Ecosystems (2012) 15: 322–335
DOI: 10.1007/s10021-011-9512-0

ECOSYSTEMS

Predicting Fire Frequency with Chemistry and Climate

Richard P. Guyette,[1]* Michael C. Stambaugh,[1] Daniel C. Dey,[2] and Rose-Marie Muzika[1]

[1]*School of Natural Resources, University of Missouri, Missouri Tree Ring Laboratory, 203 ABNR Building, Columbia, Missouri 65211, USA;* [2]*Northern Research Station, U.S. Forest Service, Columbia, Missouri 65211, USA*

Abstract

A predictive equation for estimating fire frequency was developed from theories and data in physical chemistry, ecosystem ecology, and climatology. We refer to this equation as the Physical Chemistry Fire Frequency Model (PC2FM). The equation was calibrated and validated with North American fire data (170 sites) prior to widespread industrial influences (before ~1850 CE) related to land use, fire suppression, and recent climate change to minimize non-climatic effects. We derived and validated the empirically based PC2FM for the purpose of estimating mean fire intervals (MFIs) from proxies of mean maximum temperature, precipitation, their interaction, and estimated reactant concentrations. Parameterization of the model uses reaction rate equations based on the concentration and physical chemistry of fuels and climate. The model was then calibrated and validated using centuries of empirical fire history data. An application of the PC2FM regression equation is presented and used to estimate historic MFI as controlled by climate. We discuss the effects of temperature, precipitation, and their interactions on fire frequency using the PC2FM concept and results. The exclusion of topographic, vegetation, and ignition variables from the PC2FM increased error at fine spatial scales, but allowed for the prediction of complex climate effects at broader temporal and spatial scales. The PC2FM equation is used to map coarse-scale historic fire frequency and assess climate impacts on landscape-scale fire regimes.

Key words: North America; climate; dendrochronology; fire frequency; physical chemistry.

Introduction

Climate influences, specifically temperature and precipitation, have been identified as primary controls on global wildfire occurrences in the modern era (ca. 1980-present) (Westerling and others 2006; Bernard and Nimour 2007; Krawchuk and others 2009; Parisien and Moritz 2009). Beyond climate attribution, little progress has been made toward describing the long-term physical and chemical mechanisms of fire occurrence rates or toward parameterizing fire–climate models with significant predictive ability (Swetnam and Betancourt 1990). Although recent analyses have begun exploring modern era climate–fire controls using newly developed satellite detection methods, significant gaps in our understanding of these controls remain. Fire models, particularly those describing rates of occurrence forced by climate, are needed to

Received 21 June 2011; accepted 21 November 2011; published online 4 January 2012

Electronic supplementary material: The online version of this article (doi:10.1007/s10021-011-9512-0) contains supplementary material, which is available to authorized users.

Author Contributions: RP conceived study, site selection and collection, performed research, chemistry and process model design and analysis, wrote paper; MS contributed to study design, data collection and analysis, mapping, and editing; DD performed research, data collection, wrote paper; RM contributed to data collection, editing, and paper writing.

Corresponding author; e-mail: guyetter@missouri.edu

assess carbon emissions (Kaiser and others 2009), fire–vegetation feedbacks and alternate stable states (Beckage and Ellingwood 2008), and potential climate change effects on wildfires.

North American ecosystems are strongly influenced by temperature and precipitation, two important physical–chemical factors controlling their fire regimes (Wright and Bailey 1982; Pyne and others 1996). Knowledge of the fire history record provides an ecological basis for past and future management and restoration (Swetnam and others 1999; Pausas and Keeley 2009). Much of North America is without quantitative scientifically based fire regime information. Currently, continental-scale models of fire regimes are based on vegetation associations (Keane and others 2002; Hann and others 2004) that have resulted from past climate and fire conditions. More recent modeling efforts have demonstrated the importance of climate variables as predictors in modern fire regimes (Westerling and others 2006, 2011; Parisien and Moritz 2009). In many locations, site-specific fire history may never be obtained owing to a lack of possible charcoal or fire scar chronologies. Therefore, there is value in a predictive model that synthesizes existing fire history information and formulates fire frequency estimates (for example, mean fire interval, MFI) based on the physical and chemical properties of climate. The model described in this work is useful in quantifying the role of climate in fire regimes for ecosystems lacking in empirical fire regime information.

Faced with the problems and effects of wildland fire, it is easy to overlook that fire is fundamentally a chemical reaction. As such, chemical reactants and reactions in ecosystems are subject to the principles of physics and chemistry as well as many other ecosystem processes (Figure 1). Here, we use the principles of physical and concentration chemistry along with fire history data to develop, calibrate, and validate a model that predicts MFI. The model uses climate variables via chemistry to estimate MFI. The logic of the Physical Chemistry Fire Frequency Model (PC2FM) approach and form was inspired by Arrhenius' equation—a fundamental rate equation in physical chemistry. Our overall approach combines both theoretical chemistry and fire ecology to develop an empirical model (Table 1) that translates molecular chemistry to an ecosystem process.

The PC2FM utilizes long-term (that is, multi-century) ecosystem fire event data because: (1) fires can occur infrequently (Gavin and others 2007), (2) climate–fire relationships during post-industrialization periods are masked by anthropogenic effects

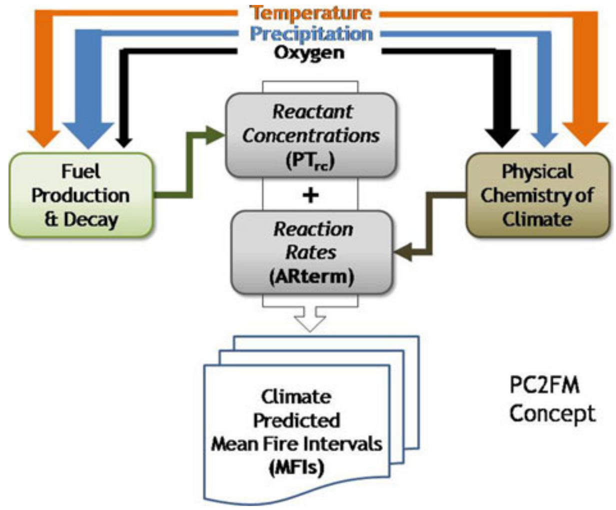

Figure 1. A conceptual diagram describing the relationship of the three climate variables (precipitation, temperature, and oxygen) used in the two model parameters (*gray boxes*) of the Physical Chemistry Fire Frequency Model (PC2FM). Temperature and precipitation are used to create a proxy for available fuel (Figure 2). Both biological and combustion processes are embedded in the PC2FM using temperature and precipitation interactions. *Arrow widths* represent the relative contribution of the climate and reaction processes in the PC2FM. Arrow colors represent temperature (*red*), precipitation (*blue*), and oxygen (*black*).

(Marlon and others 2008; Stambaugh and Guyette 2008), and (3) decades of fire suppression in many fire-dependent ecosystems may lead to underrepresentation of burning rates in modern era (~1900 to 2010 CE) fire records. Studies involving paleofire data (for example, fire scars, charcoal) show that wildfire occurrences are influenced by climate (Clark 1988; Bergeron and others 2004; Kitzberger and others 2007), vary spatially and temporally, and are affected by many finer-scale factors such as ignition rates and topography (Morgan and others 2001). Less obvious, however, are the physical–chemical relationships controlling wildfire occurrence through a continuum of climates. The calibration of physical–chemical differences affecting fire in ecosystems will be particularly important in light of potential future climate changes (Goldhammer and Price 1998; Stocks and others 1998; Westerling and others 2006).

A significant proportion of the variation in fire frequency at coarse spatial and temporal scales can be explained by terms that describe how fire depends on the influence of temperature, activation energy, precipitation, and reactant chemistry. To demonstrate this we used a functional relationship, a negative exponential, comparable to

Table 1. PC2FM Climate and Fire Inputs, Their Foundations in Fire Ecology and Chemistry, and Model Parameters and Variables

Climate and fire model inputs	Foundations in fire ecology	Foundations in fire chemistry	Model parameters and output	Variable code
Temperature means and scaling metric	Temperature influences fire behavior, fire frequency, species composition and associated fuel structure. Temperature affects the seasonality of fire occurrence and frequency (Westerling and others 2011)	Temperature influences reaction rates via kinetic energy and reactant concentrations (fuel production and decay) as well as combustion (McQuarrie and Rock 1987)	PT_{rc} and AR-term	T_{max}
	Temperature in °C, a common metric based on the properties of water, one of the basic components of ecosystems. Field measures of fire conditions are usually based on this scale (Kimmins 1996)	Temperature in K is the necessary metric for physical chemistry, based on absolute zero, energy kinetics, and thermodynamics (Atkins 1986)	PT_{rc} and AR-term	T_{max}
Precipitation as a proxy for fuel production, moisture, and humidity	Increases in humidity and precipitation require higher temperatures for the combustion, ignition effectiveness, and sustaining fire. Relative humidity is the common measure of fire conditions (Chandler and others 1983)	Increased activation energy requirements for wet fuels and decreases in collision frequency of reactants from interference by water vapor (Chandler and others 1983)	ARterm, A_o and E_a	P
	Precipitation is positively related to fuel production, fuel loading, vegetation type (grassland or forest), and fuel density. Growth rates are can rapidly or slowly replenish fuels after fires (Bond and van Wilgen 1996)	Increasing the concentration of reactants increases the rate of a reaction as calculated by 'rate laws' and reaction mechanisms (McQuarrie and Rock 1987)	PT_{rc}	P
Oxygen concentration as estimated by elevation	Average wind speed is a critical factor affecting spread rate, vegetation structure and type. Elevation, topography, and weather conditions influence wind and fire behavior (Pyne and others 1996)	Rapid oxygen additions to the gaseous reactant solution accelerate the potential concentration of the most stoichiometric limiting reactant $[6]O_2$ to $[1]C_6H_{12}C_6$ (Harris 1987)	ARterm and A_o	ppO_2
Fire frequency observed mean fire intervals (MFI)	Long-term fire frequency, intensity and rate of spread are influenced by vegetation, fuel structure, fire weather, and climate (Wright and Bailey 1982)	Reaction rate and probability based on reactant concentration and physical chemistry (Harris 1987)	Model output and calibration	MFI

Model parameters are the Arrhenius term (ARterm) and the reciprocal moisture index (PTrc).
Variable codes: T_{max} annual mean maximum temperature, P mean annual precipitation, A_o collision frequency, E_a activation energy.

reaction rate calculations applied in physics and chemistry. This modeling approach does not explain all variation in the fire frequency of ecosystems, much of which occurs at finer scales. In most ecosystems, fine-scale fuel structure, moisture, fuel type, micro-climate, geography, topography, ignition frequency, and many other local factors control the variance in fire frequency. Therefore, we derived an empirical model from three variables (temperature, precipitation, and oxygen) and combined these into two parameters that estimate fuel availability (concentration, moisture) and combustion rate processes (for example, temperature, activation energy). The physical, chemical, and mathematical formulations of the two parameters are based on experimental and theoretical chemistry. We fit the model with historical fire frequency and climate data as inputs to generate outputs of MFIs. The objectives of this model development and research were to:

1. Construct a model for use with common climatic and spatial data that would enable the climate forced fire frequency estimates at variable scales and time periods (past and future),
2. Test the use of theoretical chemistry as an approach for structuring model parameters that describe ecosystem processes.

The Concept of the PC2FM

The PC2FM modeling approach utilized the Arrhenius equation $\left(k = A_0 \exp^{-E_a/RT}\right)$ as a template for the effects of physical chemistry on fire frequency. We call this model parameter ARterm (Equation 1: $b_1 A_0 \exp^{E_a/RT}$). A second model parameter PT_{rc}, (Equation 1: $b_2\left(\frac{1}{P^2 T}\right)$ is a proxy for fuel availability (concentration and moisture) based on climate data. The details of the PC2FM's chemistry and fire ecology concepts are generally written as:

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

where MFI is the mean fire interval; b_0, b_1, and b_2 are the potential regression coefficients for the intercepts ARterm and PT_{rc}; A_o is a proxy term for molecular collision frequency; E_a is the reactant activation energy; R is the universal gas constant; T is temperature; and P is precipitation.

Rate Definitions and Analogy (MFI)

MFIs are the ecological analog of rate constants (k) in the output of the Arrhenius equation and the PC2FM's ARterm. The change from a rate constant to MFI is a change from rate to likelihood. The analogy works because weather and climate conditions are dominant factors that affect combustion and fire occurrence. The likelihood a fire will ignite and the probability that it will spread are based on the ecological and chemical characteristics of the reaction environment.

The translation from the Arrhenius rate constant (k) to the PC2FM's fire frequency rate (MFI) in reactions reflects a change in units from reactions per second to fires per year (1/MFI). The rate constant (k) and MFI are rates that scale in opposite directions. The negative sign in the Arrhenius exponential term is removed because of this difference in the rate metric between the ecological measures such as MFI (time/# combustions) and chemistry measures such as rate (# combustions/time).

Collision Frequency (A_o), Reactants, and Precipitation (ARterm)

A_o in the Arrhenius equation represents the rate of possible molecular collisions of the reactants (carbon compounds and oxygen) based on their physical and chemical properties. In ecosystems, one important non-reactant molecule (for example, water vapor) can decrease the collision frequency of reactants in gaseous combustion reactions. Fuel moisture and humidity are extremely variable in ecosystems and can lead to considerable variability in collision frequency. We use annual precipitation as a proxy for fuel moisture and humidity in ecosystems. When water vapor is introduced into a volume of dry air, the number of other molecules (primarily N_2 and O_2) in the volume must decrease. Thus, humidity decreases the partial pressure of O_2, dilutes reactants (given an equal temperature and pressure), and decreases the probability of a collision and reaction. Collisions among reactant molecules (for example, various carbon compounds and oxygen) must have a definite geometric orientation of their electrons (the steric factor in collision theory) for a reaction to occur. Because the complexity of natural carbon molecules (fuel) is great among and within ecosystems we do not differentiate among ecosystems with respect to the steric factor in collision frequency.

Activation Energy (E_a), (ARterm)

The activation energy (E_a) required to begin a combustion reaction among different wildland fuels ranges from about 80 to more than 140 kJ mol^{-1} (Roberts 1970; Ragland and Aerts 1991; Leroy and others 2010). Processes such as fuel decay and production can influence activation energy requirements even though they are often mitigated by catalysts and enzymes. We use a constant value for E_a in the PC2FM because the complexity of natural fuels and activation energies in ecosystems is not the focus of our research. We based our E_a value on literature describing activation energy dynamics in forest and carbon based fuels and model outputs for a range of E_a values. We selected a value of E_a that was a best fit for the data (132 kJ mol^{-1}) based on regression results using E_a values ranging between 100 and 140 kJ mol^{-1}.

Universal Gas Constant (R), (ARterm)

In chemistry, the universal gas constant (R) is used in the formulation of reaction equations involving gases and is needed to estimate reactant concentrations at given pressures, volumes, and temperatures. The gas constant does not have an equivalent ecological application in models of fire frequency because of the large difference in scale of application. The Universal gas constant is used in the PC2FM as the proportionality constant. The gas constant (R) is given as energy (Joules) per molar mass (mol) per a standard temperature (K).

Temperature (T), (ARterm)

Model development in extremely low temperatures indicated that the Kelvin temperature scale is necessary for determining fire intervals using physical chemistry. The physical reason for Kelvin units is that the Arrhenius equation is based on thermodynamic and kinetic theories. These theories are based on molecular forces that begin at absolute zero. Thus, we converted temperature data from Fahrenheit or Celsius to Kelvin to be consistent with the principles of physical chemistry and to allow model representation in regions with cold (<0°C) mean annual temperatures.

Fuel Concentration and Quality in Ecosystems (PT_{rc})

Fuel loading and fuel moisture are important factors controlling fire behavior and rate. Thus, a second model parameter was developed for characterizing climate effects on ecosystems via reactant (fuel) concentration and quality (moisture content). For this, we developed a reactant availability parameter (PT_{rc}) from a combination of precipitation and temperature. This parameter is not only a proxy for biomass (fuel) but for reactant availability with respect to moisture. The concentration of reactant molecules is important to reaction rates, but if they are enclosed in non-reactant molecules (H_2O) then they do not contribute to a concentration effect. This parameter was developed through model testing of MFI estimates in ecosystems that rarely burn because of very low fuel concentrations or very high fuel moisture. The function of PT_{rc} is to account for the change in the direction of reactant availability from factors controlling concentration to moisture (Figure 2). This parameter is sensitive to small differences in precipitation at very low levels (for example, annual precipitation of 10–40 cm). For instance, there are only small differences between the PT_{rc} of rarely burned deserts to frequently burned semi-arid grasslands.

Methods

Fire History Data

Development and calibration of the PC2FM utilized MFI data from throughout North America. Tree-ring dated fire scars have provided long-term records of fire frequency and fire–climate interactions from diverse forested sites across North America (Supplementary Data 1 and 2). For more than 30 years these data and other complementary

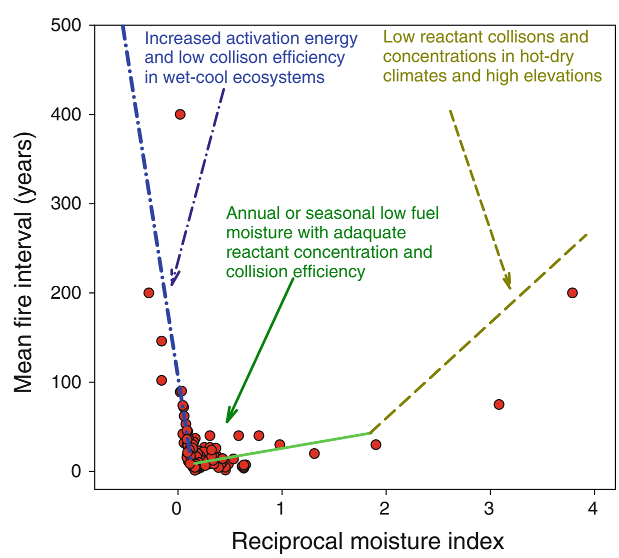

Figure 2. Observed mean fire intervals plotted against a reactant concentration and fuel moisture proxy the PT_{rc}—a parameter in the PC2FM. The *dotted-dashed line* represents regions where high fuel moisture is the most important variable controlling fire frequency, the *solid line* represents regions where fuel production is sufficient, and the *dashed line* represents regions where the low concentration of reactant is controlling fire frequency. Fuel loading and moisture are standard algorithms used in fire rate equations.

paleofire evidence (for example, charcoal) have been the foundation of fire and ecosystem theories (Dieterich and Stokes 1980; Swetnam and others 1999; Lynch and others 2004; Whitlock and others 2004). MFI data represent time periods prior to widespread industrial influences that significantly altered fire regimes through increased ignitions, fire suppression, changes in native and domestic grazing regimes, grain crop agriculture, and other land-use activities that modified or fragmented ecosystems and fuels (Pyne and others 1996). We assumed that minimizing industrial era effects on MFIs will maximize calibration accuracy of the PC2FM. The current PC2FM database includes fire history study sites across North America with annual mean maximum temperatures ranging from 261.1 to 305.1 K (−12 to 32°C), annual mean precipitation ranging from 8 to 456 cm, and MFIs ranging from 1 to more than 400 years. Annually averaged temperature and precipitation data provide the most meaningful climate data for this extensive database because they are closely related to the biological and physical constraints of annual fuel production and decay. In addition, analyses of long-term fire rates with diverse climates and fire seasons are comparable only at an annual scale or longer.

Fire scar history data were gathered from published scientific studies, new and recently completed fire scar history data sets, and the International Multiproxy Paleofire Database (NOAA). The PC2FM fire history database consisted of 170 fire scar sites (Supplementary Data 1). Sites were included in the database if they satisfied these criteria:

(1) Site fire histories were deemed important when they represented distinct climate conditions, expanded the range in the length of MFIs in the database, covered the pre-industrial period, and to a lesser extent expanded the geographical coverage of the database.
(2) We used composite MFIs as a robust estimate of the occurrence of fire within a given area (Dieterich and Stokes 1980). This type of fire interval is subject to increasing frequency of fire with increasing area, therefore, comparisons between sites necessitate comparable study areas (Baker and Ehle 2001; Falk and others 2007; Heyerdahl and others 2001). Sites included in this study averaged 1.32 km^2 in area, ranged from less than 0.10–8.1 km^2, and had a standard deviation of 1.27 km^2. Only two sites were larger than 4 km^2. Prior to analysis we found that within this range of site area differences, there was no significant correlation between site area and MFI ($r = 0.056$, $P = 0.54$) as might be expected by having variable sample areas.

Other Data and Estimates

As trees occupy a stratified sample of ecosystems that meet conditions of moisture and temperature necessary to support large woody plant growth, we needed other fire frequency data sources to characterize regions where trees do not grow or are not scarred by fires. In addition, at large spatial scales, fire scar histories are often stratified and biased because they come from tree species that grow in the positions of the landscape where fire intervals are shorter. To minimize these influences we supplemented the fire scar data with charcoal data (three sites) and expert estimates (seven ecosystems) (Schmidt and others 2002). Although many charcoal study sites exist, few were used because of their often low temporal resolution compared to fire scars on trees.

Climate Data

PC2FM parameters were tested and chosen based on physical chemistry, ecological relevance, statistical significance and explanatory power, and, to a lesser extent, ability to be mapped using a geographic information system (GIS). Currently the PC2FM utilizes three covariates of MFIs: annual mean maximum temperature (T_{max}), mean annual precipitation (P), and the estimated partial pressure of oxygen. The partial pressure of oxygen (Figure 1) is estimated from elevation (Jacobson 2005). Climate covariates represented averages for the 1971–2000 CE (30 years) period. Two other climate variables were tested for significance using correlation analysis but were not used; annual mean minimum temperature and annual mean temperature. It is possible that annual mean temperature could be substituted for T_{max}; however, T_{max} has consistently explained a greater percentage of variance during diagnostic tests. The T_{max} data used for calibration is a 'proxy' in the sense that the model period (~1650–1850 CE) is different than the climate data period (1971–2000 CE). We maintain that errors caused by this difference in time period are minimal because the temporal variability in temperature (Mann and others 1998) is small (temperature increase of ~0.4 K from 1750 to 1970 CE), particularly compared to the spatial variability that exists among sites (26 K). We subtracted 0.4 K from annual mean maximum temperatures to correct for recent warming since the period of the MFI data.

Statistical Development, Calibration and Validation of the PC2FM

The theoretical based formulation of the two parameters (ARterm, PT_{rc}) and the expected responses of the model were tested by the empirical MFI data. We used multiple regression analysis and coefficients to test parameters of the PC2FM. This was necessary because the molecular dimensions, molecular species, numeric complexity, and reactant concentrations are unknown for many important reactions in ecosystems. Regression analysis was used to develop coefficients and parameter structures of the PC2FM thereby forming the ''bridge'' between physical chemistry and ecosystem fire frequency. Regression coefficients were translated from the relatively fine-scale units of chemistry (that is, kJ^{-1} mol^{-1}, molecular reactions per second, and partial pressure of oxygen) to the landscape-scale ($\sim$1 km^2) fire frequency (MFIs) of the PC2FM.

The PC2FM equation was selected from regressions utilizing bootstrapping methods. Final model selection was based on chemical processes (that is, rate equations), knowledge of fire ecology, and test statistics such as variance inflation factors (VIFs), correlations, residual analysis, normality, variable significance and stability, and model r^2. The distribution of 100 coefficients of determination, calculated from randomly chosen halves of the data with replacement, was used to assess the models calibration, validity, and stability.

Mapping Estimates of the PC2FM

PC2FM estimates of MFIs were mapped using ESRI®ArcGIS™ software (ESRI (Environmental Systems Research Institute) 2005). Grid data of mean maximum temperature and mean annual precipitation (PRISM data; Daly and others 2004) were applied to Equation 2 to produce maps of MFIs for the pre-Euro American settlement period ($\sim$1650 to 1850 CE). A digital elevation model was used to map the partial pressure of oxygen (Jacobson 2005).

Model Prediction Responses at Different Temperatures and Precipitation

We used the PC2FM to examine the model estimates of MFI change in three ecosystem scenarios with hypothetical average temperatures: cold at 280 K, warm at 289 K, and hot at 297 K. Precipitation thresholds were defined as inflection points along MFI prediction lines where differences in precipitation changed the direction of MFI response to climate. This modeling exercise is meant to yield quantitative estimates of the interaction between the opposing effects of precipitation on fire regimes (that is, fuel amounts and moisture) at different temperature regimes. In addition, this exercise was done as a diagnostic test of the behavior and performance of the model for prediction.

Results

Model Coefficients and Statistics

The PC2FM is described by the equation:

$$\mathrm{MFI} = 0.232 + \left(2.62 \times 10^{-28} \times ARterm\right) + \left(52 \times PT_{rc}\right), \quad (2)$$

where MFI is the mean fire interval in years, ARterm is $A_o \times \left(\exp^{E_a/(RT_{max})}\right)$, $A_o = P^2/{}_{pp}O_2$, P is mean annual precipitation in cm, ${}_{pp}O_2$ is the estimated partial pressure of oxygen: 0.2095 × $(\exp^{(-0.12\ \times\ \text{elevation})})$ is the elevation in km, exp is 2.718, E_a is 132 kJ mol^{-1}, R is 0.00831 kJ mol^{-1} K^{-1}, T_{max} is the annual mean maximum temperature in K, and PT_{rc} is $1/(P^2/T_{max})$.

All variables were significant ($P < 0.001$). Multicollinearity among predictor variables was negligible, the variance inflation factor was 1.01, the correlation ($r = 0.056$) between ARterm and PT_{rc} was not significant, and the residuals were normally distributed. The 95% confidence limit for the model was ±2.5 years (Figure 3A). Model prediction limits were ±35 years. The PC2FM was calibrated with 86 observations and validated on random selections of half of the 170 data observations. Based on 100 model runs the average tested model coefficient of determination (r^2) was 0.80 (range = 0.59–0.90) (Figure 3B). We estimated the partial r^2 of the independent variables using a natural logarithmic transformation of the dependent variable (MFI). Estimates of partial r^2 were 0.60 for ARterm and 0.20 for PT_{rc}.

Mapping

We developed a model that could map spatially explicit estimates of MFIs utilizing three variables: temperature, precipitation, and the ${}_{pp}O_2$. We mapped PC2FM estimates of historic MFIs (Figure 4) for the conterminous United States utilizing gridded climate data (PRISM Products; Daly and others 2004).

Modeled Responses of Fire Frequency to Changing Climate Conditions

The PC2FM showed different responses to three different ecosystem climate scenarios. The three temperature scenarios resulted in three different

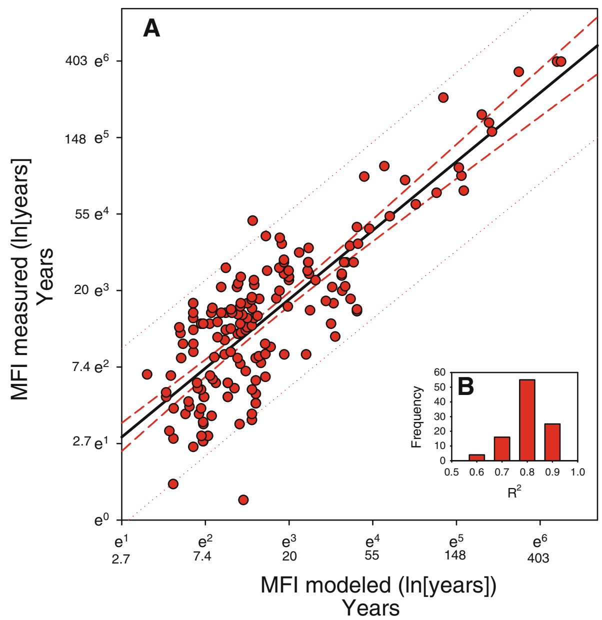

Figure 3. A Plot of predicted (base PC2FM) and observed mean fire intervals (MFIs) for all fires and their 95% confidence (*long dashed line*) and prediction (*short dashed line*) intervals. Predicted MFIs are based on PC2FM that are validated using only mean fire intervals shorter than 200 years. **B** r^2 of model estimates from 100 model runs representing random samples of ~50% of the data drawn with replacement.

threshold values for the interactive effects of temperature and precipitation on fire regimes (Figure 5). This exercise yielded quantitative estimates of the thresholds that divided the opposing effects of precipitation on fire frequency (that is, fuel amounts and moisture) at different temperature regimes. In addition, this exercise illustrated which climate parameter (annual maximum temperature or precipitation) was most important or dominant for different ecosystem climates. Based on the modeled responses, increases in precipitation in cold-dry (>40 cm) ecosystems are expected to greatly increase in the length of MFIs (decrease fire frequency) whereas increases in precipitation in hot-dry (<100 cm) ecosystems are expected to decrease the length of MFIs (increase fire frequency). Large increases in precipitation are expected to very slowly increase the length of MFIs in hot-wet (>100 cm) ecosystems.

Discussion

Domain, Range, Data, and Validation

The PC2FM predictions were validated by reasonable estimates that covered a broad range of terrestrial ecosystems from deserts to rain forests. The PC2FM predicted very long fire intervals in deserts, near glacial landscapes, as well as wet-cool and heavily fueled rainforest ecosystems. The model's explanatory power (~80% of variance) attests to the large influence of climate on controlling rates of fire at broad scales. The longest predicted MFIs in North America were in deserts (for example, Death Valley, Nevada) and near glacial landscapes where MFIs exceeded 3,000 years. The meaning or accuracy of estimates this far beyond the range of any known data is questionable. Despite this these estimates, though coarse, do fall within a plausible range and magnitude generated by the model. The shortest predicted MFIs were in regions of warm climates where vegetation can rapidly replenish fuels. Short MFI predictions (<3 years) are validated by fire scar studies (Fry and Stephens 2005; Stambaugh and others 2011; Van Horne and Fulé 2006).

The Rate (ARterm) and Fuel (PT_{rc}) Parameters

The PC2FM approach was based on rate and fuel parameters. The ARterm had the most power in explaining the variance in MFI and worked alone in ecosystems where fuel production is sufficient to allow fires to occur relatively frequently. When annual fuel production is limited, as is the case in very hot or cold-dry climates such as those representing desert or tundra ecosystems, then the importance of the ARterm was diminished compared to the PT_{rc} parameter. In these ecosystems reactant availability and/or concentration became the dominant factors and reaction rate factors become less important. PC2FM output is one of the few quantitatively based fire interval estimates for these very long fire interval ecosystems.

To illustrate the utility of model parameterization (that is, use of ARterm and PT_{rc}) we compared the results of multiple regression models without parameterization of the three variables (precipitation, temperature, and oxygen). When this multiple regression model (lacking physical chemistry theory) is attempted it resulted in models with far lower explanatory power and estimates with increased error. Bootstrapped estimates of MFI with the three variables yielded r^2 results that ranged from 0.26 to 0.56 with an average r^2 of 0.41. These results are not only far lower than our chemistry driven parameterization results (see "Results" section) but also exhibited extremely variable partial r^2 among the three variables when bootstrapped. Thus, the parameterization using chemistry nearly doubled the explanatory power of the model (that is, r^2 increase from 0.41 to 0.80).

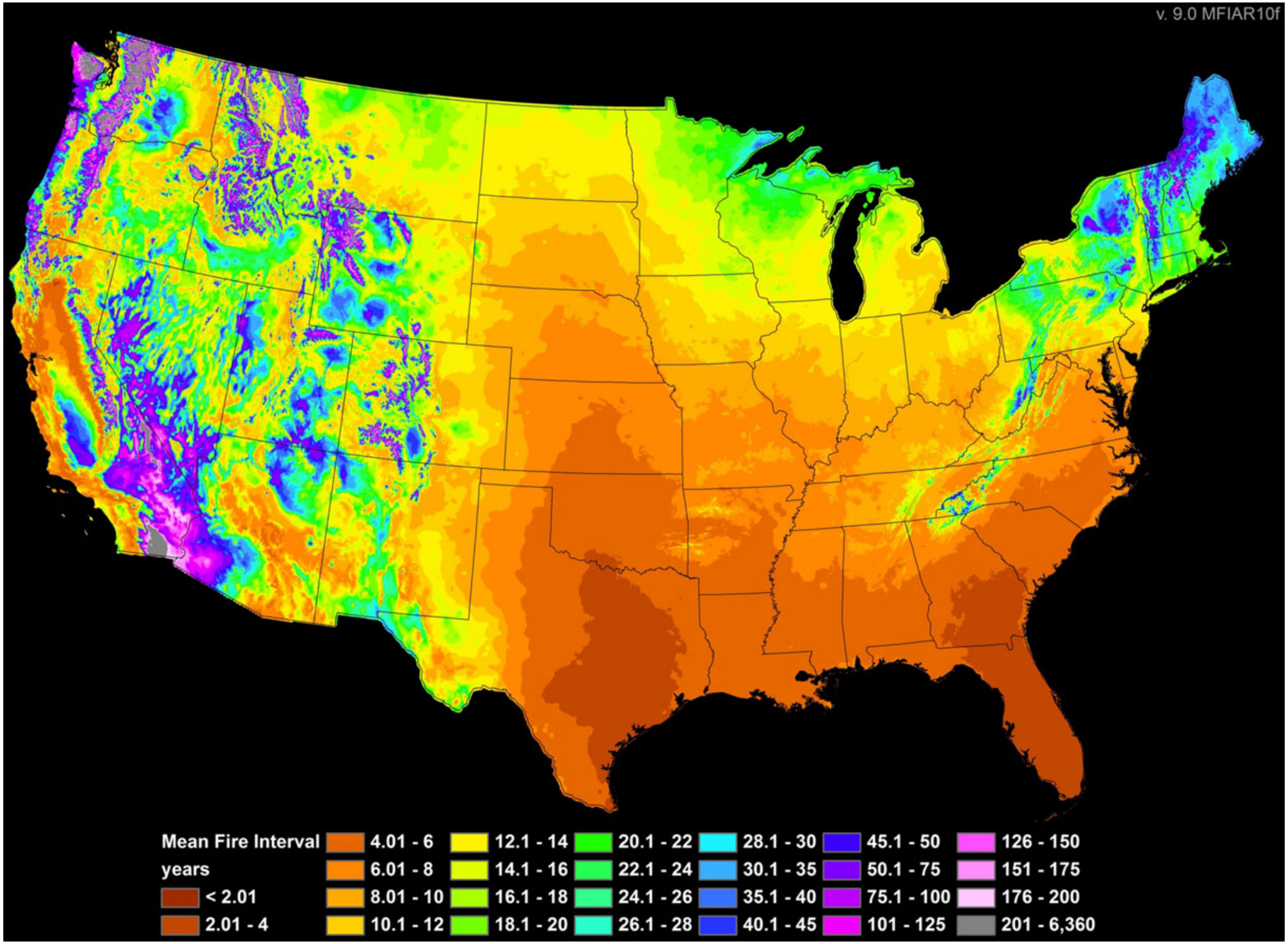

Figure 4. Historic (1650–1850 CE) MFI estimates for the presence of fire in all or part of an average 1.2 km^2 area. Mapped PC2FM estimates are based on Equation 2 using temperature, precipitation (Daly and others 2004), and the partial pressure of oxygen. Classification intervals are in 2-year classes (1–30 years), 5-year classes (31–50 years), 25-year classes (50–200 years), and a single class for intervals greater than 200 years.

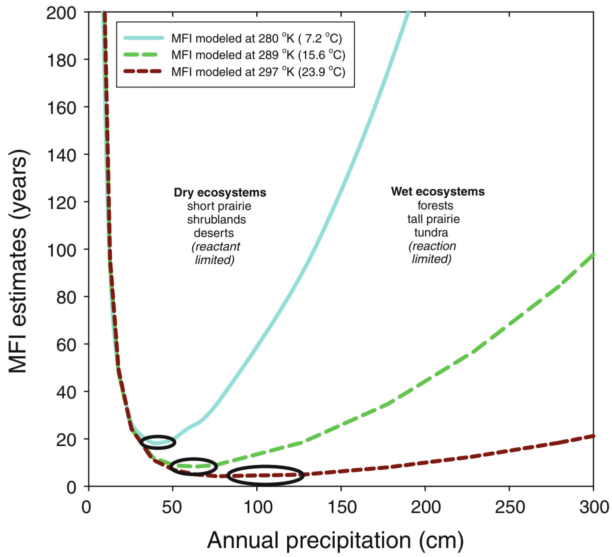

Figure 5. PC2FM modeled MFI responses to precipitation change based on three temperature scenarios. Inflection points (ellipses) at the bottoms of the model prediction curves estimate thresholds where phase changes occur for the influence of precipitation on fire frequency (MFI). These precipitation thresholds indicate a process change in the dominant ecosystem response from reactant concentrations (fuel production) in dryer ecosystems to reaction rates (temperature and moisture effects on combustion processes) in wetter ecosystems.

The dynamics of oxygen's role in combustion varies greatly from the confines of experimental chemistry to ecosystems. Despite the variability in oxygen among ecosystems, combustion reaction chemistry remains the same (six times more O_2 molecules required than fuel molecules, for example, $C_6H_{12}O_6 + 6O_2$). In ecosystems, the continual addition of this reactant by wind is extremely variable. For example, for flame combustion in a 10 m s^{-1} wind, replenishment of O_2 to a reaction site is about 40 times greater than that under conditions of near zero wind speed. The importance of wind speed in ecosystems likely outweighs the $_{pp}O_2$ in the atmosphere many fold. Although wind was not considered as a variable in the PC2FM, it could be a valuable addition in future models.

Regression Coefficients

Translating the meaning of molecular reactions into ecosystem rates requires either exact knowledge of the huge number of chemical processes in an ecosystem or the use of 'translator coefficients'. We assert that regression coefficients, as used in the PC2FM (Equation 2), can operate as a bridge between the metrics used for molecular reactions and the metrics used for ecosystems and climate. Examples of this are converting mille-seconds (chemical reaction rates) to years (mean fire intervals in ecosystems), moles (atomic weight) to reactant density (the partial pressure of O_2), opposing rate metrics (number years per fire (MFI) versus reactions per second).

The Non-Vegetation Modeling Approach

We intentionally excluded vegetation in the PC2FM because our main interest was to parameterize climate forcing of fire regimes. Nonetheless, feedback occurs between vegetation and fire frequency (Flannigan and others 2005), causing short-term forcing in fire frequency due to vegetation type. The lack of vegetation type and structure in the PC2FM may limit its ability to predict finer-scale variability (for example, <1 km^2) in fire frequency and result in increased model confidence limits (Figure 3A). Despite this, a major strength of a vegetation-free approach is the applicability of the model for predictions of fire frequency in situations where vegetation is unknown, data are unavailable, or not of primary interest. PC2FM climate-based output could provide opportunities to compare the influence of vegetation (promotion or resistance) in further affecting fire frequency.

Temperature Effect on Fire Frequency

Differences in fire frequency due to temperature arise from a number of climate, ecosystem, and chemical pathways such as the length of the fire season, duration of snow cover, relative humidity, and fuel production and decomposition. Our analysis suggests that temperature has the strongest affect on fire frequency and is an important component of the ARterm parameter as well as in the reactant availability parameter (PT_{rc}). Further tests of the PT_{rc} parameter's ability to define temperature–fire frequency thresholds would likely be useful for describing global climate change influences on fire regimes.

In the calibration of our model, we adjusted temperature means (Daly and others 2004) by -0.4 K to account for warming that has occurred between the period of fire frequency observations and temperature means. Potential shortfalls with this approach are: it is doubtful that changes in temperature have been spatially homogeneous for all sites, not all fire history records span exactly the same period, and the spatial variability of temperature fields are not known for prehistoric periods that may have been significantly different, particularly during the Little Ice Age. The effect or potential error imposed on PC2FM due to the temperature adjustment currently is not known, but could lessen the strength of predictions. An important factor to consider is that the differences in mean annual temperatures between fire history sites (spatial variability) are much larger (more than 50 times greater) than the difference imposed by the temperature adjustment (temporal variability). Nevertheless, future work considering these effects and differences may permit refinement of the PC2FM.

Balancing Contrasting Precipitation Effects on Fire Regimes

The effect of precipitation on fire frequency is complex. Although it may seem intuitive that fire frequency is relatively lower in landscapes where annual precipitation is high, this relationship is not well supported by data and literature. Increases in precipitation have a negative influence on fire frequency due to influences such as increased fuel moisture and relative humidity. In contrast, increased precipitation generally has a positive influence on fuel production. Fire history data indicate that warm regions with either high precipitation (for example, Gulf Coast) or low precipitation (for example, southwestern U.S.) can have very frequent fires.

The application of the PC2FM to three temperature scenarios with a range of precipitation values illustrated the value of this empirically validated model output for understanding relationships between precipitation, temperature, and fire frequency (Figure 5). This scenario analysis may aid in identifying threshold climate conditions for fire regimes. For example, PC2FM maps (Figure 4) and scenarios (Figure 5) show increases in precipitation will decrease MFI in the dry western regions of the Great Plains but increase MFI in the wetter eastern regions of the Great Plains.

Map Interpretations

Fire frequency maps provide an opportunity for examining the continental-scale differences in fire regimes (Figures 4, 5). Visual inspection of mapped MFIs illuminate that the southern regions of the U.S. generally burned more frequently than the northern regions reflecting a latitudinal temperature trend that is most apparent in the north–south variability of MFIs in the Great Plains where elevation, topography, and precipitation differences are minimal.

The most complex region of the U.S. with respect to spatial variability in fire frequency is the western coastal region. The existence of abrupt spatial differences in oxygen, temperature, precipitation, and their interactions result in large differences in MFIs within short spatial extents. For example, predicted MFIs from the Willamette Valley, Oregon (MFIs ~6 years) increase more than 30-fold to the high elevation areas of Mount Hood (>200 years)—a distance of 40 km. The northwestern states have both some of the longest and shortest mean fire intervals (1.3–>400 years) in the continental US (Fry and Stephens 2005; Agee 1993). Spatially, this contrasts greatly with MFI in the southeastern US where forcing of mean fire intervals by climate is relatively homogeneous from central Texas to South Carolina, a distance of over 2,000 km.

Fine-scale complexity of fire regimes is not represented in our mapping for two reasons: (1) available climate data depicting long-term climate means are relatively coarse, and (2) the focus of this model was calibration and depiction of climate effects. The PC2FM prediction map (Figure 4) has a 1 km resolution—a limitation imposed by the precision of the fire frequency data. It is important to reiterate that Equation 2 only utilizes climate data and that other potentially relevant finer-scale fire variables such as vegetation, topography, aspect, and human ignition, and land use are not considered. Omission of these variables certainly causes error in MFI estimation. For example, PC2FM MFI estimates for the Ozark Plateau (Missouri and Arkansas) lack the landscape-scale spatial complexity that has been documented through fire scar history studies and is attributed to topography (Guyette and others 2002; Stambaugh and Guyette 2008).

Ignition Frequency

The omission of ignitions (variability in the E_a term) from our model is an obvious deletion of an important frequency factor. With no ignitions (required activation energy, E_a) there can be no cascading chemical reaction. We chose not to include ignitions for several reasons: (1) little if any lightning or anthropogenic data are available for historic ignitions, (2) ignitions were not part of the climate focus of this the model, and (3) ignitions, particularly anthropogenic ignitions, have varied greatly through time.

Fire histories which incorporate human population and cultural information have shown that anthropogenic ignitions can greatly alter fire frequency (Guyette and others 2002). Where lightning ignitions are rare fire frequency is 'conditional' on human ignitions. Although previous models have used human population density as an ignition proxy (Guyette and others 2006a, b; 2010), the precise calibration between fire frequency and population density is difficult due to the uncertainty of population densities and cultural fire uses (Barrett and others 2005; Mooney and others 2007; Mooney 1928; Swanton 1952). Furthermore, we have found that, at relatively coarse spatial and temporal scales (that is, regions and centuries), fire frequency variability caused by local factors such as vegetation type, topography, grazing, and human ignitions becomes less important.

Applications

Parameterization of the PC2FM resulted from both the application of theoretical chemistry to ecosystems and validation by empirical and statistic analyses. We presented two applications of this physical chemistry concept (Equation 2 and mapping), however, other potential applications likely exist. The PC2M estimates can be useful as a comparison in considering the strength of other important non-climatic factors affecting fire frequency such as vegetation, topography, grazing, ignitions, or fire suppression. Single-site fire frequency predictions may be possible utilizing local climate data as input to the PC2FM. Estimating climate influences on MFIs in the future and distant past are another potential application of the PC2FM. Models such as the PC2FM may provide a new approach to considering the importance of environmental chemistry toward understanding ecosystem processes well beyond fire regimes. Despite the usefulness of the mapping predictions, the coefficients and variable identification of the PC2FM are important because they aid in the transfer of this approach to other continents and climate conditions.

Conclusions

The successful calibration and validation of the PC2FM model supports the hypothesis that theoretical chemistry has potential for the parameterization of variables in ecosystem studies. Understanding the model can provide ecologists with a quantitative framework for understanding climate effects on ecosystems and their fire regimes. The model and mapped estimates can provide information on fire regimes from spatial or temporal climate data or scenarios. Mapped estimates of MFIs will aid in understanding fire's historic importance in the many locations that will never have any local fire regime or historical ecology information. The model and map could be used in conjunction with soil, geology, and plant community data to examine the effects of fire on flora and fauna with some degree of independence from modeled fire histories based on species occurrences. Though the model's primary purpose is related to understanding the physical chemistry related to climate and fire, the relative effects of other fire regime factors are likely also to be better understood.

Acknowledgments

Development of the PC2FM was supported by the Joint Fire Science Program (Project 06-3-1-16), the National Park Service and Great Plains Cooperative Ecosystem Studies Unit (CESU), and the US Forest Service Northern Research Station. We thank the many authors who have made their work available through publications and the International Multiproxy Paleofire Database (see Supplementary Data 2) as well as the comments provided by reviewers.

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