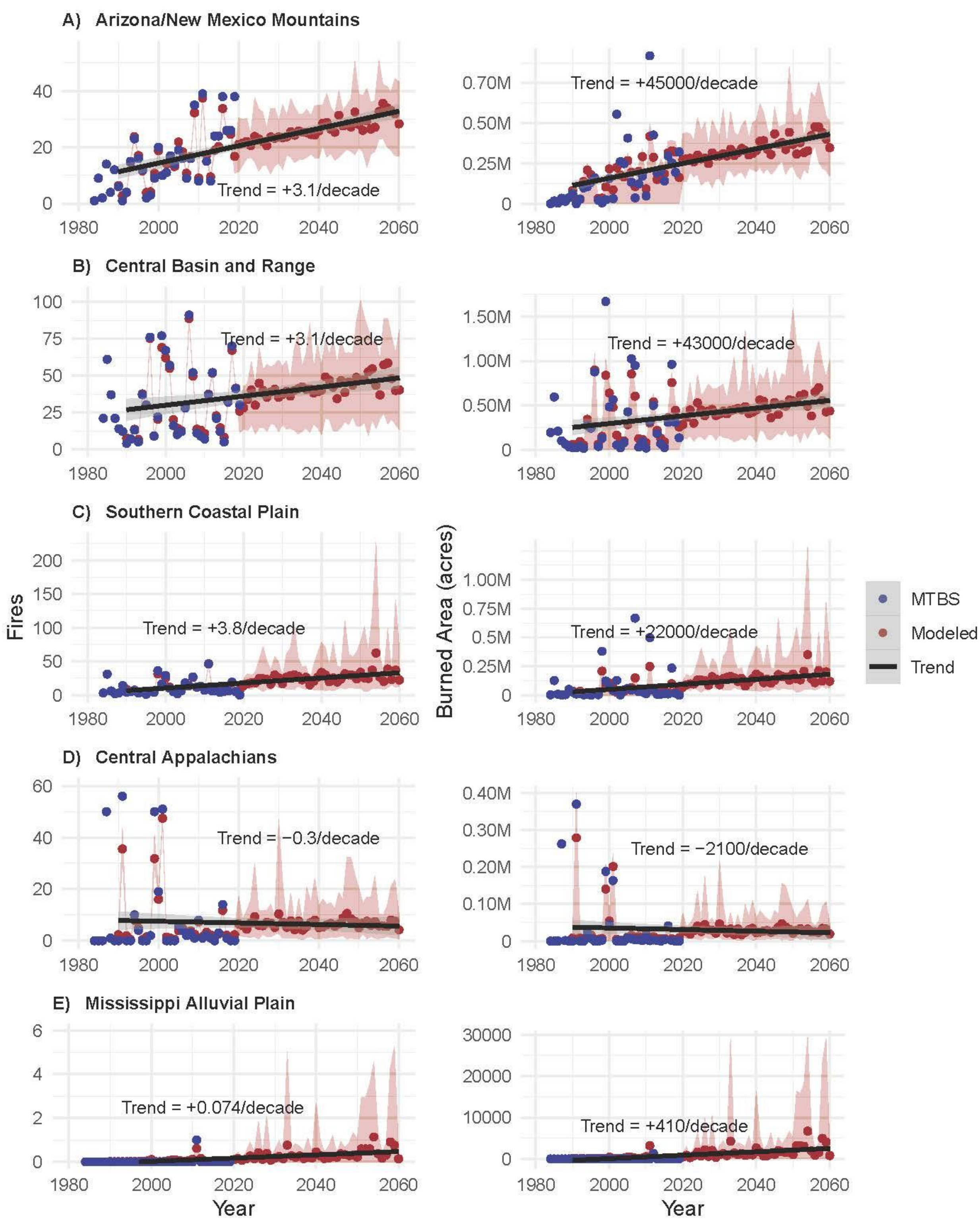

Figure 3. Trends in number of fires and area burned for selected ecoregions. Number of fires and burned area (acres) per year from the Monitoring Trends in Burn Severity (MTBS) (blue dots: 1984-2019) and median Modeled (ensemble red dots, shading is the range in median estimates from eight GCMs: 1990-2060) along with decadal trends for the A) Arizona/New Mexico Mountains, B) Central Basin and Range, C) Southern Coastal Plain, D) Central

Appalachians, E) Mississippi Alluvial Plain ecoregions. All trends, except the Central Appalachians, are statistically significant $p<0.05$.

4.2 Annual Burned area will increase 60% over the next four decades

For 1984-2019 the MTBS dataset reported a total burned area of 117M acres and an average 3.25M acres per year from large fires. The predicted total burned area for 2020-2060 is 207M acres (CI:157M, 257M) with an average 5.2M acres per year (CI: 4.28M, 6.90M) across all ecoregions (Figure 2B), an increase of 60% over the observed past burned area per year. Similar to the observed burned area per year (Figure 1D), the Cold Deserts were predicted to be the ecoregions with the largest burned area per year with the Central Basin and Range (0.46M acres/yr) (Figure 3B), followed by the Northern Basin and Range (0.34M acres/yr). Fourteen ecoregions had a predicted total burned area of less than 10,000 acres. These 14 ecoregions were the same regions that had 0 to 1 event during the 36-year MTBS record.

The Arizona/New Mexico Mountains ecoregion was predicted to have the largest increase in burned area per year for the period 2020-2060, with an increase of 0.13M acres per year and an increasing trend of 45,000 acres per decade for 1990-2060 (Figure 3A). The top five regions with the largest increasing change in burned area per year are all located in the western U.S. (Figure 1E). Eleven ecoregions mostly clustered in the South Central Semi-Arid Prairies located from Nebraska to Texas, along with Central Appalachians were predicted to have a decrease in burned area per year. Outside of the western U.S. the only regions predicted to have large increases in burned area per year are in the Southern Coastal Plains and Western gulf coastal Plains of Texas, predicted to have an average annual burned area of 0.12M acres. Other research predicts a small increase in annual area burned for the entire Southeast but for an ecoregion that includes the Southern Coastal Plain of Florida and the Middle Atlantic Coastal Plain (coastline of Georgia and Carolinas) the median annual area burned is projected to rise by 21.6% (Prestemon et al., 2016). Our model predicts the largest increases per year in burned area for much of the western U.S., but research comparing annual area burned from 1972-2015 with projections for 2010-2030, saw significantly larger change, with a greater than five times increase in annual area burned over the northwestern Intermountain U.S. (including northern Idaho, western Montana and western Wyoming), central Rockies (central Utah and northern Colorado), southern Rockies and Southwest (New Mexico and northern Arizona) (Kitzberger et al., 2017).

Similar to the percent change in total number of fires, the model predicts larger increases in burned area per year along the Mississippi River down to the Gulf Coast with large percent changes also occurring in the Southeastern Plains of Alabama, Georgia, and the Carolinas (Figure 1F). The model predicted that the Mississippi Alluvial Plain would have the largest percent change in burned area per year (372%), followed by the Southern Florida Coastal Plain (172%). In the west, the Central California Valley (171%) is predicted to see the largest percent increase in burned area per year. The model predicted that the coast from Washington to Northern California would see the greatest negative percent change (-29%) in burned area per year. The ecoregion with the second largest predicted negative percent change is the Central Appalachians (-23%). The Southern Rockies in Colorado are among the regions projected to see over 100% increase in burned area per year. Research found even greater percent changes in annual area burned with an increase of 175% for the Rocky Mountain Forest by 2046-2055 compared to 1996-2005 (Spracklen et al., 2009). They found little change in area burned by 2050 for the Eastern Rocky Mountains/Great Plains ecoregions but our model predicts the Northern Great Plains will see an average increase of 74% in burned area per year while the South-Central Prairies of the Great Plains will have an average increase of 5% with many of the ecoregions seeing slight decreases in burned area per year.

4.3 Widespread increases in the sizes of the largest fires

The places that recently had the largest burned area per year were also among the regions that had larger maximum fire sizes. The among-ecoregion median of the 90th percentile fire size from the MTBS dataset for 1984-2019 was 8,558 acres, while the largest 90th percentile fire size was 53,377 acres in the North Cascades in central Washington. These ecoregions include much of the mountains in the western U.S. that make up the Western Cordillera (Figure 1G). The 90th percentile maximum fire sizes are an order of magnitude smaller than the largest events observed in an ecoregion because the largest fires are extreme tail events while the 90th percentile value tells you that 10% of all the events in that ecoregion are larger. The ecoregions with the largest change in maximum fire size were similar to the ecoregions that had the largest change in number of fires and burned area per year. The California Coastal Mountains and Foothills are predicted to have the largest change in maximum fire size with an increase of 28,192 acres (Figure 1H) and an increasing trend of 2,000 acres per decade (Figure 4B). The Arizona/New Mexico Mountains is the ecoregion with the 2nd largest projected increase in maximum fire size of 27,869 acres or a trend of 3,400 acres per decade (Figure 4A) which is a 31% decrease from the observed trend in maximum fire sizes from 1984-2011 for the Arizona/New Mexico Mountains (Dennison et al., 2014). For the same time period, the Sierra/Klamath/Cascade Mountains ecoregion had a negative trend of over 500 acres per year (Dennison et al., 2014) for the maximum fire size, which our model predicts to reverse and increase to a trend of 158 acres per year. The Rocky Mountains and Cold Deserts are also expected to have large increases in the maximum fire size by 2060 (Figure 1H). This is consistent with the projected increases in the probability of very large fires across the continental U.S. with the largest increases occurring in regions that had observed many very large fires in recent decades including the intermountain west covering the Great Basin and Western Cordillera (Barbero, Abatzoglou, Larkin, et al., 2015).

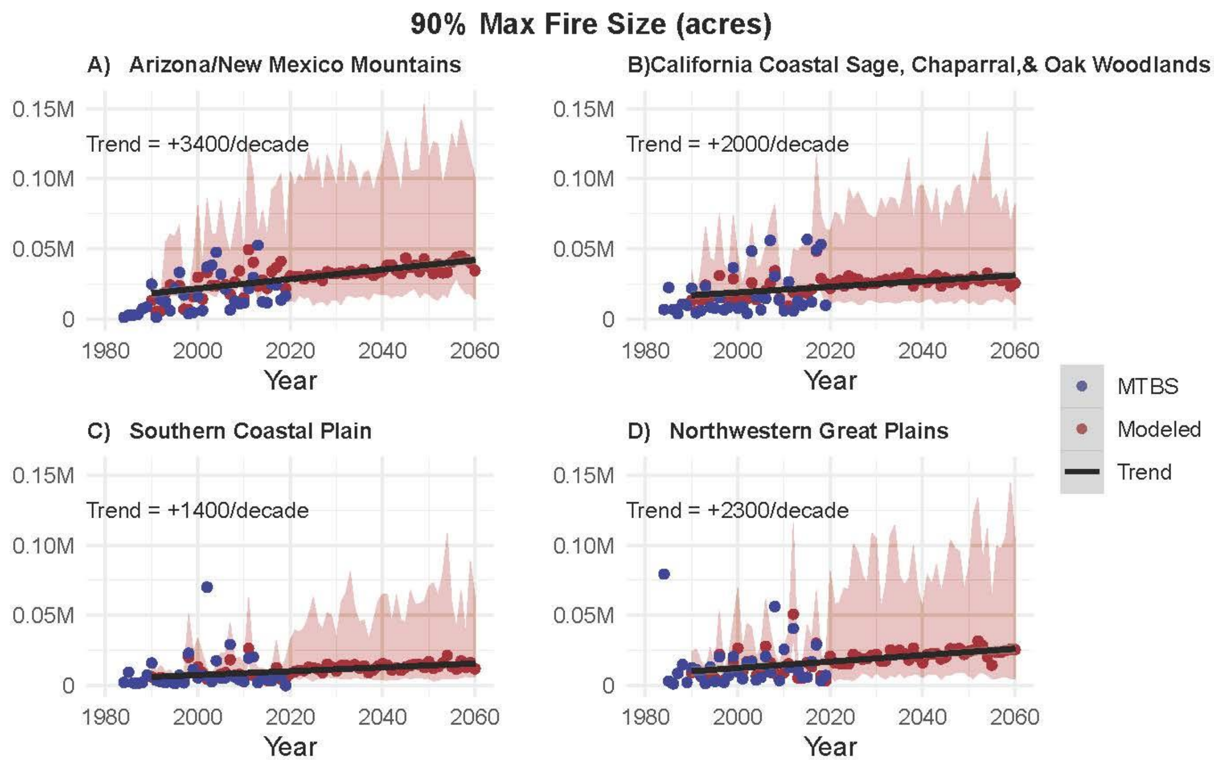

Figure 4. Trends in maximum fire size for selected ecoregions. 90% maximum fire size per year from the Monitoring Trends in Burn Severity (MTBS) (blue dots: 1984-2019) and mean Modeled 90th quantile fire size (ensemble red dots mean of eight GCMs: 2020-2060, shading is the range from the 85th quantile to the 97th quantile fire sizes) along with decadal trends for the A) Arizona/New Mexico Mountains, B) California Coastal Sage, Chaparral, and Oak Woodlands, C) Southern Coastal Plain, D) Northwestern Great Plains ecoregions. All trends are statistically significant p<0.005.

Across the U.S. our model predicts that maximum fire sizes will increase by an average of 63%. The regions expected to see the largest relative increase in the maximum fire size occur mostly in the western U.S. (including the Rockies, Sierra-Nevadas and the Great Basin regions) (Figure 1I), similar to previous research on very large fire probability (Larkin et al., 2015). The southern two-thirds of the western U.S. had a 132% linear increase in the probabilities in very large fires from 1984-2010 as well as a significant increase in probabilities across the Southeast US, especially in Florida (Barbero et al., 2014). For the southern western U.S. our model predicts a similar average increase of 128% in the maximum fire size and for the Southeastern Coastal Plains an average increase of 92% for 2020-2060 compared to the modeled 1990-2019 values, or a trend of 1,400 acres per decade (Figure 4C). In the future the mean probability of a very large fire across the western US increased 30% for 2031-2060 compared to 1950–2005 observations, with Eastern Great Basin (Idaho), Pacific Northwest, Rocky Mountains, and Southwest (Arizona and New Mexico), showing at least a 200% increase in probability of a very large fire (Stavros et al., 2014). The model predicted ecoregion with the biggest percent change in the maximum fire size is the Snake River Plain (207%).

4.4 Emerging fire regimes expected in the eastern U.S. over the next four decades

In the satellite recording era, much of the Eastern U.S. has observed minimal fire events, burned area, and maximum fire sizes (Figure 1A, D, G) but our models predict small absolute increases in the number and sizes of future events over the next four decades (Figure 1B, E, H), which lead to large increases in the percent change in the number of fires, burned area, and maximum fire sizes in the future (Figure 1C, F, I). Of the eastern regions, the Mississippi Alluvial Plain, the area surrounding most of the Mississippi River, is the ecoregion predicted to have the largest relative change in both the number of fires per year (233%) and burned area per year (372%). The Southeastern Plains in parts of western Kentucky and Tennessee are predicted to have large relative increases in the number of fires per year in the future, while the Southeastern Plains of Alabama, Georgia and the Carolinas are predicted to have large relative increases in burned area per year. These regions, along with the rest of the U.S., see increases in the percent change in maximum fire size. Our prediction of the emergence of more extreme fire regimes in these eastern ecoregions that have often been excluded from fire modeling efforts due to their recent lack of fire events shows the importance of their inclusion because managers and people living in these regions need to prepare for a future of more and larger fire events.

5. Conclusions

5.1 More extreme large fires in the west & emerging fire in the east expected in the future

Our results suggest that the observed increasing trends in the number of fires and fire size across the continental U.S. will continue over the next several decades, even on a moderate warming trajectory (RCP 4.5) and moderate population growth scenario (SSP2). In the present study, we seek for the first time to incorporate all of the key elements: number of fires and maximum fire size, in addition to area burned for the entire continental United States while accounting for human ignitions, in a single comprehensive study across all EPA ecoregions. To date, most future fire research has focused on projections of fire probability or burned area, and the relative change in these quantities, rather than the actual number of fire events—and most such studies have omitted direct anthropogenic influences on ignition likelihood (Barbero et al., 2014; Larkin et al., 2015; Stavros et al., 2014). In addition, prior research on U.S. wildfire has mainly focused on the drier western third of the country while ignoring the Great Plains and lower fire frequency zones in the southern and eastern U.S.

We find that climate change will likely cause wildfires to spread into regions where such events were rare in the satellite recording era (e.g., around the Great Lakes, along the Mississippi River down to the Gulf of Mexico), and lead to much larger wildfires that reach historically unprecedented sizes in regions where fires were historically common (e.g. the Cold Deserts and Western Cordillera). Ecoregions that are predicted to have the largest total number of fire events are not the same ecoregions that are predicted to have the largest total burned area under the same moderate (RCP4.5) climate model forcing. On a contiguous U.S-wide basis, we find that the number of large fires is expected to increase over 2020-2060. Regions that had the most fires in the past will generally remain the most frequent burning regions in the future, although the Southern Florida Coastal Plain emerges as a new frequent fire region. Further, we find that the changes in percent area burned in the future (+60%) slightly larger than the percent increase in the number of fire events (+56%)—and that maximum fire size increases more (+63%) than either of the other two metrics. Though our modeling predicts larger relative increases in burned area in the Eastern U.S., where large fires were rare in the observed record, the largest absolute increases in area burned occur in the West (specifically, the Western Mountains and Cold Desert ecoregions).

The fact that overall burned area as well as maximum fire size increases by a larger increment than the number of fires suggests a possible non-linear relationship between climate change and the most extreme wildfires, as has been hinted at in recent research based on observed trend in the U.S. West (Juang et al., 2022). This may relate to the relatively stronger climate signal, compared to the anthropogenic ignition signal—though we note that both forcings could potentially be underestimated if either climate change or population growth occur faster than the intermediate scenarios used in this study. Historically, it is the largest wildfires that are most likely to exceed active firefighting efforts (for a variety of reasons including rapidly expanding perimeters, the increased likelihood of expanding amid complex topography, and/or firefighting resource exhaustion). Although active fire suppression is not explicitly included in our modeling, it is plausible that any underlying non-linear empirical relationships in the real-world fire training dataset—on which active suppression occurred in many cases—is nonetheless indirectly represented in the predictive model. Either way, one key implication of our predictions is that much larger future fires will increasingly challenge suppression efforts in a warming climate—perhaps acting as a positive feedback to maximum fire size.

One key conclusion from our study is the high likelihood of more frequent and larger extreme fire events in most parts of the U.S. Regions currently experiencing few fires will see the smallest relative increases in maximum fire size, while the places that burn regularly will see the largest relative increases as well as the largest maximum fire sizes. Most of the southeastern ecoregions are among those expected to see the largest relative increases in the number of fires and acres burned per year, while the western ecoregions see the largest relative increases in 90th percentile maximum fire sizes. Previous work demonstrated that total annual area burned in a given region is strongly influenced by the largest wildfires (Stavros et al., 2014), but as our results show there can be significant increases in maximum fire sizes despite minimal increases in annual burned area in the same ecoregion. It has already been recognized that human ignitions affect the spatial patterns of large fires (Balch et al., 2017; Chelsea Nagy et al., 2018), and the very largest fires are driven by different climatic conditions compared to other large fires in the western and eastern U.S. (Barbero et al., 2014; Stavros et al., 2014). However, our own previous work developing the predictive model used in the present study suggests that ordinary events provide information on extremes, which would not be the case if extreme events were driven by completely unique climatic conditions from the ordinary events (Joseph et al., 2019). Previous studies have also excluded agricultural areas (deeming them “non-burnable”) and regions that experienced fewer than five very large fires in their training data—but in the present study, these are some of the regions we project to have the largest relative increase in maximum fire size (including the Central Valley of California and parts of the Great Plains). In the only other study (to the authors’ knowledge), that uses Bayesian statistics and climate from multiple GCMs to predict very large fire occurrence across the CONUS, the authors only considered 16 ecoregions (Podschwit et al., 2018)(rather than the 84 ecoregions in the present work).

5.2 Model Caveats

Our model does not include explicit vegetation information, rather is using the ecoregions as proxy. Without explicit vegetation information there is no vegetation feedback (i.e already burned area not being able to be burned again within a certain timeframe)(Parks et al., 2015) or changes in vegetation distribution and subsequent climate-fire relationships. We limited our scope of study like others who realize that future changes in fire will require simulation of vegetation response to both climate and disturbance including fire (Kitzberger et al., 2017). Some research found when vegetation change is included in future fire modeling the total burned area increases dramatically compared to if it is excluded (Liu & Wimberly, 2016) while others found when future projections accounted for interactions among prior fires on surface and canopy fuel availability area burned reduced by 14.3% for in the Sierra Nevada compared to projections where only climate drivers were considered (Hurteau et al., 2019). The GCMS that provided the climate data for this study can represent fire occurrence but poorly and there is no agreement between models on past fire occurrence and how it might change in the future (Kloster & Lasslop, 2017). Future fire predictions are present in some GCMS in CMIP6 but none are able to capture the extent of current extreme fire events (Sanderson & Fisher, n.d.).

Another caveat to our analysis comes from the calibration/validation based on the MTBS dataset. The MTBS burned area data derived from the Landsat satellite has a return interval of 16 days so may miss short fires in areas with rapid post-fire regeneration like in grasses (Li & Guo, 2018). MTBS has a threshold of over 405 ha in the west and when researchers included smaller fires then the total burned area would increase by 116% in the US (Chelsea Nagy et al., 2018). The short time period of analysis also contributes to this caveat; some ecoregions are sufficiently data sparse (possibly due to low fire activity or frequency, small ecoregion area, or other factors) that complicate future predictions.

5.3 Public and Policy Significance

By including regions often excluded or overlooked along with the human impact on ignitions, our study provides a more complete prediction for the future of fire across all regions in the U.S. The projected increase in fire has substantial yet notably different ecological, societal, disaster response, and public policy implications for the Western and Eastern U.S. (respectively). In the West, which has a recent history of frequent and large fires, the future fire regime will only become more extreme—with ever greater influences on the forests and other ecosystems, populated areas via direct fire threats as well as indirect air pollution hazard related to smoke, and raising the prospect of even greater need for resources allocation to fire management and response. In the East, where fires in the 20th century were rare or non-existent for some ecoregions, the emergence of unprecedented fire events is likely to challenge existing fire management systems and ecosystems alike, and may well be a shock to many communities not accustomed to fire in their regions. Currently the U.S. Department of Agriculture (USDA), Forest Service Wildfire Crisis Implementation Plan only covers 8 Western States with no mention of the Eastern U.S. (USDA Forest Service, n.d.). For these reasons, it will be increasingly important to develop cohesive national wildfire policies (Plan A, 2013) that account for future fire predictions across the wide range of background ecologies, climates, and human geographies that will be interacting in a warming climate.

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Open Research

The following publicly available datasets which were inputs to the fire models can be found:

1) Monitoring Trends in Burn Severity (https://mtbs.gov/direct-download)
2) GridMET (https://www.climatologylab.org/gridmet.html)
3) Integrated Climate and Land Use Scenarios (https://www.epa.gov/gcx/iclus-fourth-national climate-assessment)
4) Multivariate Adaptive Constructed Analogs (https://climate.northwestknowledge.net/MACA/index.php)

The new data generated for this analysis by R code will both be available on ScienceBase at the following DOI (https://doi.org/10.21429/2qa8-wr60) by the end of the month but can be made available to reviewers upon request.

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Supporting Information template

Earth's Future

Supporting Information for

"Fires of Unusual Size: Future of Extreme and Emerging Wildfires in a Warming United States (2020-2060)"

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Contents of this file

Introduction

The following provides more details about the fire count and burn area models along with the results from the eight Global Climate Models that were averaged to get the ensemble results presented in the main text.

Text S1. Model Details

a. Fire Occurrence Model

The model represents counts as a zero-inflated negative binomial random variable. This approach allows us to simultaneously account for the zero-inflation and overdispersion observed in the fire count data. The model defines a probability mass function for fires over 405 ha (approximately 1000 acres) in each ecoregion *s* (spatial scale s = 1,....,S) and time step *t* (monthly scale t = 1,....,T). The location parameter $\mu_{s,t}$ and the structural zero inflation parameters $\pi_{s,t}$ were able to vary in space and time. A log link function ensured $\mu_{s,t} > 0$ while a logit link function ensured $\pi_{s,t} \in (0,1)$. Linking by spatial and temporal units so that $\pi = (\pi_{s=1,t=1}, \pi_{s=2,t=1}, \ldots, \pi_{s=S,t=1}, \pi_{s=S,t=2}, \ldots, \pi_{s=S,t=T})$ as well as for μ, the location and zero inflation parameters were modeled by

$$\log(\mu) = \alpha^{(\mu)} + X\beta^{(\mu)} + \varphi^{(\mu)} + \log(a)$$

$$\text{logit}(\pi) = \alpha^{(\pi)} + X\beta^{(\pi)} + \varphi^{(\pi)}$$

where $\alpha^{(\mu)}$ and $\alpha^{(\pi)}$ are scalar parameters of intercepts, X is a design matrix (S × T) × *p* where

p is the number of input features, β and φ are column vector parameters with $\beta^{(\mu)}$ and $\beta^{(\pi)}$ being length *p* and $\varphi^{(\mu)}$ and $\varphi^{(\pi)}$ of length S × T with spatiotemporal adjustments, and *a* is an areas offset vector for the spatial units *s* repeated for each time step *t*. A multivariate horseshoe was used sharing information between the zero inflated and negative binomial location parameters (Peltola et al., 2014).

b. Burned Area

The model response y_i is the number of hectares burned over 405 ha for the i^{th} fire event occurring in each spatial unit s_i at time step t_i. The model included covariate dependence through the location parameter: $\mu_i = \alpha + X_{(s_i,t_i)}\beta + \phi_{(s_i,t_i)}$, where α is an intercept parameter, $X_{(s_i,t_i)}$ is a row vector from the design matrix X, β is a vector of coefficients of length *p*, and $\phi_{(s_i,t_i)}$ is an adjustment for the spatial unit *s* and time step *t*. For the lognormal burned area model a univariate horseshoe prior was used.

c. Accounting for nonlinear forcing

The design matrix was created to include the spatially nonlinear effects of meteorological variables and population density. To account for the nonlinearity and to allow the coefficients for each basis vector to vary spatially we used B-splines (Wood, 2017). The univariate B-splines for the meteorological drivers and population density each had five degrees of freedom, generating 30 basis vectors. Interaction effects were added between each basis vector and the ecoregions to account for the spatial variability in the nonlinear effects (Brezger and Lang, 2006; Kneib et al., 2009). The interactions between ecoregions is captured through the hierarchical nesting of the 3 ecoregions levels; such that coefficients in level 3 may be related to coefficients in the level 2 ecoregion that contains the level 3 ecoregion and so forth up to level 1 which contains the level 2 ecoregion and a global effect. The interactions effects for each of the 30 basis vectors for each ecoregion level were included to allow information sharing across ecoregion level and ecoregions of similar of ecology. An adjustment for the global intercept for each ecoregion level was included to account for any spatial variability that is not related to population density or climate. This leads to a matrix of 3,472 values, that includes many zero values, that will increase the efficiency of computing μ and π. The random effects in space and time were created “using a temporally autoregressive, spatially intrinsically autoregressive formulation (Besag and Kooperberg, 1995; Banerjee et al., 2014)” (Joseph et al., 2019).

d. Posterior predictive inference for finite sample maxima

Joseph et al. (2019) compared empirical maxima to the predicted distribution of maxima to ensure that models capture tail behavior. They also performed predictive checks for the proportion of zero counts and totals for count and burned area models. Posterior predictive inference for finite sample maxima obtains a “distribution over maxima by marginalizing over unknowns including the number of events, size of each event and the parameters of their distributions (Marani and Ignaccolo, 2015)” (Joseph et al., 2019).

S2. **Individual GCM predictions**

Out of all the models the IPSL and MRI predicted significantly fewer fires per year and burned area per year than the others, with the Had_ES model predicting approximately 2.5 times more fires and burned area than the IPSL model.

Model	Burned Area Per Year	Number of Fires Per Year
CanESM2	5.66M (min:3.47M; max:13.58M)	571 (min:393; max: 898)
CNRM_CM5	5.96M (min:3.79M; max:10.39M)	558 (min:419; max: 851)
CSIRO	6.23M (min:4.21M; max: 10.64M)	605 (min:432; max: 990)
Had_CC	6.53M (min: 4.39M; max: 9.82M)	661 (min:495; max: 952)
Had_ES	7.71M (min: 4.58M; max: 13.89M)	738 (min:527; max: 1116)
IPSL_MR	2.58M (min:1.64M; max: 7.25M)	300 (min:221; max: 749)
MIROC	5.91M (min:3.92M; max 9.25M)	608 (min:457; max: 849)
MRI	4.12M (min: 2.93M; max: 13.72M)	414 (min:314; max: 607)

Table S1. Median predicted burned area per year (acres) and number of fires per year from 2020-2060 for the Contiguous U.S. along with the minimum and maximum from the 2000 iterations run per model.

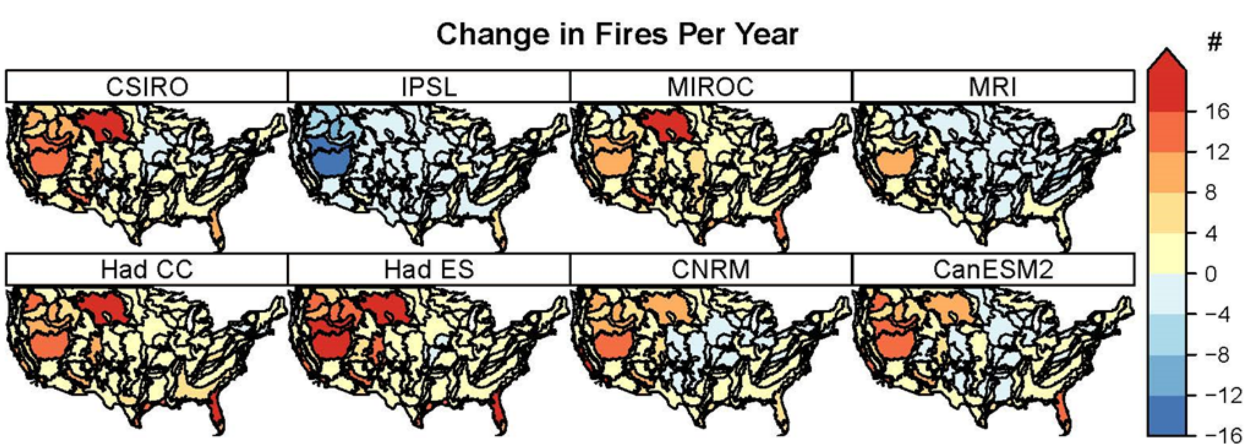

Figure S1. Change in the number of fires per year per ecoregion comparing predicted 2020-2060 vs. modeled 1990-2019 values for each of the eight GCMS.

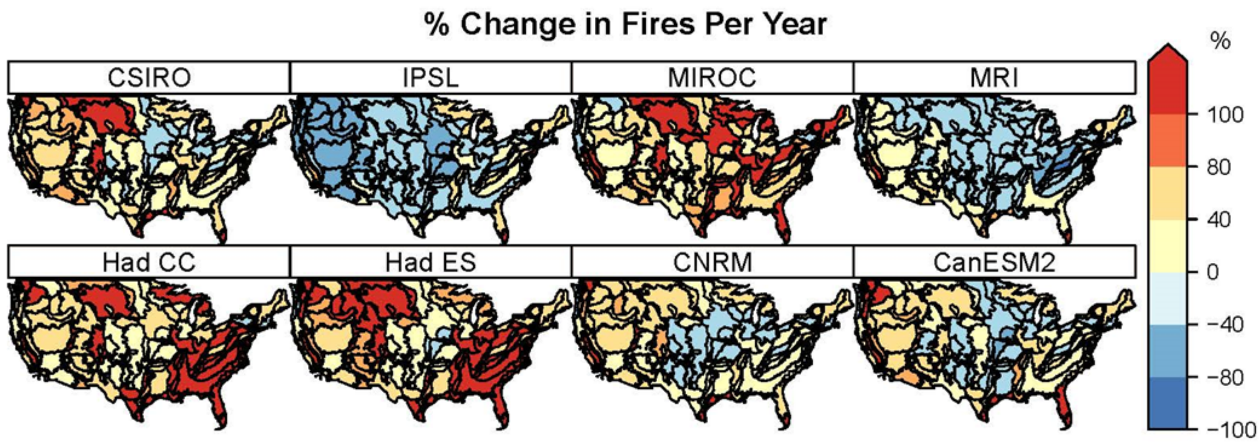

Figure S2. Percent change in the number of fires per year per ecoregion predicted 2020-2060 vs. modeled 1990-2019 for each of the eight GCMs.

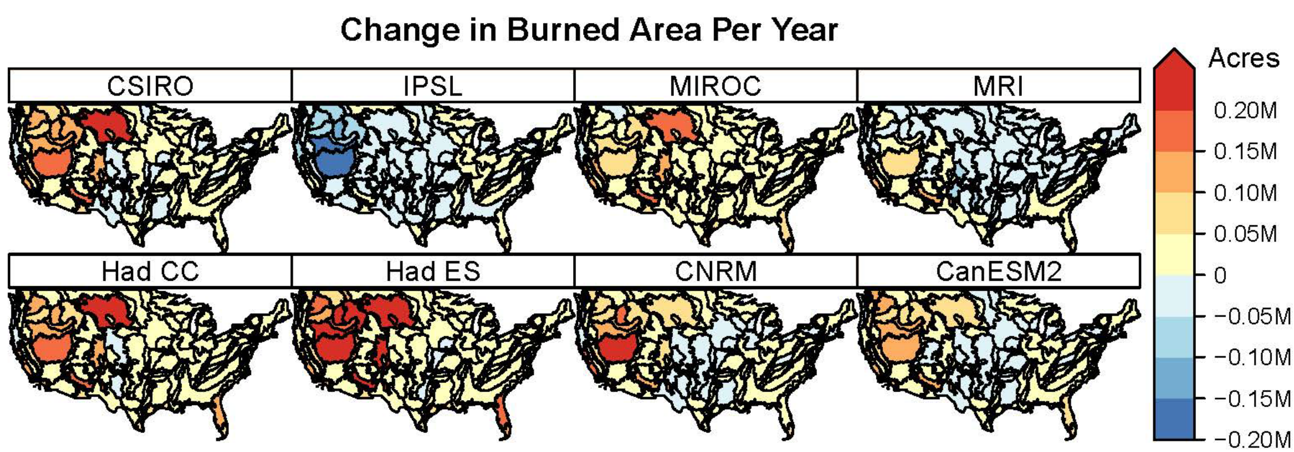

Figure S3. Change in Burned Area per year per ecoregion comparing predicted 2020-2060 vs. modeled 1990-2019 values for each of the eight GCMS.

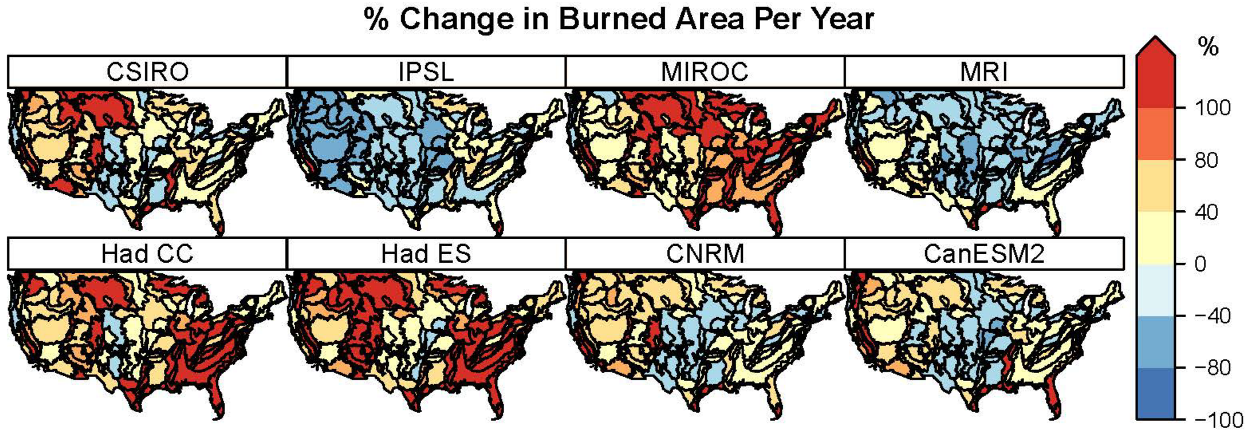

Figure S4. Percent change in Burned Area per year per ecoregion comparing predicted 2020-2060 vs. modeled 1990-2019 values for each of the eight GCMS.

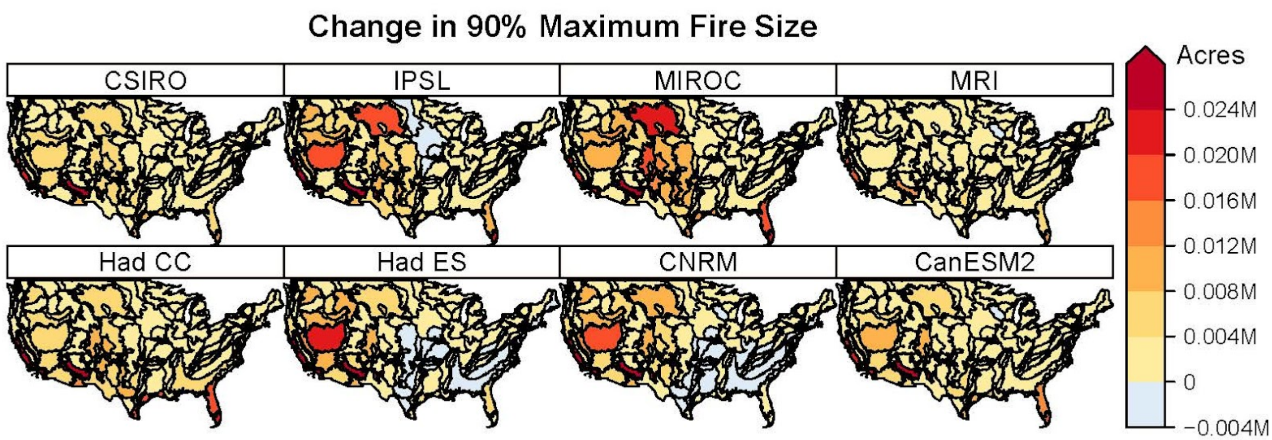

Figure S5. Change in 90% Maximum Fire Size per ecoregion comparing the predicted 2020-2060 vs. modeled 1990-2019 values for each of the eight GCMS.

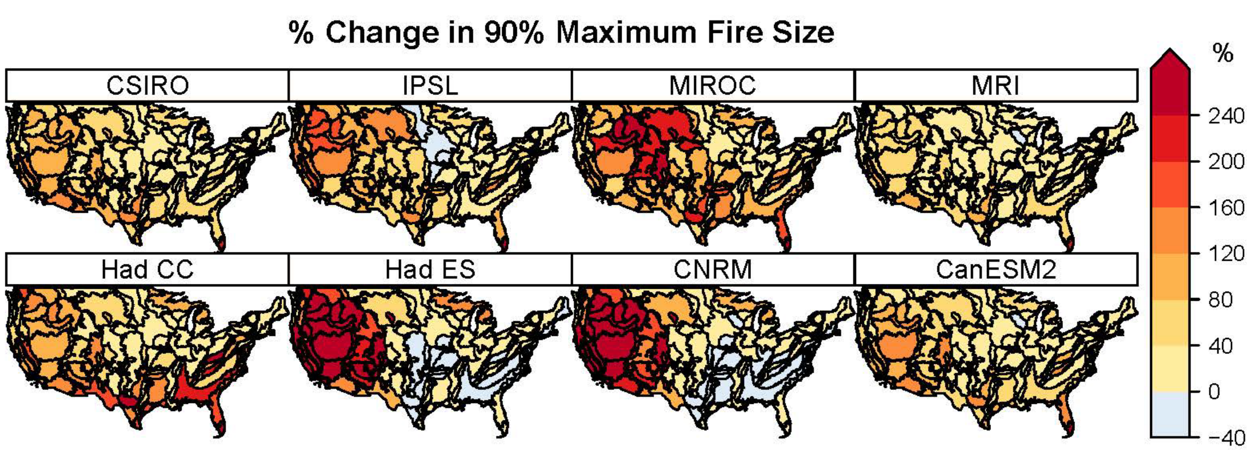

Figure S6. Percent Change in 90% Maximum Fire Size per ecoregion comparing the predicted 2020-2060 vs. modeled 1990-2019 values for each of the eight GCMS.