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forest ecology

Future Fire Probability Modeling with Climate Change Data and Physical Chemistry

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Climate has a primary influence on the occurrence and rate of combustion in ecosystems with carbon-based fuels such as forests and grasslands. Society will be confronted with the effects of climate change on fire in future forests. There are, however, few quantitative appraisals of how climate will affect wildland fire in the United States. We demonstrated a method for estimating changes in fire probability based on future climate simulations of temperature and precipitation. The probability of a fire occurring in a particular climate was extracted from the Physical Chemistry Fire Frequency Model (PC2FM) and represented the rate of change in fire due to climate. Climate output data from two global climate models (GCMs) were applied to the PC2FM to estimate changes in fire probability. We calculated change in fire frequency and probabilities from the difference between current and future climates and mapped climate-forced percentage change in fire probability under each GCM for the nation at a 1.2 km^2 scale. Future fire probability estimates increased in cooler northern and high elevation regions but decreased slightly in some hotter and drier regions of the southwestern United States. Our approach's greatest strength may be reliance on only climate data and the simple principles of physical chemistry; many other nonclimatic factors that affect fire are often difficult to predict in the distant future.

Keywords: fire scars, dendrochronology, physical chemistry, ecosystems

The details of the physics and inorganic chemistry of fire may seem distant from the large-scale fires burning in forests, however, wildland fire is fundamentally a chemical reaction of carbon compounds and oxygen resulting from complex ecological and abiotic factors (Chandler et al. 1983). Carbon bond formation and breakdown occur within primary ecosystem processes such as growth, decay, and burning that are all affected by climate. The probability of fire will change as basic combustion processes are exposed to new more varied climates (Mann et al. 1998, Parisen and Moritz 2009). The rate of wildland fire spread and occurrence are a function of the environment and reactants in a chemical reaction (Atkins 1986, Guyette et al. 2012). We consider rate as the number of fires per year and fire occurrence based on evidence of fire (fire scars) in an approximately 1.2 km^2 area during 1 year.

The use of physics, chemistry, and climate data to formulate wildland fire models allows for estimates of changes in future fire regimes (fire occurrences) based on climate data from GCMs. Whether the reaction environment is a laboratory benchtop at room temperature or an ecosystem with changing temperature, precipitation, and reactant concentrations, the fundamentals of combustion reactions play a central role (Chandler et al. 1983, Bernard and Nimour 2007). The modeling approach presented here (Figure 1) had been validated by temporal fire rate data (Guyette et al. 2012), many years of experimental physics and chemistry (Atkins 1986, Harris 1987, McQuarrie 1987), fire ecology (Wright and Bailey 1982), and fire history (Swetnam et al. 1999, Pyne et al. 2010). Although other models exist that attempt to estimate the effects of vegetation, society, and future climate on fire regimes, they are often more complex, less quantitative, and have less certainty with regard to many future conditions (Flannigan et al. 2005, Archibald et al. 2013). The PC2FM (Figure 1) is based on concepts that have resulted from years of experimental physics and chemistry involving temperature and reactant concentration, many long-term fire history records, and has been vetted in peer review (see Supplemental Data in Guyette et al. 2012, National Oceanic and Atmospheric Administration (NOAA)/Paleofire Database 2009).

The temporal and spatial scale of the PC2FM data covers a diversity of fire regimes across North America (Whitlock et al. 2010). This breadth of variance gives the model power that cannot be derived from sites with limited climate conditions and temporal depth. However, the model's virtues (diversity of fire regimes and simple climate variables) are also potential shortcomings. The list of ecosystem variables that affect fire frequency and intervals is long and includes natural and human ignitions, topographic variables,

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$$MFI = \underbrace{A_o e^{E_a/RT}}_{(ARterm)} + \underbrace{1/(P^2/T)}_{(PT_{rc})}$$

PC2FM variables	Equation component	Fire ecology & theory	Chemical and physical processes
Mean annual precipitation	A_o	*Relative* humidity and fuel moisture decreases rates of burning	H_2O inhibition of O_2 and $C_6H_{12}O_6$ collision frequency (Fuss et. al. 2002)
Mean annual precipitation	PT_{rc}	Photosynth., decay, fuel (Kozlowski et al. 1991)	Carbon bonds & reactant concentrations
Temperature and precipitation	E_a	Varied carbon based natural fuels (Shoujie et al. 2013)	Model constant for mean activation energy (Roberts 1970)
Mean maximum temperature	PT_{rc}	Fire season, fuels, (Westerling et al. 2006)	Photosynthetic rate (Kozlowski et al. 1991)
Mean maximum Temperature	*ARterm*	Fire probability based on fuel conditions & temperature, °F , °C	Thermal molecular energy, degrees K (Atkins 1986)
Estimated ${}_{pp}O_2$	A_o	Elevation effects on oxygen concentration	Reactant concentration & reaction stoichiemetry

Figure 1. A listing of the concepts and processes of the PC2FM: climate variables and proxies, equation components, fire ecology theory, and physical chemistry processes. Directly below the equation are the names of the reaction environment component (*ARterm*) and the reactant concentration term (PT_{rc}). *MFI* is the mean fire interval, the A_o term is $P^2/{}_{pp}O_2$, $e = 2.718$, $E_a = 132$ kJ mol^{-1} and is a constant in this model formulation, $r = 0.00831$ kJ mol^{-1} K^{-1} (the universal gas constant), P = annual precipitation in cm, T = degrees K.

vegetation, fuel characteristics, wind, and fire weather. The PC2FM does not address these variables because it was developed to avoid these local and short-term factors and focus only on climate as an overarching influence.

The statistical formulation, calibration, and validation of the PC2FM began by breaking down wildland fire into a reaction environment parameter (*ARterm*) and a reactant concentration parameter (PT_{rc}), the two basic conditions of any nonnuclear chemical reaction (Figure 1). We used multiple regression analysis to test the terms and the model empirically with mean fire interval data from 170 sites, more than 3,400 trees, containing 30,000 fire scars (see Supplemental Data in Guyette et al. 2012). Regression coefficients translated the relatively fine-scale units of chemistry (i.e., kJ^{-1} mol^{-1}, molecular reactions per second, and partial pressure of oxygen) to landscape-scale units (~1 km^2) that are relevant to fire frequency, mean fire intervals, and probability. PC2FM variables were significant ($P < 0.001$), multicollinearity among predictor variables was not significant, and residuals were normally distributed. Based on many model runs the average tested model coefficient of determination (r^2) was 0.80 (range = 0.59 to 0.90). Partial r-squares were 0.60 for *ARterm* and 0.20 for PT_{rc} terms.

The PC2FM approach in this study allows for direct temperature and precipitation inputs that affect reactant collisions and reaction rates required for modeling combustion in future climates and ecosystems. Direct precipitation input is a proxy for the amount of water in the atmosphere (humidity) and reactants (fuels) and estimates how this reaction inhibitor blocks the molecular collisions of oxygen and fuels in ecosystems. The quantitative modeling of wildland fire probability will improve with new data on fire frequency, improved modeling approaches, and better climate projects from future global change models. However, applying the PC2FM model to output from GCMs allows the extrapolation of future fire regimes based on climate projections that can be applied at a continental scale.

In this study, our objectives were to develop a modeling framework for estimating fire frequency and probability changes in future fire regimes based on climate change data and produce spatially explicit predictions of changes in fire frequency due to projected climate conditions at the end of the century in the United States.

Methods

Application of the PC2FM

A short review of the PC2FM method will aid in its application in the context of this research, predicting change in fire probability. The PC2FM used the Arrhenius equation ($k = A_0 exp^{-Ea/RT}$) as a physical chemistry concept to formulate the effects of climate on wildland fire (Guyette et al. 2012). This Arrhenius equation has been used in other fire, weather, and climate applications (Bernard and Nimour 2007, Perminov 2007, Mandel et al. 2009). The PC2FM is represented by two components, one the *ARterm* and two the $PT_{rc,}$ component (precipitation over temperature), which estimates fuel availability (concentration and moisture) based on climate data (Equation 1; Figure 1). The PC2FM is written as

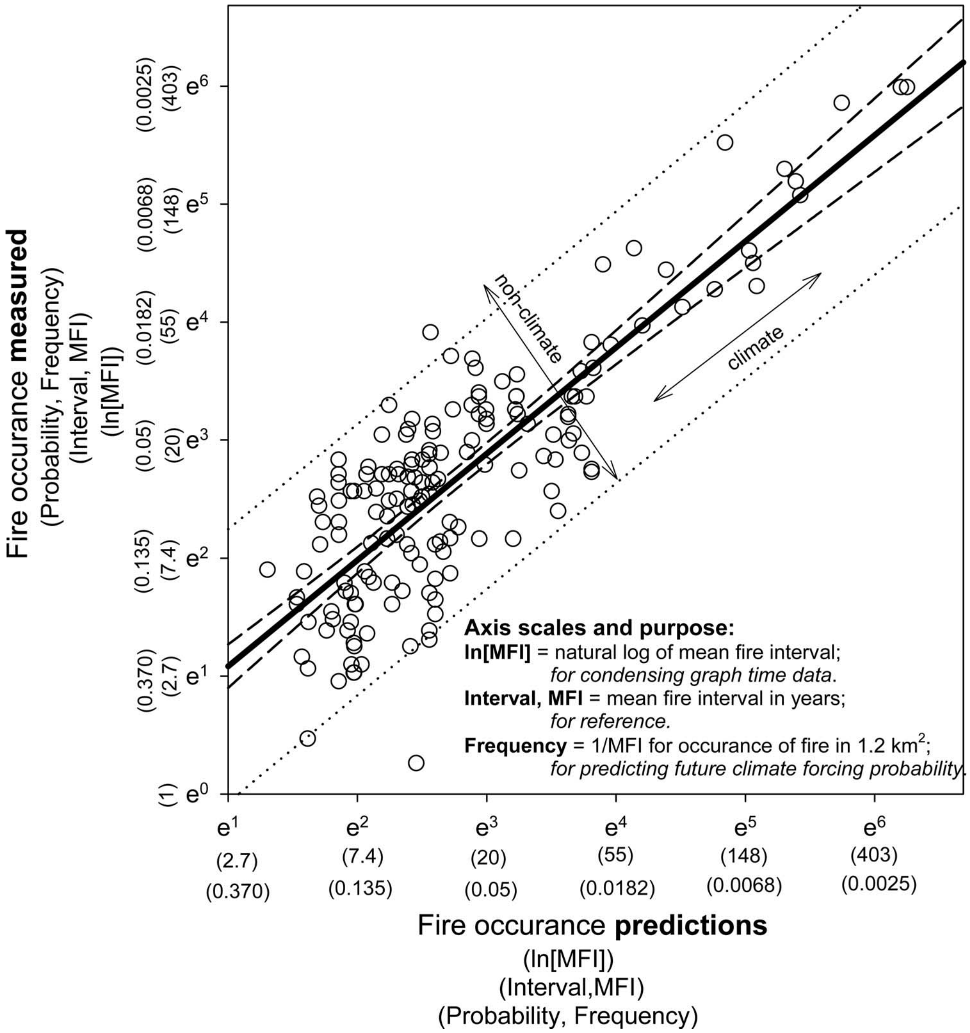

Figure 2. PC2FM regression data, estimates, and probabilities for fire frequency in the United States. The labeled "climate" line represents the climate-driven rates of fire frequency and probability based on the regression line. The "nonclimate" line represents the regression residuals caused by nonclimatic forcing from topography, ignitions, and many other factors.

$$MFI = 0.232 + (2.62 \times 10^{-28} \times ARterm) + (52 \times PT_{rc}) \tag{1}$$

where *MFI* is the mean fire interval (years), the *ARterm* represents the reaction environment, and the PT_{rc} represents the estimated reactant concentration and quality.

Mean fire intervals (MFIs) are an ecological measure of time and fire occurrence. They are the chemical analog of time and relative frequency and are based on rates of combustion reactions. The analogy works because the reaction environment and reactant quality (concentration and condition) are dominant factors that affect the likelihood of fire occurrence in both the laboratory and landscape. The probabilities of fire ignition and spread are based on the ecological and chemical characteristics of the reaction environment. Turning landscape measures such as MFI (time interval/occurrences) into rate metrics such as frequency or probability (occurrences/period) allows for the use of time and fire data in model calibration (Figure 2) (Swetnam et al. 1999, Heyerdahl et al. 2001).

Climate Data and Simulations

We selected two GCMs to determine the potential variance in fire probability based on their different climate output. The Coupled General Circulation Model 3.1 T47 (CGCM) (Flato et al. 2000) from the Canadian Centre for Climate Modeling & Analysis is a "middle of the road" conservative model that is similar to many other global climate change models. The GFDL-CM2.1 model (GFDL) (NOAA 2009) was selected because it differs in methods and output and is from a different source. These models differ in processes, scale, and metrics. The metrics used, how they are used (constants or variables), and the model coefficients used for each metric can influence outputs. Even small differences in initial forcing values can result in large differences when the models are run hundreds of times. Some examples of differences in radiative-forcing factors between the models used in this paper include the use of ozone as a constant (CGCM) or as a variable (GFDL) and the modeling of radiative forcing using atmospheric SO_4. Other differences include processes that are difficult to measure and model such as deep ocean circulation, melting rates of ice, thermohaline circulation, and spatial scale. Spatial scale is an important and well-documented factor in all climate-fire modeling (Whitlock et al. 2010). The spatial scale of the GFDL climate output is finer than that of the CGCM (Figure 3). GCM model cell sizes change with latitude and longitude. GCM cells are 3.75 degrees for CGCM and 2.5 degrees for GFDL beginning at the equator.

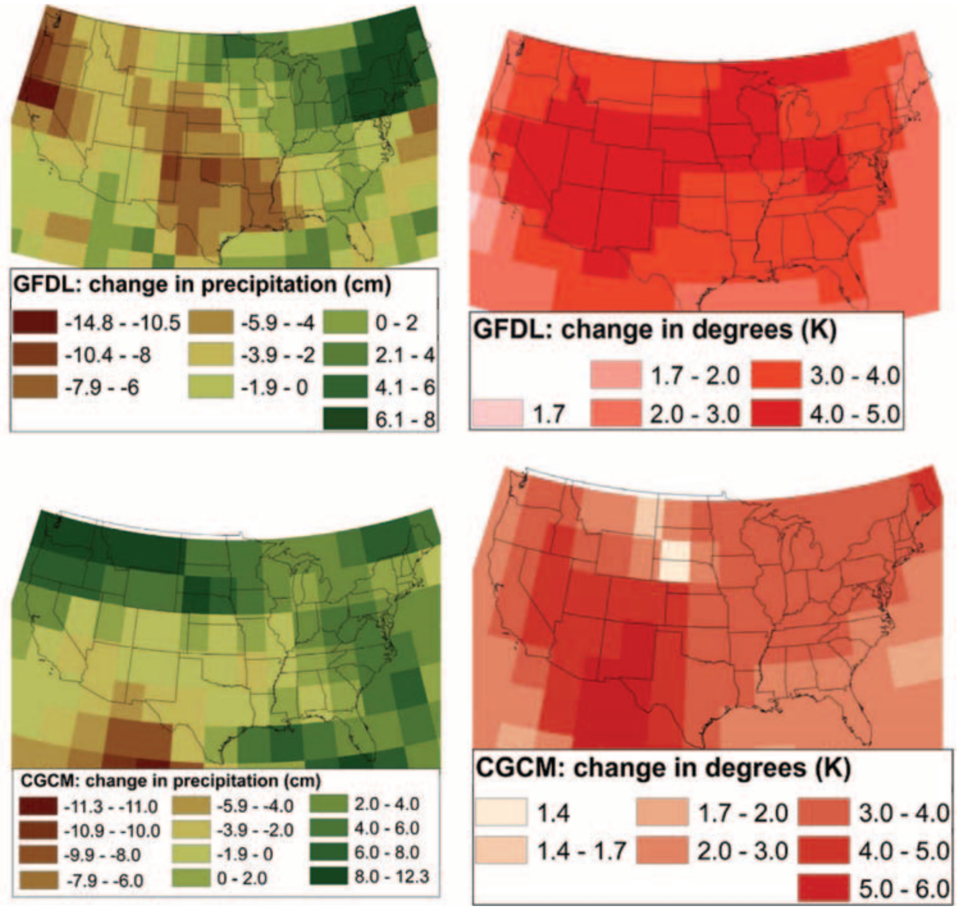

Figure 3. Maps of changes in precipitation (on the right) and mean maximum temperature (on the left) in the United States. Climate data changes are based on model hind casts ("control period") for 2001 and 2020 average data and future casts circa 2081 to 2100 with two different climate change data simulations: top—GFDL CM2.1 and bottom—CGCM 3.1 T47.

We used the two GCMs with hind-cast and future temperature and precipitation metrics that could be summarized for two time periods, 2001–2020 and 2081–2100 AD in the conterminous United States; herein, these are, respectively, referred to as *control* and *future* time periods. Mean annual precipitation and mean maximum temperature between the control and future climates in overall magnitude and spatial pattern for each GCM (Figure 3). Fire probability was derived for each GCM through the PC2FM.

Transforming Fire Intervals into Climate-Forced Fire Probabilities

The observed rate of fire occurrence at a specified scale is an estimate of its probability. We used the classic relative frequency approach to estimate the annual probability of a fire occurring in a 1.2 km^2 area (Keller and Warrack 1997). We transformed time and fire data as measured in years (mean fire interval) into a physical definition of relative frequency and probability (1/fire free interval). The probability of the reciprocal allowed for the conversion of the mean fire intervals that are derived from the output of the PC2FM equation into probabilities of fire occurrence based on climate. Treating fire events as event-wave periods considers landscape basics of fuel production, reactant concentration, decay, and longer-term precipitation effects. The conversion to frequency extracts the probability of fire occurrence for a specified time (annual) at a specified scale (1.2 km^2) from the climate forcing of the model (PC2FM). Climate–fire calibrations were based on the thousands of years of data of fire occurrence (see Supplemental Data in Guyette et al. 2012). The general physical concept (Equation 2) that transforms time intervals to probabilities of occurrence is

$$cff\ \mathrm{yr}^{-1}\ \mathrm{km}^{-2} = 1/MFI_{@tt}. \tag{2}$$

where $cff\ \mathrm{yr}^{-1}\ \mathrm{km}^{-2}$ is the probability of climate-forced fire occurrence calculated as the relative frequency of a fire per year per square kilometer and $1/MFI_{@tt}$ is one divided by the mean fire interval at time *tt*. Equation 2 uses relative frequency to estimate fire probability (Keller and Warrack 1997). Equation 3 uses PC2FM output mean fire intervals to predict the climate-forced change in fire probability or relative frequency (*cff*) from a "control" (*tc*) climate period ($1/PC2FM_{@tc}$), and a future (*tf*) climate period ($1/PC2FM_{@tf}$) and then uses differencing to estimate positive or negative percent of change in fire probability (*CFP*)

$$CFP = ((1/PC2FM_{@tf} - 1/PC2FM_{@tc})/1/PC2FM_{@tc}) \times 100 \tag{3}$$

The reciprocal expressions in the three terms in parentheses of Equation 3 cancel out and simplify the calculation to Equation 4

$$CFP = ((PC2FM_{@tf} - PC2FM_{@tc})/PC2FM_{@tc}) \times 100 \tag{4}$$

Defining Fire Probability Estimates

We define different change in fire probability (CFP) outputs of the PC2FM future prediction as "the percent change in climate driven fire probability" based on the use of only climate variables for estimating fire probabilities. The model does not include the many important nonclimatic fire variables such as land use, human population, or the number of fire departments that may have profound effects on future fire regimes. The abstraction to the change in probabilities between past and future climates allows climate-forced probabilities to be applied to many types of data sets that may be of interest in planning at large spatial scales.

Mapping Simulation

Fire probability estimates for mapping require attention to the size of spatial units for control and future climate periods. Here, climate estimates for the conterminous United States were used as input into the PC2FM and were derived from hind casts and future casts of each GCM. This method allowed not only comparisons of identical spatial extent but also for change over time using individual climate modeling methods. In this study, we also used the peer-reviewed formulations of the PC2FM to estimate fire probabilities for the compared climate periods based on the outputs of both climate models. Mapping fire probabilities requires attention to developing class direction, range, and hue for breadth of probability given by a particular GCM-PC2FM output. The probability class sizes are defined by the frequency of distribution of their occurrence. We used more intense color saturations to create greater representation of the changes in fire probability while less intense color saturations to represent smaller changes in probabilities. Probability classes begin at zero (no change) and are scaled as increases (> 0) and decrease (< 0). The classes below zero are smaller in probability range than the classes above zero. Outliers in the distribution of probabilities represent very small areas (e.g., top of a mountain or nonvegetated deserts), which were not used to create mapped probability classes.

Results

Regional GCM-PC2FM Fire Probability Comparisons

PC2FM outputs based on the two GCM data sets depicted both similarities and differences in estimates of future fire probabilities. Fire estimates from both the GFDL and the CGCM data showed increased fire probabilities in the northern Rocky Mountain and northwest regions (Figure 4) (Heyerdahl et al. 2008). For both global change model inputs, the fire probabilities in Great Plains changed with latitude: GFDL (−12 to 60%) and CGCM (−20 to 20%) and temperature (Stambaugh et al. 2008). Decreased fire probabilities (negative percentage) were predicted for the hotter southern plains region. Some of the largest differences in fire probabilities predicted by the models were in the southwestern United States (Figure 3). Here, the CGCM data resulted in decreased future fire probability (0 to −30%) while the GFDL data resulted in increased fire probability (near 0 to greater than 40%; Figure 3). In the northeastern United States, the two global change model outputs into the PC2FM resulted in no difference in direction (all positive outcomes) but some differences in their magnitude (GFDL = ∼ 40%, CGCM = 80%). In the southeastern United States, PC2FM outputs based on the two models resulted in increased fire probabilities with some latitudinal differences in magnitude (GFDL = ∼ 0–90%, CGCM = 10–70%). The largest increases in fire probabilities for both climate models were in Appalachia, a montane region known for fire activity during dry spring and fall seasons (Lafon et al. 2005).

Continental Trends in Changing Fire Probabilities

Fire probability estimates were mapped for both GFDL and CGCM climate change data simulations (Figure 4). Although regional fire probabilities varied by GCM and region across the continental United States in their response to future temperature and precipitation inputs into the PC2FM, the overall spatial area of the continent showed more increases in fire probability than decreases (many more red hues than blue in Figure 4). These positive increases in overall fire probability are consistent with results from other future-fire climate modeling efforts (Xu et al. 2013). Climate-forced changes in fire probability in the United States were between −40 and over 275% for the GFDL and the CGCM. The predicted future fire probabilities already fall into the range of documented past and current fires in many North American climates. The largest increases in fire probabilities were in colder and wetter ecosystems where temperature and precipitation are affected by latitude and elevation (e.g., the Northern Rocky Mountains) while the few decreases in fire probability were in hotter and dryer ecosystems. Overall, there are more increases in fire probabilities in the northern than in the southern United States.

Discussion

Model Integration and Mapping

For the objectives of this study we wanted to keep the framing and method for the PC2FM fire probability changes as straight forward as possible. Thus, we temporally compared only current and future forecasts from the same global change models (CGCM, GFDL) to "drive" the PC2FM predictions. When comparing different spatial scale model estimates for different time periods, problems in estimating fire probability due to the spatial scale of temperature and precipitation data arose. In the fire probability maps (Figure. 4) probability estimates are calculated from two of the model components of PC2FM (Equation 1; Figure 1) that have different influences in different ecosystems (Guyette et al. 2012). For example, the fuel production and availability as calculated by the reactant concentration term (PT_{rc}) is very important in many dry and/or cold ecosystems where reactant (fuel) concentration can be a major factor limiting fire reactions. In the continental United States, the spatial majority of ecosystems produce enough fuel but have fire probability restrictions due to reaction rates limited by climate (too much water or too cold). Often fine-scale modeled climate data when matched with large spatially scaled GCM data will result in exaggerated fire probabilities due solely to the differences between model scales. For example, both low (deserts) and high elevation (mountain) ecosystems with annual temperature differences occur in the large cells of the GCM climate output. Thus, GCM cells with high elevation variance can have misleading fire estimates at small individual scales.

Unbiased Climate-Forcing Results

Separating climate from the many variables that effect wildland fire probability is a difficult and debated matter. Many indirect climate effects influence management and biological changes (e.g., biotic effects on fuels). Climate effects on animal species and their population can result in dramatic effects on wildland fire (Jenkins et al. 2013). Estimating changing fire probabilities using only the framework of physical chemistry and climate allows for a more

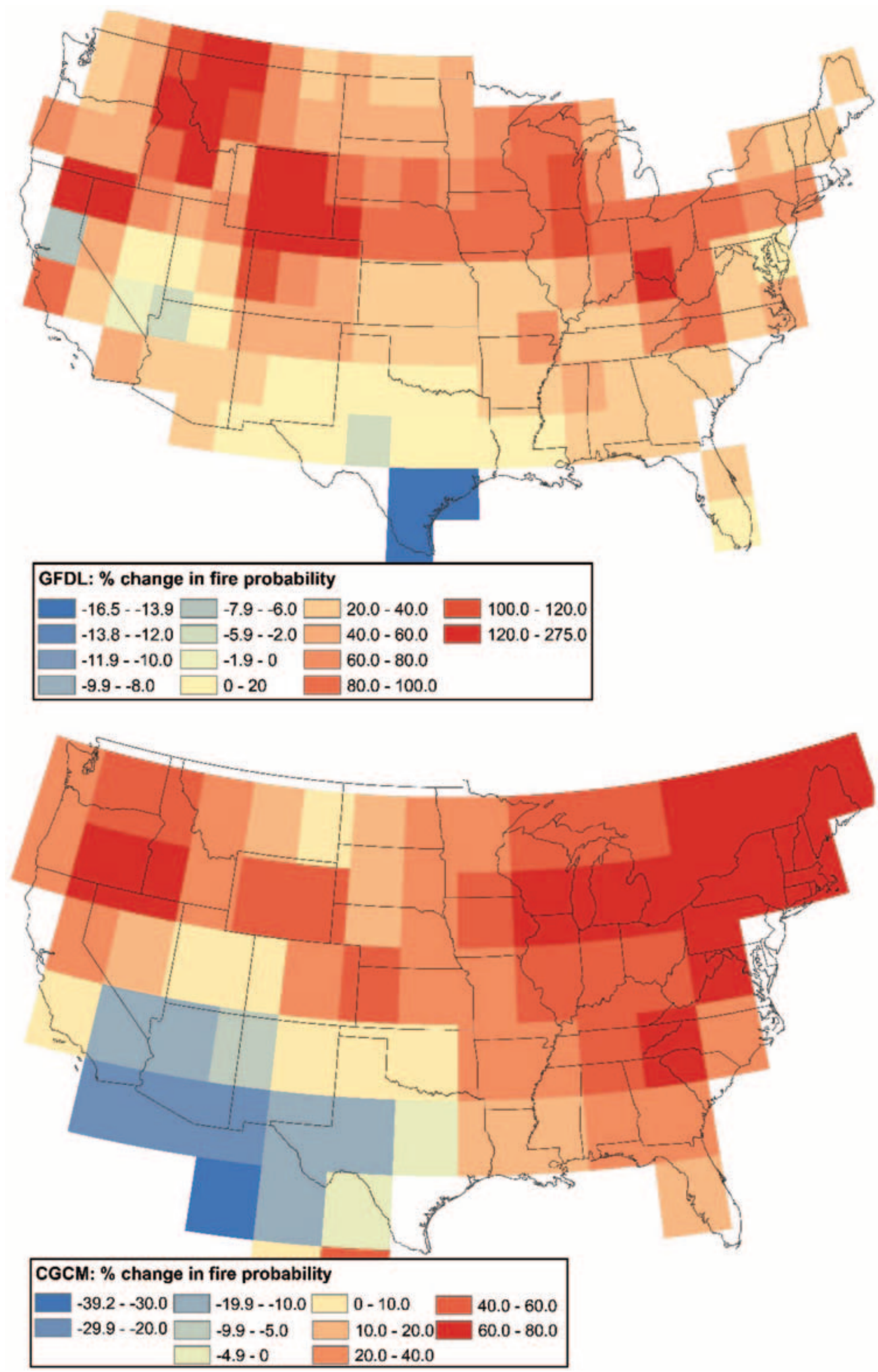

Figure 4. Coarse-scale mapping of climate-driven changes in the probability of fire occurrence in the United States on 1.2 km^2 areas in 2100 based on GFDL CM2.1 data (top) and CGCM 3.1 T47 (bottom).

focused if somewhat limited model using climate change data as overarching fire variables. Thus, the climate-forcing predictions are less biased with respect to changes in land use, vegetation, the number of fire departments, and so many other important, but nonclimatic changes. A major result of the application of the PC2FM in this work is the resulting framework for recalculating fire probability with near future GCM data.

Using Physical Chemistry to Quantify the Interactions between Temperature and Precipitation

The Arrhenius concept in the PC2FM quantifies the exponential effects of temperature in degrees K (*ARterm*) and the dual or quadratic effects of precipitation (both *ARterm* and PT_{rc}). The exponential and unidirectional effects of temperature increase the apparent importance of this variable in most regimes. The complex opposing effects of precipitation on reactant quality (fuel moisture) and quantity (fuel concentration) mask the importance of this climate variable. Threshold values for the switch in precipitation forcing (from concentration to reaction environment) have been hypothesized (Guyette et al. 2012). Reactant concentration threshold values range from about 40 to 100 cm annual precipitation based on ecosystem average temperatures. These abiotic factors, although difficult to identify from mapping output, are critical to the rates and probabilities of combustion reactions.

Temperature versus Precipitation Drivers of Fire

We used precipitation as a proxy in the PC2FM for two contrasting influences on wildland fire: humidity and fuel moisture inhibit fire rates and the production of fuel increases with available water at a given temperature. These effects were quantified by precipitation (Figure 1) in both the rate term (*ARterm*) and the fuel reactant concentration term (PT_{rc}). Ecosystem precipitation can both increase and decrease the probability and rate of wildland fire (Davis and Miller 2004, Collins et al. 2013). These contrasting positive and negative forces quantitatively diminish the total effect of precipitation because of their opposing directions of influence. On the other hand, the effects of temperature alone on reaction rates (*ARterm*) are never negative and are primarily positive in ecosystems with even a moderate amount of fuel. Nonetheless, temperature can have a dual effect on reactant concentration by constraining fuel production in ecosystems by being too hot (Death Valley) or too cold (Greenland Ice Cap) at a given precipitation. While the single exponential effect of temperature (in K) on the natural logarithm (e) can greatly increase the rate of reactions, the hotter an ecosystem gets, the steeper or more rapid the reaction rate changes.

Precipitation Data Uncertainty in Fire Modeling

Many of the climates in the world are not well predicted with regard to fire events as positive or negative in response to precipitation. Precipitation effects on landscape reactions and reactants are important for many reasons such as fuel moisture, fuel productivity, and humidity (Anderson 1970, Nelson 1984). Fire models that do not include the two-prong effects of precipitation (negative reaction rates and positive reactant concentration) are missing an important forcing factor.

Precipitation events are caused by many interacting factors. Small differences in model coefficients among any of these factors will influence estimated rates and seasons of precipitation. Thus, precipitation is more difficult to predict than temperature because of the influence of multiple factors. Predicting precipitation with models based on many unknown future metrics and their complex interactions makes precipitation forecasts difficult and uncertain but still important for fire prediction models (Allen and Ingram 2002, Ma and Xie 2013). Current research suggests that we are headed for complex changes that include increased precipitation variance in storm output, humidity, and long-term pluvial-drought periods (Allan and Soden 2008, Giorgi et al. 2011).

Annual Climate and Fire Variability

The PC2FM approach relies on average annual values of precipitation and temperature over long periods. Yet fire occurrence is most often problematic because of extreme dryness and high temperatures in a season or year. Although we predicted average fire probabilities based on climate averages, many ecosystems vary greatly in annual temperature and precipitation from year to year and season to season. Inter- and intra-annual variation in temperature and precipitation may greatly accentuate fire variability beyond average changes in GCM-PC2FM predictions and may potentially produce some extreme new fire-climate conditions (Groisman and Easterling 1994). For example, the northeastern United States has a highly variable seasonal fire climate: wet and cold then dry and warm conditions in the same year. Wet conditions make for abundant fuel production (concentration) in the growing season, while potentially dry-warm conditions in the spring, summer, or fall enhance reaction rates and fire spread.

Climate Change Forcing Already Here

Although we used GCM data of current climate as a control period, it is debatable in which period to place the control climate. Climate change is hypothesized to have already begun with temperature increasing over the last 160 years. The forcing of more frequent and larger fires is now happening in many ecosystems and may be due partly to climate. For example, some recent large fires (in the temporal framework of the global change models), such as the 1988 Yellowstone National Park, occurred in some of the regions with the highest fire probability changes in this study (darkest reds; Figure 4) (Westerling et al. 2011).

Unique Conditions in the Southwest

As might be expected, fire probabilities in most, but not all, ecosystems increased with temperature (Figure 4). The primary importance of temperature in drought and fire regimes has been suggested in many studies (Xu et al. 2013). Future predictions of fire probability based on temperature alone may be robust due to more reliable temperature prediction compared to precipitation. Future precipitation is more difficult but is integral to fuel production and moisture in the PC2FM (Figure 1). However, the effects of increasing precipitation, water, and humidity are too great on the reaction environment (*ARterm*) and fuels (PT_{rc}) to be ignored (Nicholls et al. 1996, Karl and Knight 1998). Water variables affect all parts of the combustion reaction from collision frequency to fuel concentration and availability (Figure 1). The variance in CGM precipitation outputs results in much of the variance between fire probability estimates (Figure 3). The predictive value of the PC2FM compared to other fire models may be in quantifying the physical and chemical interactions between the water, combustion, and fuel. The exceptions to increasing fire with increasing temperature (blue color coded regions in Figure 3) occur in fuel-limited dry regions where increased temperature can decrease fuel production and continuity.

Two reasons for the nonintuitive mapping results in the southwestern United States are: mapping resolution is much larger than model resolution and ecosystems changing from reaction rate limited to concentration rate limited are abundant in the Southwest. The southwestern United States is a complex of ecosystems from fuelless deserts to high mountain forests. Annual precipitation ranges from < 10 to more than 125 cm. There is no doubt that decreasing precipitation and increasing temperature will decrease plant growth (fuel production), especially in dry ecosystems that are already fuel-limited systems. Much of the land area of the Southwest is comprised of ecosystems with less than 50 cm of annual precipitation. Despite the large scale of global climate change estimates of temperature, our model predicted that the southwest will have decreased probabilities of fire. If the climate mapping data were finer scale, one would expect increasing fire probability in the few cooler and wetter high elevation ecosystems. Also, below about 50 cm of annual precipitation, at southwestern temperatures, the effect of precipitation on fire in ecosystems switch from reaction rate driven to primarily fuel limited very rapidly (Guyette et al. 2012). This is true with any reaction rate, a first lesson at the chemistry bench; the greater the reactant concentration, the faster the reaction will occur.

Limitations

The physics and chemistry of climate forcing in fire regimes will not change and can be used to bridge temporal and spatial landscapes, but vast amounts of variance in fire regimes results from human ignitions, fire suppression, land use, real estate value, fire department location, roads, and with the temporal and spatial scale of interest. These nonclimatic factors can overwhelm climate effects, especially during short periods and at small spatial scales. Thus, our predictions are limited to only potential climate effects and do not include many other important factors. It would be remiss of us to make absolute estimates of fire probabilities in the distant future without addressing the many nonclimatic factors. Thus, unlike prediction of past mean fire intervals using climate (Guyette et al. 2012), predicting future mean fire intervals for regions with greatly changed nonclimatic factors would not be appropriate. Only the extent (percentage) of change due to climate effects on fuel and combustion can be predicted or simulated.

Physical Chemistry Model Calibration with Diverse Data Sets

Although there are many ways to address fire in the future, our presentation here allows for the use and model calibration with many types of climate-fire data. These include state-level fire numbers with average state temperature and precipitation, Moderate Resolution Imaging Spectroadiometer (MODIS) fire starts and temperature and precipitation, local fire department annual fire records and climate, and long-term fire scar records as used to calibrate the PC2FM presented here.

Summary

The framing of future climate effects on future fire regimes will change with the strength and calibration of global climate data sets, their inputs, and modeling improvements. The results of this fire modeling approach will be adaptable to new climate simulations and the increasing range of new fire calibration data. This approach's greatest strength may lie in using only climate data and the simple principles of physical chemistry. The many other nonclimatic factors that affect fire are often difficult to predict in the distant future. Additionally, many nonclimate variables are perhaps even less predictable than temperature and precipitation given 50 to 100 years of potential rapid changes in human technologies, societal needs, and values.

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