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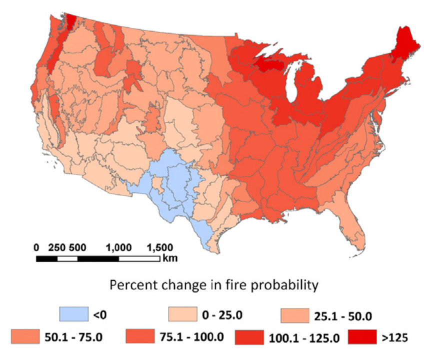
HIGHLIGHTS

- PC2FM is used to project shifts in 21st century fire regimes due to climate change.
- Fire probability is predicted to increase across the conterminous US.
- Increasing temperatures primarily account for projected rising fire probabilities.
- Pyrome analogs illustrate uncertainty in projections of future fire probability.
- PC2FM provides a useful compromise between empirical and processed-based fire models.

GRAPHICAL ABSTRACT



Projected changes (%) in annual fire probability from baseline (1971-2000) to late century (2070-2099) based on Greenhouse Gas Emissions Scenario RCP 8.5.

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ABSTRACT

Globally increasing wildfires have been attributed to anthropogenic climate change. However, providing decision makers with a clear understanding of how future planetary warming could affect fire regimes is complicated by confounding land use factors that influence wildfire and by uncertainty associated with model simulations of climate change. We use an ensemble of statistically downscaled Global Climate Models in combination with the Physical Chemistry Fire Frequency Model (PC2FM) to project changing potential fire probabilities in the conterminous United States for two scenarios representing lower (RCP 4.5) and higher (RCP 8.5) greenhouse gas emission futures. PC2FM is a physically-based and scale-independent model that predicts mean fire return intervals from both fire reactant and reaction variables, which are largely dependent on a locale's climate. Our results overwhelmingly depict increasing potential fire probabilities across the conterminous US for both climate scenarios. The primary mechanism for the projected increases is rising temperatures, reflecting changes in the chemical reaction environment commensurate with enhanced photosynthetic rates and available thermal molecular energy. Existing high risk areas, such as the Cascade Range and the Coastal California Mountains, are projected to experience greater annual fire occurrence probabilities, with relative increases of 122% and 67%, respectively, under RCP 8.5 compared to increases of 63% and 38% under RCP 4.5. Regions not currently associated with frequently

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occurring wildfires, such as New England and the Great Lakes, are projected to experience a doubling of occurrence probabilities by 2100 under RCP 8.5. This high resolution, continental-scale modeling study of climate change impacts on potential fire probability accounts for shifting background environmental conditions across regions that will interact with topographic drivers to significantly alter future fire probabilities. The ensemble modeling approach presents a useful planning tool for mitigation and adaptation strategies in regions of increasing wildfire risk.

1. Introduction

Anthropogenic climate change is expected to profoundly alter wildland fire regimes globally (Bowman et al., 2014). Documented increases in fire frequencies (Enright et al., 2015), fire season (Westerling et al., 2006), extended droughts (Cook et al., 2015; Gonzalez et al., 2018), and exceptional fire behavior across many ecosystems (Flannigan et al., 2001; Goetz et al., 2007; Boer et al., 2020) collectively indicate that changes in fire regimes can be both abrupt and dramatic. Developing rigorous projections of potential future changes in fire regime characteristics is an important contribution to the ongoing societal assessment of the consequences associated with releasing large quantities of greenhouse gases into the atmosphere. Moreover, such projections can be used by managers and decision makers to inform adaptation strategies that are developed in response to, and in anticipation of, changing wildland fire regimes.

Projecting potential responses of wildfire to future climate changes is complicated by the complex and often imprecisely defined concept of a 'wildland fire regime'. Typically, a fire regime refers to the combined aspects of fire frequency, intensity, severity, spatial extent, seasonality, type (surface, ground, crown, or mixtures of these), predictability, and interactions with other disturbances (Agee, 1993). Some physically-based models and agent-based models are able to comprehensively model fire regimes by explicitly representing fire weather, behavior, and effects that account for changes in vegetation through carbon modeling (Hulse D et al., 2016; Keane et al., 2004; Scheller et al., 2019). Examples of such models that have been used to study changing fire regimes include LANDIS-II (Scheller et al., 2007; Creutzburg et al., 2017; Krofcheck et al., 2019), Fire-BGC (Keane et al., 1996, 1999), and MC 1 and 2 (Bachelet et al., 2015; Sheehan et al., 2015). Because these models are at least partly constructed from physics-based first principles, it is possible to explore potential nonlinear interactions and feedbacks between vegetation and fire under changing and potentially novel climates (McKenzie et al., 2004), but doing so often requires detailed information on site conditions (e.g., temperature, precipitation, soils), fuels, and aspects of plant community structure and composition.

Computational advances have facilitated the use of these resource-intensive models at ever-improving spatial-temporal extents and resolutions. For example, Finney et al. (2011) developed a stochastic model, the large-fire simulation system (FSim), which simulates fire ignition and growth for 10,000 to 50,000 years of artificial weather using the Energy Release Component (ERC) to capture the daily and seasonal variability of moisture of different fuels in each of 134 Fire Planning Units (FPUs) in order to achieve national coverage of burn probabilities. However, resource and computational limits still impose significant constraints on research designs that employ this approach. In particular, more robust treatments of uncertainty about future fire regime changes in response to planetary warming remain difficult to pursue. Rigorously assessing the scientific and epistemological uncertainty about future climate change impacts through, for example, incorporating results from multiple climate models and greenhouse gas emission scenarios is a critical component of any risk assessment that seeks to avoid overconfident decision making (Terando et al., 2020).

Alternatively, simpler and computationally inexpensive empirical models can be used that apply statistical relationships between the observed climate and some reduced set of fire regime characteristics such as fire frequency, severity, or area burned (e.g., Parks et al., 2014; Whitman et al., 2015; Terando et al., 2017). Fire weather indices derived from meteorological parameters and broad-scale climate indices, for example, have been used to infer the direction and magnitude of future changes in fire activity for areas ranging from regions to continents to the entire globe (e.g., Westerling et al., 2006; Krawchuk et al., 2009; Moritz et al., 2012; Hurteau et al., 2014; Calheiros et al., 2021). While empirical approaches can be applied more easily over large domains and can better entrain large datasets into an uncertainty analysis, their simplicity precludes detailed modeling of fire regimes whose characteristics depend on multiple factors that vary across finer spatial and temporal scales (Shen et al., 2019). Further, empirical models may not capture relevant spatial heterogeneity in fire, leading to spatially inaccurate estimates of future fire activity (e.g., Boulanger et al., 2014). We note that this tradeoff between model complexity and treatment of uncertainty in global change impacts research is well-known and is analogous to the tradeoff identified when choosing whether to employ statistical or dynamical downscaling of Global Climate Models (GCMs) to derive decision-relevant climate change projections (Fowler et al., 2007; Maraun et al., 2010).

One promising approach is to use a simplified physically-based model that is computationally fast but has a first-principles framework that can still capture important fundamental (and often nonlinear) aspects of climate-fire regime interactions. A similar concept exists in physical climatology, where simple and computationally inexpensive zero- or one-dimensional energy balance models (Hartmann, 2016) have long been used to predict Earth's surface temperature based on radiation theory. In the fire-climate research community, the Physical Chemistry Fire Frequency Model (PC2FM: Guyette et al., 2012) is one such model that could potentially bridge this gap between complexity, mechanistic fidelity, and computational cost. PC2FM was developed from a chemical reaction rate equation to model a single variable, fire frequency or Mean Fire Interval (MFI), as a product of reactant concentrations (based on factors affecting fuel production and decay) and reaction potential (based on the physical chemistry of climate and fire). The model is parameterized using just three variables: mean maximum air temperature, mean annual precipitation, and elevation (used to estimate the partial pressure of oxygen).

PC2FM utilizes multi-century, annually-resolved natural archive records of fire events (e.g., tree-ring dated fire scars) to empirically calibrate and validate the rate equation used to model climate-forcing of fire frequency. Across North America, thousands of localized fire scar event records exist, which provide important information for defining fire regimes through time and across diverse climates, vegetation conditions, and ignition types. Some of the major strengths of these datasets include their ability to capture the effects of low frequency climate variability (e.g., oscillations; Kitzberger et al., 2007), detect non-stationarity and perturbations (e.g., humans; Taylor et al., 2016), and an ability to filter post-Industrial Revolution periods when fire regimes underwent extreme swings in anthropogenic fire activity that distorted or masked fire-climate associations (Parisien et al., 2016). PC2FM thus offers an improvement over purely empirical approaches that relate fire records to climate observations but fail to be explicit about the mechanistic relationships (i.e., physics and chemistry), which often limits their out-of-sample predictive skill, and complex ecosystem modeling approaches that continue to face computational constraints (Petter et al., 2020). Further, PC2FM is consistent with multiple studies that have identified precipitation and temperature as leading climate variables controlling fire frequency at local to continental scales (Krawchuk et al., 2009; Parisien and Moritz, 2009).

In this study, we employ PC2FM to assess how future anthropogenic climate change could alter wildland fire frequency and the pyrogeography of the conterminous United States (CONUS). We use projections from an ensemble of 20 downscaled GCMs under two scenarios representing a lower and higher climate forcing scenario (Representative Concentration Pathway, RCP 4.5 and RCP 8.5, respectively) to project future changes in annual fire probability. This approach allows us to: 1) draw on the strengths of PC2FM to estimate climate change impacts on fire regimes at continental scales based on fundamental physical constraints on fire ignition, fire spread, and fuel availability, and 2) robustly characterize uncertainties and potential for high-impact outcomes in future fire regime changes using a large ensemble of high-resolution downscaled climate models under alternative scenarios. Using USDA Forest Service Pyrome boundaries and climatology from a historical baseline period (1971–2000), we map and explore projected fire regime changes at management- and planning-relevant scales for both midcentury (2040–2069) and end of century (2070–2099) conditions. We then analyze drivers of projected changes and explore the implications of our results for informing adaptation strategies.

Our use of PC2FM to calculate annual fire probabilities is not meant to provide a simulation of the true realized year-to-year wildfire ignition and spread probability over some unit area. Rather, the modeled fire probabilities establish the expected physically-constrained upper limits of fire frequency. This approach is similar to the use of potential evapotranspiration rather than actual evapotranspiration, which is much more difficult to observe and model, to provide an estimate of the overall available energy supply in water balance modeling (Milly, 1994). As with potential evapotranspiration, modeling an area's 'fire potential' can provide useful information for decision makers seeking a scale-independent measure of underlying wildland fire conditions.

2. Methods

Through characterization of the role that climate and atmospheric composition play in constraining both biological (fuels) and combustion (ignition) processes, PC2FM estimates MFI (in years) unconstrained by geographic extent or current conditions (e.g., vegetation, land use) as:

$$MFI = b_0 + b_1 A_0 e^{E_a/RT} + b_2 \left(\frac{1}{\left(P^2/T\right)} \right) \tag{1}$$

where A_0 is a proxy term for molecular collision frequency; E_a is the reactant activation energy; R is the universal gas constant; T is annual average temperature; P is annual average precipitation, and b_0, b_1, and b_2 are coefficients estimated from historical fire scar data as described below (Guyette et al., 2012).

The model was calibrated using historical fire scar data spanning from the 17th to 19th centuries that have provided long-term records of fire frequency and fire–climate interactions from diverse forested sites across North America. During model calibration, these coefficients were estimated using multiple regression analysis together with bootstrapping methods. Test statistics such as variance inflation factors, correlations, residual analysis, normality, variable significance and stability, and r square were used to validate the model. All variables were significant ($P < 0.001$). Multicollinearity among predictor variables was negligible. Readers are referred to Guyette et al. (2012) for more details on model concept, calibration, and applications. Note that we have chosen to report the inverse of the MFI, fire probability, in our results (Guyette et al., 2017).

When applying PC2FM across a large region like the CONUS, the resulting patterns of fire probability are driven by patterns of productivity and the likelihood of fire ignition and spread which are, in turn, linked to climate (Guyette et al., 2012). Future changes in fire regimes are therefore predicated on how changing combinations of temperature and precipitation (along with interrelated humidity, evapotranspiration, and other factors) are related to changing fire probabilities. Further, as a reaction rate equation, PC2FM has no geographical bounds, so fire ecology concepts (e.g., climate–fire interactions) can be expanded through combustion chemistry to potentially reveal unique fire frequency responses within the climate space (Guyette et al., 2017; Stambaugh et al., 2018).

The structure of the PC2FM equation, being dependent on just three physical parameters, also informs our a priori hypotheses about the expected effects of anthropogenic climate change on fire regimes. Specifically, mid- and late-century warming across the CONUS would be expected to increase fire probability for most locations by causing more evaporative demand, which would increase fuel drying rates in the absence of commensurate amounts of precipitation. This would lengthen the wildfire season, particularly in climates with large seasonal precipitation cycles, increasing the chances of ignition and facilitating subsequent fire spread. The relationship with precipitation is nonlinear, however, because increasing amounts of precipitation in fuel-limited conditions can also increase fire probabilities, to a point, through enhanced fuel production and connectivity (Guyette et al., 2012).

We project annual fire probability over the 21st century with climate data from the MACAv2 dataset (https://climate.northwestknowledge.net/MACA/). This dataset was created by statistically downscaling GCM data using a modification of the Multivariate Adaptive Constructed Analogs (MACA) method, which has been shown to be preferable to direct daily interpolated bias correction in regions of complex terrain through its use of a historical library of observations and multivariate approach (Abatzoglou and Brown, 2012). The MACA dataset: 1) includes data downscaled from 20 GCMs that were part of the Coupled Model Intercomparison Project (CMIP5; Taylor et al., 2012); 2) is a high-resolution (~ 4 km) gridded dataset of surface meteorological conditions; and 3) has been used in a number of studies examining potential impacts of future climate change (e.g., Sheehan et al., 2015; Wang and Wang, 2020), including those associated with fire (e.g., Kupfer et al., 2020). Elevation data are downloaded from https://landfire.gov/ (U.S. Geological Survey, 2017) and resampled from 30 m to 4 km to match the spatial resolution of the MACA data.

Fire probability is calculated for each CONUS 4 km grid cell using MACA data for three time periods: hindcast historical conditions (1971–2000), mid-century conditions (2040–2069), and late century conditions (2070–2099). We calculate fire probability for all 20 GCMs under two greenhouse gas emissions scenarios: RCP 8.5, a higher emissions pathway that serves as a scenario without any specific emissions reduction target, and RCP 4.5, a lower emissions scenario that is consistent with significant reductions that stabilize emissions, atmospheric greenhouse gas concentrations and radiative forcing of the climate system. Generating results using data from multiple GCMs and under different emissions scenarios is necessary to address uncertainty about future climatic conditions (e.g., Hawkins and Sutton, 2009; Terando et al., 2020). Because fire probability is simply the inverse of MFI, we present only results for fire probability, although we discuss related impacts on fire intervals, where relevant.

We assess the magnitude of change in fire probability from the historical baseline to future periods for each GCM x RCP combination in terms of both absolute change (Fire probability $_{\text{future}}$– Fire probability $_{\text{historical}}$) and percent change in fire probability, calculated as:

$$\left(\left(\text{Fireprobability}_{\text{future}} - \text{Fireprobability}_{\text{historical}}\right)/\text{Fireprobability}_{\text{historical}}\right) \times 100 \tag{2}$$

Calculating absolute and relative measures of fire probability provides a more complete view of fire regime change, for example, allowing us to distinguish among areas with similar projected absolute changes in fire probability but starkly different changes from historical conditions.

To highlight the management implications and risks associated with changing fire regimes, we calculate and map the mean fire probability of all grid cells within 'pyromes' for historical and future (mid- and late-21st century) conditions. In much the same way that ecoregions define relatively large areas of land or water that contain geographically distinct assemblages of natural communities and species, pyromes are regions with a characteristic historical fire regime. Here, we use pyrome boundaries mapped by the USDA Forest Service and defined on the basis of fire season start and end dates, modality, large-fire size, and total area burned (Short et al., 2020). We also examine changes for 10 regional pyrome groups that span a range of historical fire regimes and that contain ecosystems and landscapes in which fire management is actively used to achieve different ecological, economic and societal objectives (Fig. 1).

Initially, we forecast projected changes in fire probability using hindcast climate values from the MACA dataset to provide a historical baseline. To assess how well those values match fire probabilities derived using observed conditions, we also calculated fire probabilities using climate values from the gridMET dataset (http://www.climatologylab.org/gridmet.html). This dataset was used to train the statistical model used in the development of the MACA downscaled dataset and so retains the same spatial resolution of 4 km. As a basis for comparison, we calculated the Mean Absolute Error (MAE) of predicted fire probability, defined as the absolute value of the difference between the forecasted values (based on MACA data from 1971 to 2000) and the 'actual' values (based on gridMET data from 1979 to 2000) for each grid cell within a pyrome under all 20 GCMs. This provided a distribution of MAE values within each pyrome for each GCM, allowing us to compare the magnitude of the mean and standard deviation of the MAE values within each pyrome for each GCM to the observed mean and standard deviation of fire probability. Patterns of annual fire probabilities calculated by PC2FM using the gridMET observational dataset (Fig. 2A) and hindcast fire probabilities derived from the multi-model mean of the MACA dataset (Fig. 2B) were very similar. Further, MAE values across pyromes (calculated based on individual GCM errors) were very small, ranging from 0.0005 to 0.0144. We therefore use the MACA hindcast period as our baseline for comparison to the results from the two projection periods (2040–2069 and 2070–2099).

Finally, we analyze the interactions among climate variables and fire probability at management-relevant scales in two ways. First, we develop 'pyrome analogs' using a process similar to that involved in climate-analog mapping (e.g., Williams et al., 2007; Hallegatte et al., 2007). This is done by first determining the fire probability, maximum temperature, and annual precipitation for each pyrome under the historical baseline conditions and projected late-century conditions for all 20 GCMs. For each pyrome, we compare its future conditions to the historical baseline conditions at all other 127 pyromes by calculating the pairwise multivariate Mahalanobis distance. The Mahalanobis distance (D_M), which is analogous to a multivariate version of Euclidean distance, is calculated as:

$$D_M(X)^2 = X^T \Sigma^{-1} X \tag{3}$$

where X is the matrix of variable distances between each pyrome for each GCM and the multi-model mean for that pyrome, and Σ is the sample covariance matrix. The resulting pyrome with the minimum

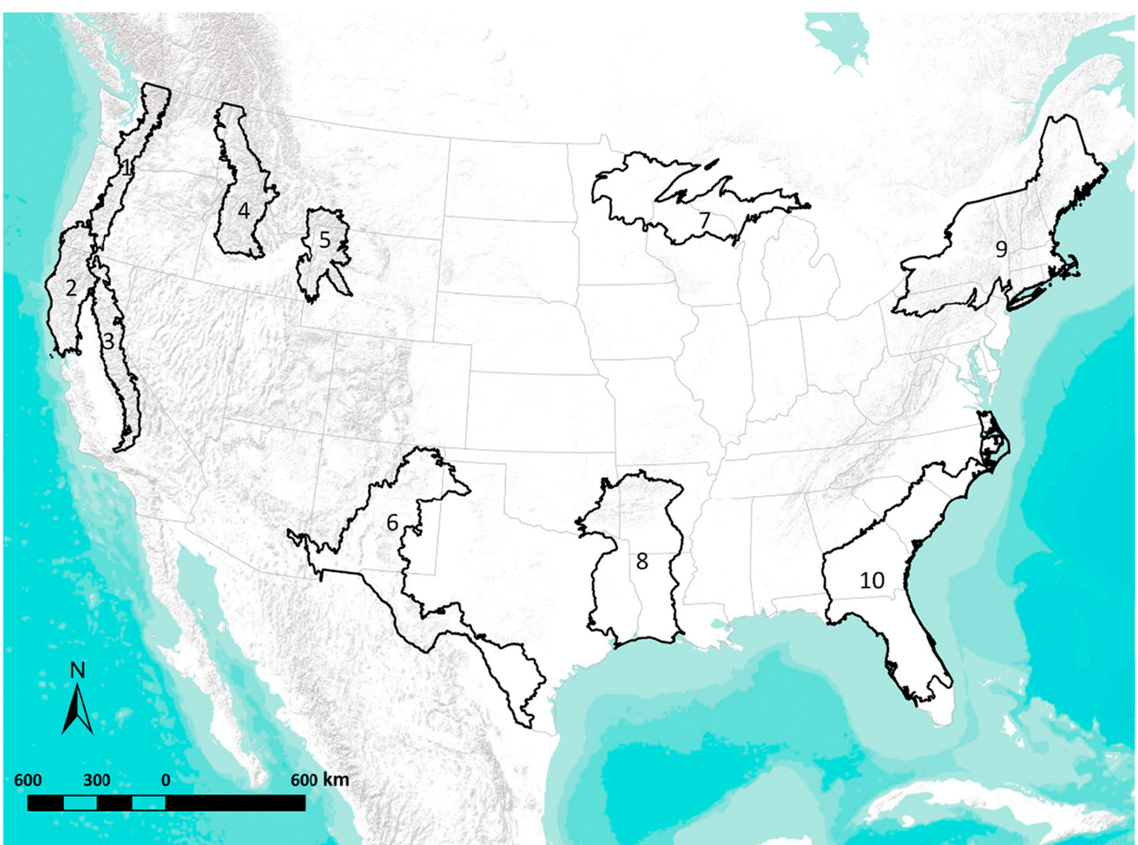

Fig. 1. Pyrome groups used to examine regional changes in mid- and late-century fire probability: 1) Cascade Range, 2) Coastal California Mountains, 3) Sierra Nevada, 4) Northern Rockies and Idaho Batholith, 5) Middle Rockies, 6) South Central Deserts, Plains and Uplands, 7) Upper Great Lakes, 8) Texarkana, 9) Northeast, and 10) Southeastern Coastal Plain.

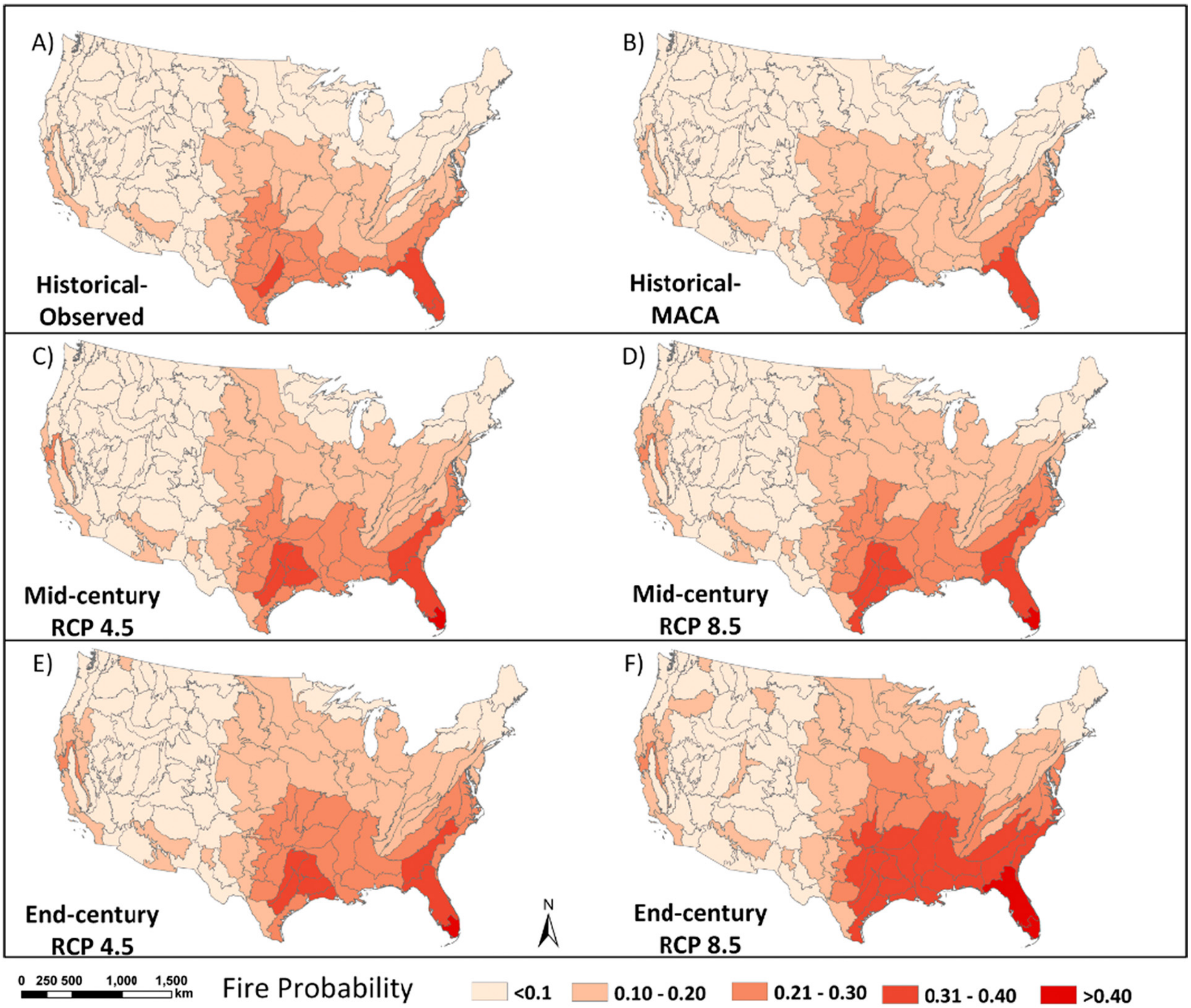

Fig. 2. Fire probability as calculated by the Physical Chemistry Fire Frequency Model for (A) observed historical conditions based on gridMet (1979–2000), (B) the 20-member ensemble mean conditions for the historical (1971–2000), mid-century (2040–2069) and late century (2070–2099) conditions under two greenhouse gas emissions scenarios: the 'lower' emissions scenario, RCP 4.5 (C and E) and the 'higher' emissions scenario, RCP 8.5 (D and F).

distance value represents the contemporary pyrome analog with the most similar conditions (fire probability, temperature, and precipitation) to those projected for the given pyrome in the future. By repeating the process for all 20 GCMs, we are also able to better characterize the degree of structural uncertainty across the climate model ensemble and within the three variables that defined the Mahalanobis distance.

We complement these pyrome analog analyses by graphing all 128 pyromes on the basis of their baseline fire probabilities and the amount of change that they are projected to experience by the end of the century under RCP 8.5. Contours of historical maximum temperature and precipitation created by R (R Core Team, 2017) are then superimposed onto these graphs to identify climate-related gradients associated with pyrome-level fire frequency. These relationships are then generalized to the scale of the regional pyrome groups to conceptualize broader, projected regional responses of fire probability within the context of current climate variables.

3. Results

3.1. Patterns of fire probability

Patterns of projected changes in fire probabilities across the CONUS emerge by mid-century (Fig. 2C and D) and become clear by century's end (Fig. 2E and F), especially for the RCP 8.5 scenario (*note: values provided below represent the multi-model means from all 20 GCMs under RCP 8.5 for the end-of-century time period, unless stated otherwise. Complete pyrome-level results are provided in the supplementary material*). For nearly all of the CONUS, fire probability is projected to increase over the 21st century, with the magnitude of change varying by region. For example, fire probabilities for pyromes in the Southeast, which are already among the highest in the US under baseline conditions (0.21–0.31), are projected to increase, with annual probability values exceeding 0.35–0.43 in most pyromes by the end of the century (Fig. 2F). This pattern of even higher potential annual probabilities in a region where fire historically occurred with very high frequency extends across the southeastern U.S. from central Texas to Virginia, with the greatest proportional increases in the lower Mississippi River valley and Florida panhandle (Fig. 3).

Annual probabilities are also projected to increase in fire-prone western pyromes, especially those in mountainous areas (Fig. 3). A few of the most notable changes include pyromes located in: a) the Cascade Range, where fire probabilities more than double from historical conditions for multiple pyromes; b) the northern Rocky Mountains and Idaho Batholith (93–94% increases in annual fire probability for pyromes within the region); c) the middle Rocky Mountains (91–92% increases); d) the Klamath Mountains and North Coast Ranges in the Coastal California Mountains Region (74–78% increases); and e) the

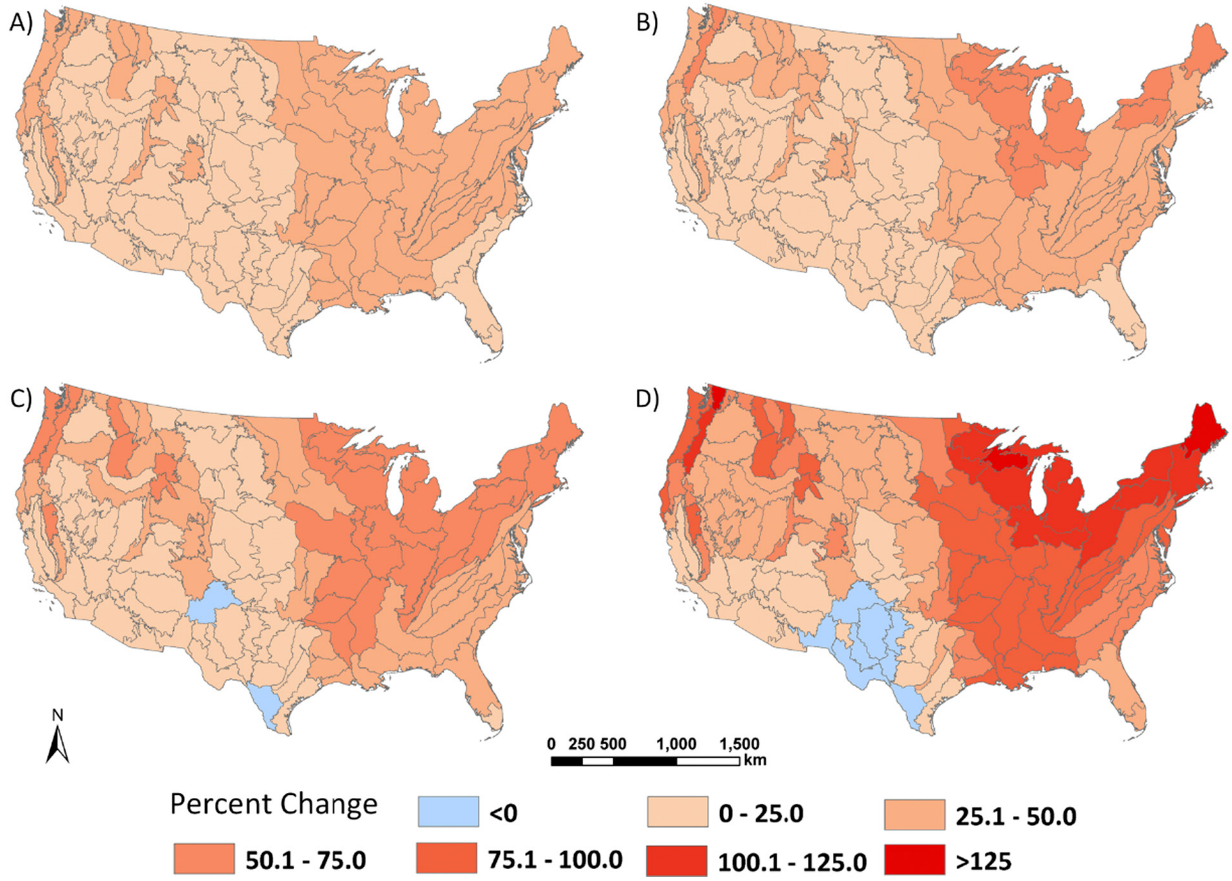

Fig. 3. Projected percentage change in annual fire probability across time periods and emission scenarios. A) RCP 4.5 mid-century (2040–2069), B) RCP 4.5 late century (2070–2099), C) RCP 8.5 mid-century (2040–2069), and D) RCP 8.5 late century (2070–2099). Values are the multimodel mean of PC2FM output using downscaled climate data from 20 GCMs.

Sierra Nevada (63–81% increases). In the northwestern Cascades, the projected result is a dramatic decrease in mean fire interval from roughly 150 years to just over 60 years, with other areas experiencing similar decreases in fire return intervals.

In pyromes across the Upper Great Lakes (Minnesota, Wisconsin, Michigan), fire probabilities are historically low (0.05–0.07) but are projected to increase to 0.11–0.14 by the end of the century (Fig. 2). While these absolute changes might seem small, they represent a nearly 120% increase in fire probability from the historical baseline, which is among the highest percentage increases projected nationally (Fig. 3). The ensemble model results indicate similar magnitude changes in fire probability across the northern tier of states and into the Northeastern U.S.

The exception to the prevailing pattern of increased fire probability is for pyromes in west Texas and eastern New Mexico, where ensemble fire probability shows minor changes or even decreases in more arid pyromes (Fig. 3). Pyromes in the region experience slight increases in fire probability by mid-century (1–3%) and late-century (3–5%) under RCP 4.5, while predicted changes under RCP 8.5 range from a 3.2% increase to a 0.4% decrease by mid-century and a 1.9%–7.8% decrease by the end of the century. The South Central New Mexico Mountains, the lone mountainous pyrome in an area of high desert and shortgrass prairie, was the sole exception to this pattern, increasing in fire probability for both time periods and scenarios (mid-century: 6.6% and 9.8% and late-century: 8.4% and 7.6%, for RCP 4.5 and 8.5, respectively).

3.2. Changing climate and fire regimes

The identification and display of pyrome analogs for the end-of-century time period under the RCP 8.5 scenario provides a relatable, place-based assessment of climate change and illustrates how temperature and precipitation influence the overall level of uncertainty in projecting future analog conditions (Fig. 4; see Fig. S1 for the results for RCP 4.5). Pyromes are rank-ordered along the y-axis on the basis of their late-century ensemble temperature (Fig. 4A), precipitation (Fig. 4B), and mean fire probability (Fig. 4C). The analog pyrome, i.e. the pyrome with the minimum Mahalanobis distance calculated for each GCM from its temperature, precipitation, and resulting PC2FM fire probability, is similarly rank-ordered along the x-axis in each panel. The pyromes ordered along the y-axis each potentially have 20 different pyrome analogs that could be spread across the 128 pyromes ordered on the x-axis because we compared conditions under all 20 GCMs. Although the order of pyromes differs between the three variables in Fig. 4 (e.g., the warmest pyrome will not necessarily be the wettest pyrome or the pyrome with the highest fire probability), the calculation of the closest analog pyrome is only performed once. As such, the coloring of the cells in the three panels always depicts the same set of results. Regardless of the cell's location across the three panels, the color represents the number of climate models which project that the future climate-fire regime for the pyrome on the y-axis will be most similar to the corresponding pyrome's historical climate-fire regime (shown on the x-axis). Each panel is thus a reconfiguration of the single analog pyrome calculation based on an ordering of pyromes from lowest to highest temperature, precipitation and fire probability (Fig. 4A).

Results of the pyrome analog analysis highlight the non-linear interaction between the climate variable constituents of PC2FM, as well as the varying magnitude of, and directionality of projection uncertainty for the two climate variables that propagate into the overall level of fire probability uncertainty (Fig. 4). For example, the pyrome analogs

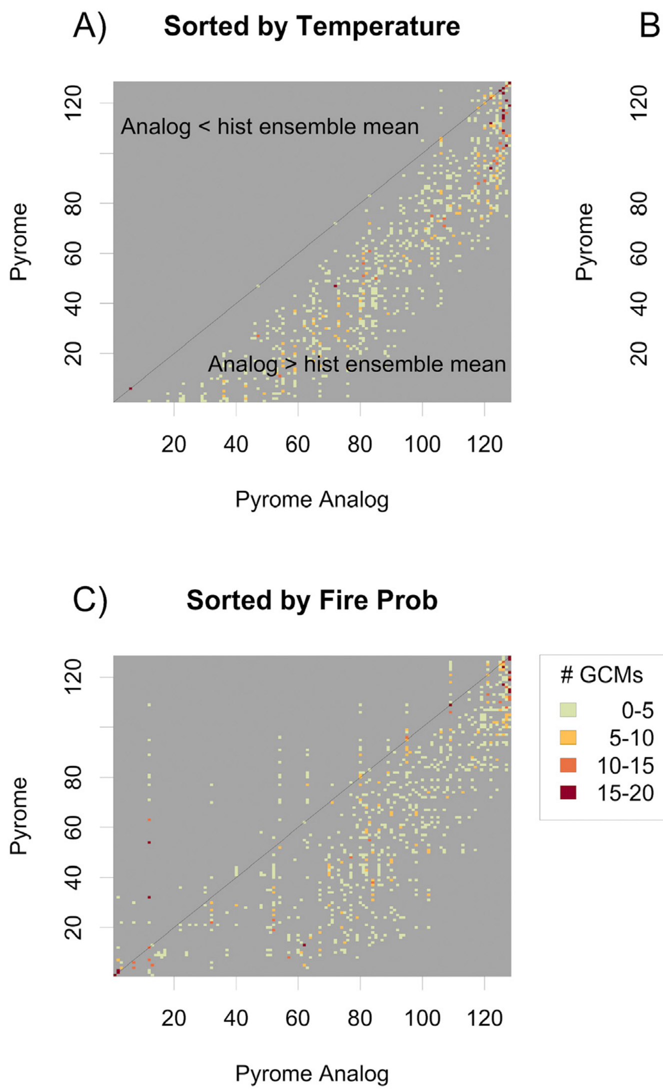

Fig. 4. Distribution of closest analog pyromes with respect to annual maximum temperature (A), annual precipitation (B), and fire probability (C). Filled cells in the matrix plots depict the number of GCMs projecting a particular pyrome (X-axis) as being the closest analog to the pyrome of interest (Y-axis) for the end-of-century time period under the RCP 8.5 climate scenario. Analogs were based on the Mahalanobis distance calculated over the three variables, with the historical ensemble mean values used to represent the pyrome's baseline conditions. See text for further details.

as ordered along the temperature axis (Fig. 4A) are almost universally spread across cells located in higher ranked positions, reflecting the role that warming temperatures play in both the Mahalanobis distance calculation and in determining fire probability in the PC2FM equation. The analog results for the precipitation axis (Fig. 4B), however, show a similar level of dispersion along the x-axis, with the location of analogs straddling both wetter and drier pyromes. Uncertainty propagates into the fire probability analogs (Fig. 4C), with some GCMs indicating that a few pyromes whose ensemble mean fire probability is of high rank have analog pyromes with very low ranked fire probabilities. This situation could occur when, for example, some ensemble members project much warmer and drier conditions in the future, leading to lower fire probabilities associated with a lack of fuels (i.e. aridification).

Mapping pyrome analogs further illustrates patterns of, and uncertainty in, future fire probability in the context of projected climate change. Three different pyrome analog maps are shown that depict increasing levels of consensus in the climate model ensemble for the RCP 8.5 end-of-century scenario (Fig. 5). The Interior Plateau pyrome is an example of high *ensemble uncertainty*, with ten different pyromes possibly being projected as the closest analog to its present day climate-fire regime (Fig. 5A). Possible analogs stretch from nearby pyromes immediately equatorward to the fully sub-tropical peninsular Florida pyrome. Greater model consensus is shown for the Missouri Coteau pyrome (Fig. 5B), with nearly half of the ensemble GCMs ($n = 8$) projecting that the Northern High Plains pyrome would be the closest climate-fire regime analog by the end of the century. However, while the ensemble uncertainty decreases compared to that shown for the Interior Plateau in Fig. 5A, the *spatial uncertainty* increases due to a single GCM projecting that the Arizona/New Mexico Mountains, located more than 1500 km to the southwest of the original pyrome, would be the closest climate-fire regime analog. Finally, the Western Mojave Basin and Range pyrome exhibits the highest level of ensemble agreement, with only two possible analog pyromes (Fig. 5C), but these results represent yet another form of uncertainty, *analog uncertainty*. Due to its location, this pyrome already experiences extremes in temperature and precipitation (relative to the domain extent). The high level of ensemble agreement ($n = 17$), pointing to the Sonoran Desert pyrome as the closest climate-fire regime analog, is likely a function of a lack of additional pyromes in the domain extent with climate conditions that are even hotter. As such, this likely represents a 'no-analog' climate scenario, at least with respect to the CONUS.

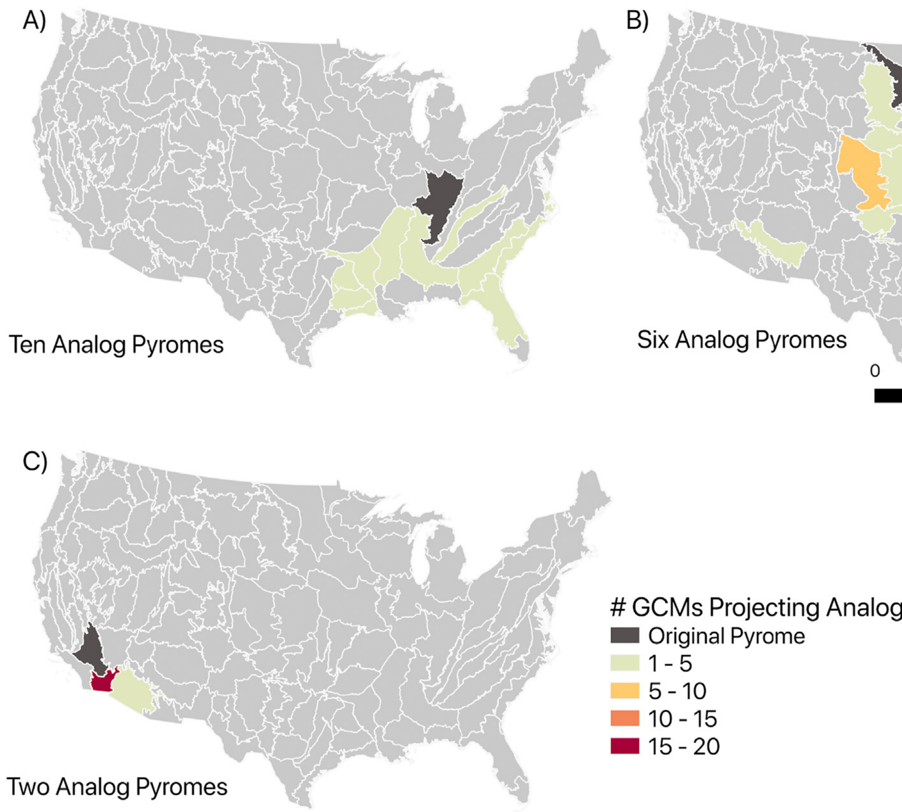

Fig. 5. Examples of pyrome analogs as calculated with the 20-member climate model ensemble for the end-of-century period under the RCP 8.5 climate scenario. Analogs are based on the Mahalanobis distance calculated from three variables (annual maximum temperature, annual precipitation, and annual fire probability). Values for the 'Original Pyrome' are taken from the climate model ensemble mean calculated over the historical period (1971–2000).

Spatial summaries of uncertainty in the climate-analog and fire probability projections are displayed in Fig. 6. Generally and across all GCMs, there are more potential analog pyromes projected in the middle of the CONUS and fewer in the southeastern, northwestern, and southwestern regions (Fig. 6A, RCP 4.5; Fig. 6B, RCP 8.5). The variation in potential pyrome analogs is consistent with the different forms of uncertainty associated with the example pyromes in Fig. 5. However, the Coefficient of Variation (CV) calculated from the ensemble of fire probability projections indicates that the level of fire probability in a pyrome is also an important contributing factor to the total projection uncertainty (Fig. 6C and D).

With respect to the end-of-century RCP 8.5 results (which exhibit the greatest warming and the highest levels of uncertainty), three distinct pattern combinations are apparent between the pyrome analogs and the CV mapping. First, in the southwestern region, there are few projected pyrome analogs but also high CV values. This likely reflects the analog uncertainty identified in Fig. 5, and the fact that there are high CV values further supports this possibility because the relatively larger ensemble variance (relative to the mean fire probabilities) would be expected to result in more potential pyrome analogs if they existed within the CONUS. This contrasts with southeastern pyromes, which exhibit few alternative pyrome analogs but also have low CV values. While the small number of pyrome analogs could similarly reflect analog uncertainty (particularly in the far southern Florida pyrome bordering the ocean), the low CV values also suggest that the relatively high fire probabilities reduce the uncertainty in potential analog futures. Finally, across the middle of the CONUS, and in particular in the north-central pyromes, many pyromes have a large number of potential pyrome analogs, but also have lower CV values. In this region, several pyromes are clustered together with similar levels of higher fire probabilities and low variance in projected probabilities. So although the CV values are generally lower, the number of potential analogs is high because similar fire regimes are present across a large area, indicating that small differences in projected changes would still be consistent with the present-day fire regime characteristics found across a wide range of pyromes.

Graphing pyromes by their current fire probability versus projected 21st century changes reinforces findings from the pyrome analog analysis regarding climatic drivers. Under historical baseline conditions, there are clear differences in fire probability related to temperature (Fig. 7A) and precipitation (Fig. 7B), with temperature generally being the dominant factor. These graphs also demonstrate that the pyromes projected to experience the greatest percent changes in fire probability over the remainder of the century are those in colder climates with moderate to high precipitation (pyromes in the upper left of Fig. 7A and B).

Aggregating pyrome-level results to the scale of the ten regional pyrome groups allows us to highlight areas where, for example, fire probability was historically high (> 0.20) and is projected to increase moderately (ca. 30–70% increase), including eastern Texas and Arkansas (Texarkana) and the southeastern Coastal Plain (Fig. 7C). Regional pyromes with lower historical fire probabilities (< 0.08) are arranged along a gradient of percent change from: 1) the driest region (the South Central Deserts, Plains and Uplands), which experiences a slight decline in fire probability as warmer and drier conditions limit biomass production, to: 2) the northernmost pyromes (the Cascade Range, the Upper Great Lakes, and the Northeast), where warming conditions lead to significant increases in fire probability. The spatial structure of this gradient underscores the importance of interpreting patterns of fire regime change within the context of regional climatic changes.

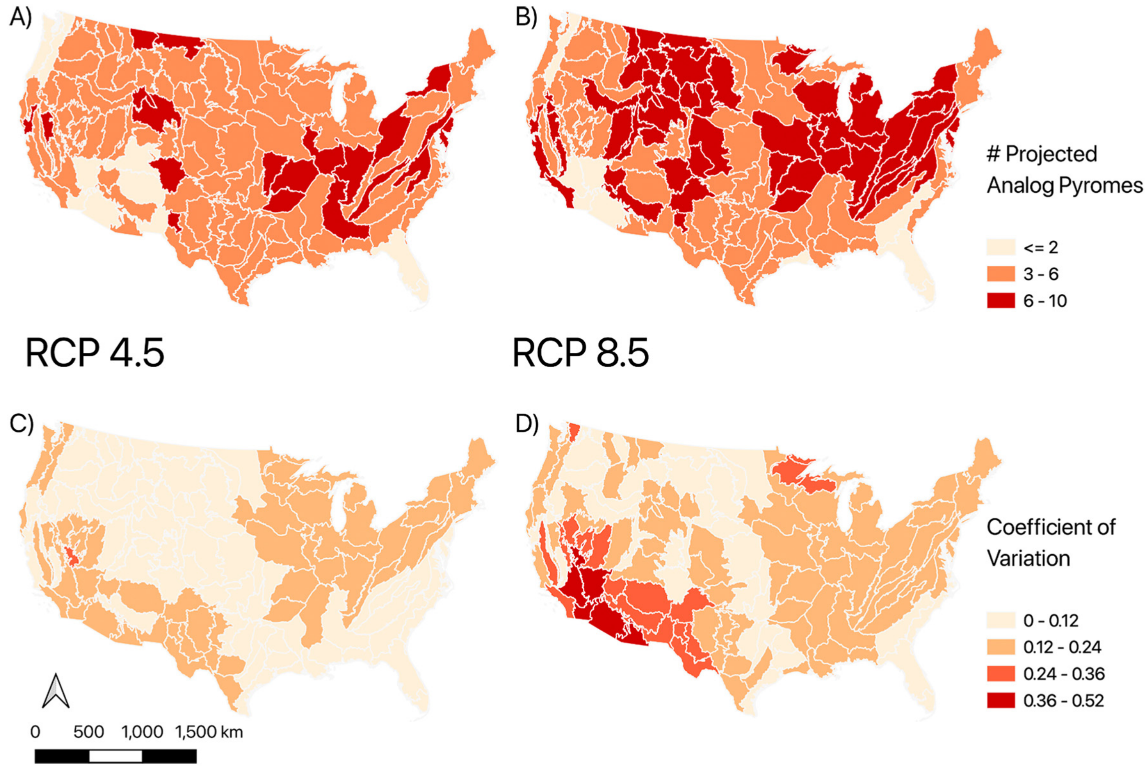

Fig. 6. End of century analog and fire probability uncertainty. Top row: number of different analog pyromes projected for each pyrome by the end of the century from the downscaled climate model ensemble for the A) RCP 4.5 and B) RCP 8.5 scenarios. Bottom row: the coefficient of variation calculated from the climate model ensemble projections of end-of-century fire probability for the C) RCP 4.5 and D) RCP 8.5 scenarios.

4. Discussion

4.1. Patterns and climate drivers of changing fire regimes

Our analyses point to increases in fire potential, expressed as the upper limits of fire probability across the CONUS, that are discernible by mid-century and manifest broadly across pyromes and regions by 2100, with few exceptions. These predicted changes could significantly restructure fire regime patterns across the CONUS, resulting in novel ecological and societal effects. Increasing wildfire frequencies in many forested pyromes, for example, have been linked to conversion to shrublands, which can drastically alter ecosystem functioning and services (e.g., Coop et al., 2020).

While historical fire regimes are structured along gradients of both temperature and precipitation (Fig. 7), rising temperatures are the primary cause of modeled increases in fire probabilities due to the uniform directionality of temperature change (warming; Fig. 4A) that positively influences the chemical reaction environment through enhanced photosynthetic rates and increased thermal molecular energy (Guyette et al., 2012). The projected precipitation changes, in contrast, are bi-directional (both drier and wetter conditions) in space and across GCMs (Fig. 4B). This outcome has the effect of increasing projection uncertainty (Fig. 4C), which is then compounded by the nonlinear effect of precipitation in the PC2FM equation.

When interpreted within the context of historical fire patterns and current management concerns, our results underscore the significance of projected changes in fire probability. Fires are historically infrequent in northwestern (e.g., the Cascade Range), northern (e.g., the Upper Great Lakes), and northeastern pyromes, but are predicted to experience 50–100% increases in potential fire probabilities under both RCP 4.5 and RCP 8.5 by the end of the century as productivity increases (due to increased temperature) and fuels experience greater drying (due to increased evaporative demand and/or decreased precipitation; Fig. 3). In recent decades, large wildfires in these areas have not only had surprising effects (e.g., burning in areas normally too cold and wet to ignite), but have inundated large metropolitan areas with persistent and hazardous smoke levels (e.g., Seattle, Portland, Willamette Valley, and Vancouver, BC; Zou et al., 2019). Pyromes in other dry western forests in the northern and middle Rocky Mountains, including the Yellowstone Basin, have a history of similarly large and costly wildfires that challenge current fire suppression resources. Projected changes in fire regimes in northern California (e.g., the Sierra Nevada, Klamath Mountains, and North Coast Ranges) are likewise noteworthy given that state's record fire year in 2020, when wildfires burned ca. 1.7 million ha in the state. These projected fire probability increases occur in pyromes with recent megafires that rank among the largest, most lethal and most damaging in the state's recorded history, including the Tubbs Fire (2017), Camp Fire (2018), Carr Fire (2018), Rim Fire (2013), and the majority of the 2020 wildfires, including the August Complex, the largest fire on record.

Beyond the prevalent pattern of increasing fire probabilities across the CONUS, our approach allows for nuanced analysis and identification of nonlinear interactions among drivers of potential changes in fire regimes. In arid locations such as the Chihuahuan Desert, West Texas Plateau, and shortgrass prairies of eastern New Mexico, future fire probability is projected to change very little under the RCP 4.5 scenario or to even decrease under RCP 8.5 as warming and drying conditions decrease site productivity and limit fire return intervals through aridification. In short, similar patterns of warming and drying conditions, as is projected across much of the western CONUS, can result in markedly different responses depending on prevailing site conditions.

Patterns of changing fire probability in the southeastern USA provide an example of the practical importance of understanding the complex patterns and drivers of change. Historically, this region had the highest fire probability values in the CONUS (Fig. 2A), with PC2FM projections and observed MFI's of 2–4 years, confirmed by fire-scar history evidence from numerous studies (Stambaugh et al., 2011; Stambaugh et al., 2017; Rother et al., 2020). While increases in projected fire probabilities exceed 50%, fires already occur frequently in this area, primarily in the

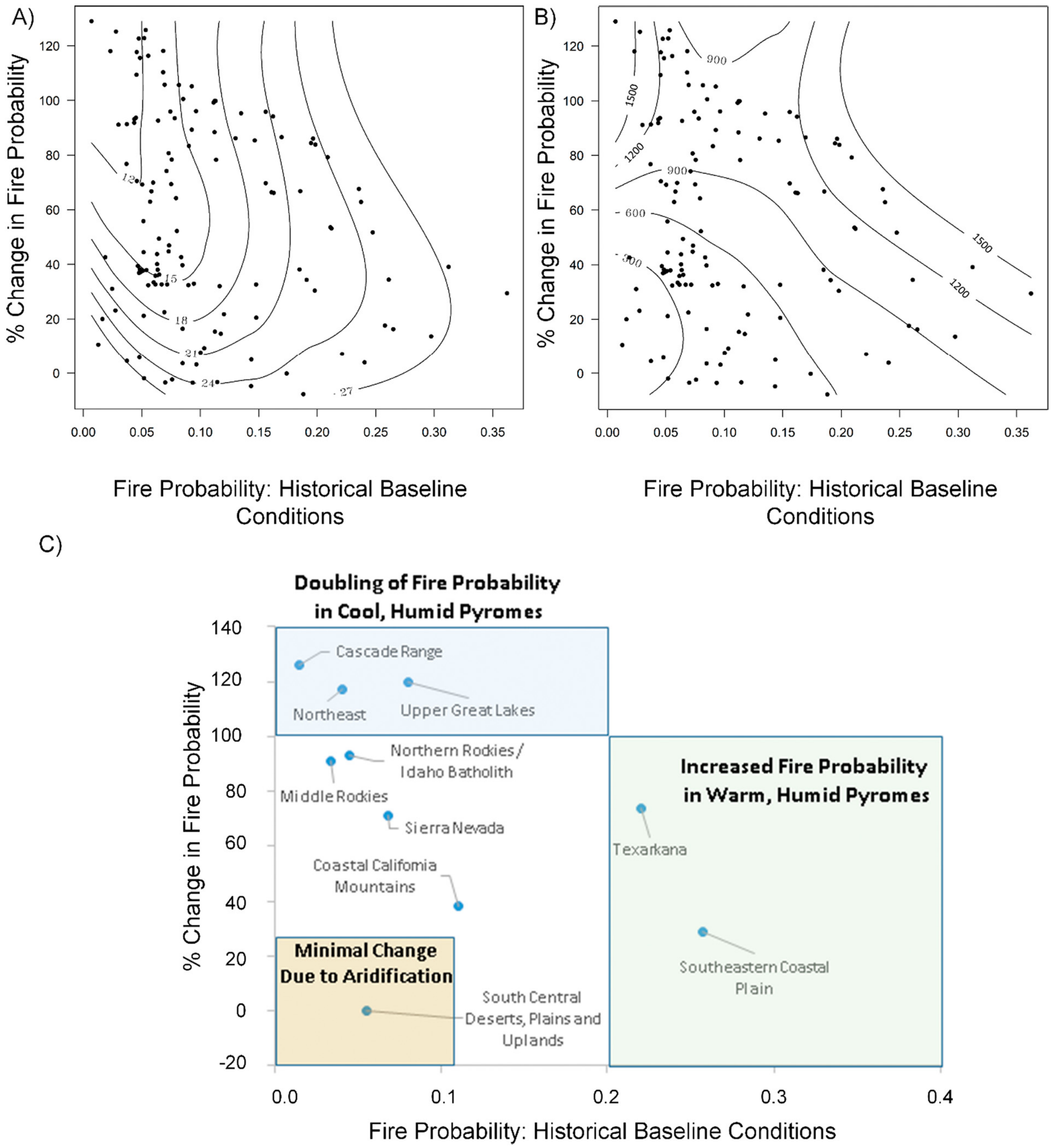

Fig. 7. Relationships between climate and changing fire probabilities. (A) and (B) Scatterplots of fire probability from PC2FM for 128 pyromes in the contiguous U.S. under historical baseline conditions (1971–2000) vs. projected changes by the end of the 21st century under RCP 8.5. Contours of baseline temperature (A) and precipitation (B) were derived using R. (C) Fire probability from PC2FM for 10 regional pyrome groups under historical baseline conditions (1971–2000) vs. projected changes by the end of the 21st century under RCP 8.5. Values represent the means of all pyromes within the group. Pyrome locations are shown in Fig. 1.

form of prescribed fires used to reduce hazards and maintain habitat (Melvin, 2018). Thus, the ecological consequences of that projected increase in the Coastal Plain may be negligible. However, because prescribed fire is the dominant source of burned area in the Southeast, any changing climatic patterns could further reduce prescribed fire activities (Kupfer et al., 2020) and exacerbate wildfire risk (Prestemon et al., 2016; Terando et al., 2017; Carter et al., 2018).

4.2. Application to adaptation planning

With the growing consensus that changing climates will result in widespread increases in fire frequency over the remainder of the 21st century (Moritz et al., 2014; Carter et al., 2018), the development of proactive mitigation and adaptation strategies will continue to benefit from access to models that facilitate a rigorous assessment of potential changes in fire regimes at a range of spatial scales. Using a large ensemble of downscaled climate models as inputs into PC2FM allows for a more thorough treatment of known uncertainties that is critical for long-term fire and conservation planning. Confidence assessments of ensemble model predictions, particularly through the lens of analog pyromes, will allow managers to evaluate the present value of management actions which often take decades to realize desired outcomes (e.g., silvicultural decisions and species recovery strategies). A similar approach has already shown relevance in managed mitigation strategies and long-term planning for prescribed fire activities (Kupfer et al., 2020).

Our results provide value for planning the scale, extent, or relevance of mitigation strategies and treatments within pyromes projected to see significant shifts in fire probabilities (Fig. 6). Because species are adapted to the characteristics of past fire regimes, particularly fire frequency, modifications to fire regimes wrought by future climate change may slow or accelerate species range movements that are projected or already underway (Iverson and Prasad, 2001). Understanding potential changes in future fire regimes, including the spatial distribution of analog pyromes, will be helpful for predicting ecological trajectories, complex ecosystem feedbacks in fire-prone communities and for informing new fire management and conservation strategies (Ager et al., 2017). As an example, the Department of Defense has mandated that installations address climate change considerations when updating or revising their.

Integrated Natural Resource Management Plans every five years. Our results provide insights into potential changes in fire regimes at a scale and time horizon appropriate for supporting such analyses (e.g., Stein et al., 2019).

4.3. Caveats

The results of this study are subject to several caveats. First, the fire probabilities presented are calculated at the scale of 4 km pixels, the resolution of the downscaled climate model output, and then averaged for individual pyromes. We recognize the limitations of PC2FM fire probability predictions are such that inferences made involving processes occurring at these (or even finer) scales must be taken with caution. At these scales, idiosyncrasies of exogenous factors, including land use, non-native species, and human dimensions will play increasingly important (if not dominant) roles in determining the actual annualized fire probability. Similarly, this model combination and ensemble approach does not include local factors of soils, vegetative hysteresis, or non-native species in predictions of potential fire probability. For example, projected changes in fire probability may shift in response to invasions by non-native species that alter fuel availability, such as the potential expansion of buffelgrass (*Cenchrus ciliaris*) in areas of the South Central Deserts, Plains, and Uplands (e.g., de Albuquerque et al., 2019). Such disruptions may affect the calibration of PC2FM by disrupting the expected equilibria between climate and fuels in these systems over long time periods. Nevertheless, the good model fit exhibited by PC2FM to historical fire frequency data (Guyette et al., 2012) increases confidence in the interpretability of these results as they relate to potential ecological changes under altered fire regimes.

Additionally, while we assume that our analysis captures a significant portion of the true uncertainty about 21st century climatic change in response to anthropogenic greenhouse gas emissions, we do not claim to capture the full range of uncertainty. It is possible that this analysis could still include bias due to errors and simplified representations of physical processes in the downscaling method and in the numerical climate models. Further work to improve the calibration and accuracy of PC2FM would also be beneficial. For example, understanding the influence of seasonal, as opposed to annual climate variables on fire probability, would potentially increase confidence and salience of PC2FM without significantly increasing model complexity. When taken in the context of analog fire regimes, these results can be valuable in assessing the scale, extent, or relevance of mitigation strategies applied within pyromes projected to undergo significant shifts in fire probabilities.

5. Conclusions

The complexity of pattern and process that characterize wildland fire regimes can limit the ability to conduct comprehensive analyses of the potential impacts of anthropogenic climate change across an area as large as the CONUS. Such analyses are a critical component of risk assessments that could be used by decision makers during the development of adaptation plans, as well as in the broader global effort to understand the myriad costs associated with the continued use of fossil fuels. Our results represent a rigorous, physically-based assessment of spatial patterns and uncertainties associated with changing potential fire probabilities, which can form a common base for comparison across vastly different management, habitat, and land use contexts. Subsequent interpretation of predicted future fire probabilities can be informed by dominant land uses (forested vs. agricultural) and management actions, which modify how fire potential is actualized within a pyrome. For example, increased potential fire probability will understandably be less of a concern in areas currently dominated by row crop agriculture and more of a concern in wildlands that intermix with human communities.

In contrast, rigorously characterizing uncertainty in projections of shifting fire regimes through more complex ecosystem process-based modeling (e.g., Scheller et al., 2007; Sitch et al., 2008; Medvigy et al., 2010; Liang et al., 2017) would pose a significant challenge at the continental scale given the data and computational requirements. In turn, this implicit domain extent and resolution constraint limits the ability of decision makers to use these results to inform more comprehensive adaptation strategies in regions with significantly different fire regimes in close proximity (e.g., California). While more complex ecosystem models will continue to represent a critical tool to explore local-scale processes and carbon cycling in response to climate change, it is not currently feasible to conduct a robust uncertainty analysis as part of a climate change assessment on the scale represented in this study. Refining models and methods that provide greater certainty in projections of future climate-fire relationships will continue to be a priority in many management contexts as a means to facilitate and accelerate adaptation to changing climates.

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CRediT authorship contribution statement

PG and KJH designed the study. PG, AJT, and TLL analyzed the data. PG, AJT, JKH, JAK, JMV, and MCS wrote the manuscript.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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