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# Global patterns of interannual climate-fire relationships

**John T. Abatzoglou**[1], **A. Park Williams**[2], **Luigi Boschetti**[3], **Maria Zubkova**[3], **Crystal A. Kolden**[4]

[1]Department of Geography, University of Idaho, Moscow, 875 Perimeter Dr., Moscow, ID 83844 USA, jabatzoglou@uidaho.edu, (208) 885-6239

[2]Lamont-Doherty Earth Observatory of Columbia University, New York, NY USA

[3]Department of Natural Resources and Society, University of Idaho, Moscow, ID USA

[4]Department of Forest, Range and Fire Sciences, University of Idaho, Moscow, ID USA

## Abstract

Climate shapes geographic and seasonal patterns in global fire activity by mediating vegetation composition, productivity, and desiccation in conjunction with land-use and anthropogenic factors. Yet, the degree to which climate variability affects interannual variability in burned area across Earth is less understood. Two-decades of satellite-derived burned area records across forested and non-forested areas were used to examine global interannual climate-fire relationships at ecoregion scales. Measures of fuel aridity exhibited strong positive correlations with forested burned area, with weaker relationships in climatologically drier regions. By contrast, cumulative precipitation antecedent to the fire season exhibited positive correlations to non-forested burned area, with stronger relationships in climatologically drier regions. Climate variability explained roughly one-third of the interannual variability in burned area across global ecoregions. These results highlight the importance of climate variability in enabling fire activity globally, but also identifies regions where anthropogenic and other influences may facilitate weaker relationships. Empirical fire modeling efforts can complement process-based global fire models to elucidate how fire activity is likely to change amidst complex interactions among climatic, vegetation, and human factors.

### Keywords

climate; fire; global; ecoregions

## 1. Introduction

Fire is an integral component of global ecosystems and the broader Earth System through its influence on the terrestrial carbon cycle (Bond & Keeley, 2005; Bowman et al., 2009). Fire is both a natural disturbance process prevalent across most land surfaces and an anthropogenic disturbance process with regular ignitions from humans, particularly in pastoral and agricultural areas where it is often used as a tool (Cochrane, 2003). Fire can also be a hazard to some ecosystem services, the built environment, as well as human health

Correspondence to: John T. Abatzoglou.

(Johnston et al., 2012; Reid et al., 2016) as evidenced by recent extreme fire events associated with extensive loss of human life (Boer et al., 2017; Bowman et al., 2017; Cruz et al., 2012). Increased fire activity in portions of the globe in recent decades (Field et al., 2016; Kasischke & Turetsky, 2006; Turetsky et al., 2015; Westerling, 2016) has brought international attention to improve efforts of fire monitoring, modeling, and prediction across scales (Williams & Abatzoglou, 2016).

An array of biophysical and anthropogenic factors influence fire activity. Fire requires sufficient biomass, flammability, and ignition sources (Krawchuk *et al.*, 2009; Bradstock, 2010). These factors often provide constraints on fire activity both spatially (Krawchuk *et al.* 2009) and temporally (Abatzoglou & Kolden, 2013; Littell, Peterson, Riley, Liu, & Luce, 2016), with the influence of individual factors varying across vegetation productivity gradients (Krawchuk & Moritz, 2011; Pausas & Bradstock, 2006; Pausas & Ribeiro, 2013). The influence of anthropogenic activities, including land-use modification, human ignitions, and fire suppression, further complicate the influence of purely biophysical drivers of fire activity (Andela et al., 2017; Balch et al., 2017; Bistinas, Harrison, Prentice, & Pereira, 2014; Marlon et al., 2012; Parisien et al., 2016). Anthropogenic activity can both dampen (e.g., Marlon *et al.* 2012) and magnify (e.g., additional biomass burning during droughts, Randerson *et al.* 2005) biophysical drivers and enablers of fire (Taylor, Trouet, Skinner, & Stephens, 2016). The dynamic nature of weather and climate relative to other factors implicate atmospheric processes as the predominant macroscale driver of temporal variability in fire activity (e.g., Aldersley *et al.* 2011). Regional studies have shown that climate variability explains a majority of the interannual variability in burned area in some regions, but less in others (Archibald, Nickless, Govender, Scholes, & Lehsten, 2010; Jolly et al., 2015; Urbieta et al., 2015). However, such analyses have been limited geographically, leading to a gap in understanding of how climate variability affects fire variability across terrestrial systems globally. The impacts of climate variability on both episodic fire events and longer-term fire trends have received increased attention in recent years due to observed changes in fire activity (Andela et al., 2017; Turco et al., 2016; Westerling, 2016). Efforts to better understand how climate factors contributed to observed changes (Abatzoglou & Williams, 2016; Holz et al., 2017), and how fire activity will change in the coming decades in response to climatic and non-climatic drivers (Knorr, Jiang, & Arneth, 2016; Moritz et al., 2012; Pechony & Shindell, 2010) are essential to refine estimates of changes in biogeochemical cycling, vegetation composition, and fire-related hazards.

Empirical approaches have been developed to better understand how climate contributes to fire activity. Pyrogeographic approaches that exploit geographic variability in time-invariant factors, including long-term climate averages, have been an effective tool for understanding spatial variation in fire regimes (Krawchuk & Moritz, 2014; Parisien et al., 2012; Parks et al., 2015). However, such approaches often omit the influence of climate variability. An alternative approach focuses on exploiting temporal variability in regional fire activity as it relates to top-down climate drivers, while omitting bottom-up controls. Numerous regional studies have explored such climate-fire relationships using multi-decadal fire records acquired from a variety of sources, including regional fire atlases, remotely sensed datasets, and dendrochronology records. Most studies characterize climate-fire relationships along a continuum, ranging from flammability-limited regimes in mesic regions, where fuel aridity coincides with enhanced fire activity (Abatzoglou & Williams, 2016; Barbero, Abatzoglou, Steel, & Larkin, 2014; Urbieta et al., 2015), to fuel-limited regimes in semi-arid regions, where pluvial conditions enhance the production of biomass that enhances fire activity in subsequent seasons (e.g., van der Werf *et al.*, 2008; Bradstock, 2010). The strength of such climate-fire relationships varies across this continuum (McKenzie & Littell, 2017; Pausas & Paula, 2012) consistent with the concept that vegetation productivity and fuel availability serve as key limiting factors for fire (Bradstock, 2010). However, these studies have primarily been conducted for sub-regions of the globe using a variety of datasets, time periods, and methods, impairing the ability to compare climate-fire relationships geographically across the planet.

While regional fire datasets can span more than a century, global burned area datasets are temporally limited by the availability of remotely sensed data. For example, the widely used Global Fire Emissions Database (GFED, van Der Werf *et al.* 2017) covers 1997 to present. The maturation of such global fire datasets allows us to begin exploring how interannual variability in climate shapes fire activity across terrestrial land surfaces. This study specifically examines the strength and direction of relationships between interannual variability in burned area and climate at ecoregion scales across the globe for forested and non-forested areas, and how such relationships vary across gradients of climate, productivity, anthropogenic land use, and tree density. We additionally ask how much of the interannual variability in fire activity globally over the last two decades was shaped by climate variability and identify regions where climate variability exerts a strong influence on burned area.

## 2. Materials and Methods

### 2.1 Datasets

The advent of monitoring fire globally using remotely sensed data has provided an opportunity to develop active fire (Giglio, Descloitres, Justice, & Kaufman, 2003) and burned area datasets (Giglio, Loboda, Roy, Quayle, & Justice, 2009; Roy, Boschetti, Justice, & Ju, 2008). Satellite-derived fire data provide systematic macroscale information on global fire activity that is used to estimate fire emissions, inform ecosystem and land management, conduct fire hazard analysis, and perform fire model benchmarking (Hantson et al., 2016). Such data are not without their caveats. For example, the relatively short period of record of spaceborne sensors may be inadequate for capturing information in small regions with long fire return intervals (e.g., Krawchuk and Moritz, 2014), may omit fire detection in persistently cloudy regions (Giglio, Randerson, & Werf, 2013), and may not capture fine-scale information due to relatively coarse spatial resolution (Boschetti, Flasse, & Brivio, 2004; Kolden, Lutz, Key, Kane, & van Wagtendonk, 2012).

We used the monthly GFED version 4.0 dataset (GFED4). GFED4 provides estimates of global fire activity at 0.25° resolution from 1997 through 2016 by combining calibrated active fire counts for the 1997–2000 period with burned area detections from 2000 onwards (Giglio et al., 2013). Monthly burned area for land cover classes mapped by the MODIS Global Land Cover Product (MCD12) (Friedl et al., 2010) was aggregated to two classes that compromised >95% of all global burned area: (1) forested areas and (2) non-forested

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areas that include grasslands, shrublands and savanna. Note that burned area in this context includes wildfires, prescribed fires, and land-use fires (e.g., pastoral burning). We excluded burned area in cropland land cover classes. While fires in croplands can represent a large fraction of burned area in some regions, cropland fires are often small and challenging to unambiguously map from satellite data, often occur outside of the primary fire season following harvest, exhibit less interannual variability than non-cropland burned area, and are subject to fluctuations in cropping choices, policies, and agricultural practices (Hall, Loboda, Giglio, & McCarty, 2016; Korontzi, McCarty, Loboda, Kumar, & Justice, 2006; McCarty, Korontzi, Justice, & Loboda, 2009). Given known temporal data issues in the GFED4 data (e.g., changes in satellite data source, van Der Werf *et al.*, 2017), we provided supplemental climate-fire analysis using the latest Collection 6 MODIS Burned Area Product (MDC64A1) from 2002–2016 (Giglio *et al.*, submitted) as supplemental figures.

Climate datasets were acquired from the European Centre for Medium-Range Weather Forecast global reanalysis (ERA-Interim) at 0.75° resolution, except for precipitation, for which we used the Multi-Source Weighted-Ensemble Precipitation (MSWEP) data from Beck, van Dijk, et al., (2017) at 0.5° resolution. Precipitation data were interpolated to the grid resolution of ERA-Interim. We calculated monthly accumulated precipitation (P), mean vapor pressure deficit (VPD), and mean Penman-Monteith reference evapotranspiration (ETo). Monthly P and ETo data were used to run a simple water balance model (e.g., Willmott *et al.* 1985; Dobrowski *et al.* 2013) that accounts for soil and snowpack water storage and tracks both water usage through actual evapotranspiration (AET) and climatic water deficit (CWD), defined as the difference between ETo and AET. Finally, following Bowman *et al.* (2017) we used daily maximum temperature, wind speed, and minimum relative humidity from ERA-Interim along with daily accumulated precipitation from MSWEP to calculate the daily Fire Weather Index (FWI) using the Canadian Forest Fire Danger Rating System.

We additionally incorporated ancillary geospatial data layers to explore potential factors that contribute to differences in the strength of climate-fire relationships across ecoregions and across gradients. These data include (1) the human footprint index (WCS & CIESIN, 2005), which expresses the relative influence of anthropogenic pressure on global land accounting for factors such as population density, land use, and accessibility, all of which have noted impacts on fire activity (Bowman et al., 2009); (2) tree density (Crowther et al., 2015); (3) mean annual net primary productivity (NPP) from the MODIS MOD17 Global Vegetation Production Product (Running et al., 2004); and (4) a climatology of annual lightning density (Cecil, Buechler, & Blakeslee, 2014).

### 2.2 Methods

Previous efforts have examined climate-fire relationships at the native resolution of gridded global fire datasets (Andela et al., 2017; Bedia et al., 2015). However, the influence of top-down climate drivers on fire activity at smaller spatial scales is complicated by bottom-up drivers, including vegetation and anthropogenic factors, as well as the stochastic nature of fire and ignitions. We used global ecoregions (Olson et al., 2001) as our spatial unit of analysis following previous studies, as ecoregions attempt to account for commonality in vegetation assemblages through which climate-fire relationships are mediated (Littell, McKenzie, Peterson, & Westerling, 2009; Pausas & Ribeiro, 2013). All gridded datasets were aggregated using a simple summation (GFED4) or arithmetic average (other data) of voxels within the boundaries of each of the 815 ecoregions. Finally, we excluded burned area in ecoregions where the land cover (forest or non-forest) comprised less than 20% of the ecoregion (e.g., forest burned area was omitted if forest land cover <20%) or if the ecoregion contributed to less than 0.001% of the global burned area for the vegetation class. These criteria reduced the number of ecoregions to 389 and 216 for forested and non-forested burned area, respectively. The areas considered in the analysis accounted for approximately 90% of the burned area globally. A total of 306 ecoregions only contributed forested burned area for analysis, 133 ecoregions only contributed non-forested burned area, and 83 ecoregions contributed burned area for both land-cover classes. Note that we do not define an ecoregion as forest or non-forest, but rather only discern burned area of land cover types within an ecoregion.

Both the seasonality and duration of fire activity varies globally due to climatic and human factors (Jolly et al., 2015; Knorr, Kaminski, Arneth, & Weber, 2014). We isolated the fire season in each ecoregion following the concepts of Archibald, Lehmann, Gómez-Dans, & Bradstock (2013) who defined the fire season as the calendar months of the year that contain > 80% of the burned area. However, we further constrained this to be defined as the minimum number of consecutive months that contain > 80% of the burned area. These ecoregion-specific fire seasons were used exclusively to isolate seasonal windows for climatic analysis. We quantified the annual total burned area for each ecoregion as the sum of GFED4 monthly burned areas from March-February, adopting the fire year definition proposed by Boschetti & Roy (2008), corresponding with the global nadir in fire activity. Figure 1 shows fire characteristics in terms of annual average fraction of vegetation burned and fire seasonality for global ecoregions.

Interannual climate-fire relationships were explored using Pearson's correlation between climate metrics and the base-10 logarithm of fire-year burned area. We constrained our analysis to climate data covering three temporal periods to facilitate a comparison across global ecoregions: one period concurrent to the fire season and two periods prior to the fire season. Concurrent relationships used climate data averaged over the months of the fire season including a one-month buffer leading into the fire season (e.g., average of daily FWI). Antecedent relationships were constrained to precipitation. We considered 12-month accumulated precipitation over two antecedent periods, one ending 2-months prior to the onset of the fire season, and the other ending 14-months prior to the onset of the fire season. Previous research has shown that precipitation during the previous 1–2 growing seasons influences biomass production and subsequent fire activity (Archibald, Roy, Wilgen, Brian, & Scholes, 2009; Swetnam & Betancourt, 1998), but we acknowledge that this effect applies to other time scales (e.g., Andela et al., 2017). A 2-month buffer prior to the fire season was used to avoid conflating antecedent conditions with those that directly influence fuel moisture during the fire season. Statistically significant correlations were identified as $p<0.05$.

We examined the degree to which interannual climate-fire correlations varied across gradients of several time-invariant characteristics: NPP, HFI, tree density, and lightning-frequency, and mean annual CWD. This was facilitated using bivariate generalized additive models (GAM, R Core Team 2017; Wood and Wood 2017) between correlations and each of the aforementioned variables. GAMs allow response curves to use nonparametric smoothed functions rather than a predetermined (e.g., linear) relationship between response variable and predictor, thus enabling added flexibility for exploring nonlinear relationships. GAMs are often developed using several explanatory variables where the model consists of the summation of values from response curves from individual variables (Krawchuk *et al.* 2009), but have also been used in exploratory bivariate data analysis to resolve nonlinear relationships (e.g., Pausas and Ribeiro 2013).

We exclusively used bivariate GAMs to help elucidate how climate-fire correlations varied across gradients of individual landscape characteristics. We did not use GAMs in their traditional multivariate model-building sense given the collinearity across predictors. GAMs were developed specifically for interannual climate-fire correlations with CWD concurrent to the fire season – a proxy for fuel availability controls on fire activity, and correlations with precipitation 14–25 months prior to the fire season - a proxy for fuel accumulation controls on fire activity.

Finally, simple linear models leveraging these interannual climate-fire relationships were developed to gain a first-order estimate of the degree to which climate variability shapes patterns of global fire activity. We opted to use linear models over more complex model forms due to their ease of interpretation, as well as to avoid overfitting with nonlinear models given the small population size of our data. Four models were developed for each ecoregion and vegetation type. Each model used one antecedent precipitation time period and one concurrent measure of fuel aridity (CWD, FWI). Notably, we did not find that alternative measures of concurrent fuel dryness (e.g., VPD, precipitation during the fire season) contributed to substantial additional explained variance. The model that maximized the explained variance of base-10 logarithm of annual burned area was selected. We chose to use parsimonious models that restrict the selection of predictors to a compact set that have shown utility in previous studies but acknowledge that additional climatic and non-climatic predictors could be used in a more sophisticated modeling effort.

## 3. Results

### a. Global climate-fire correlations

Climate-fire correlations exhibited distinct biogeographical patterns across the globe (Fig. 2). Strong positive correlations between measures of fire-season fuel aridity (CWD and FWI) and forest burned area were seen for a majority (52% and 51%, respectively) of the 389 ecoregions, particularly in boreal forests as well as tropical forests in southeast Asia and South America. Significant positive correlations with aridity were also seen across forests in temperate ecosystems including the American West, southeastern Europe, and southern Australia. These patterns are consistent with, but somewhat weaker, than those obtained using the shorter MODIS fire record (Fig. S1). Significant negative correlations between burned area in forests and precipitation during the fire season were found in 35% of ecoregions, while significant positive correlations to VPD during the fire season were seen in 42% of ecoregion (Fig. S2). Similar patterns of concurrent climate-burned area correlations were evident in non-forested areas with significant positive correlations between fuel aridity and burned area in 27% of the 216 ecoregions. However, fire season aridity correlations in non-forested areas were generally weaker than those in forested areas.

Accumulated precipitation 14–25 months antecedent to the start of the fire season was generally weakly correlated with burned area in forests (Fig. 2). Antecedent precipitation in the 2–13 months prior to the fire season exhibited more widespread significant negative correlations to forest burned area in 22% of ecoregions, most notably in Indonesia, highlighting the potential effect of precipitation deficits on fuel aridity. By contrast, climate-fire relationships for non-forest burned area showed distinct *positive* correlations between precipitation 14–25 months prior to the fire season and burned area in 15% of ecoregions, primarily those in semi-arid areas including much of interior Australia and southern Africa. Generally weak and mixed correlations were seen between cumulative precipitation 2–13 months prior to the fire season and non-forest burned area with a few significant positive correlations in subtropical Australia. A supplemental figure showing correlations between burned area and antecedent precipitation over different temporal windows is provided in Supplemental Figure S2.

## b. Climate-fire relationships across gradients

Relationships between the strength of interannual climate-fire correlations across ecoregions exhibited distinct differences across a moisture gradient (Fig. 3). Concurrent CWD-burned area correlations were positive and strongest in mesic regions with relatively low mean annual CWD (<500 mm) and decreased substantially in regions where mean annual CWD > 1200 mm, supportive of the geographic patterns seen in Figure 2. Similar interannual CWD-burned area correlations across a gradient of mean annual CWD were also seen for non-forest burned area. The GAM explained approximately 14% of the inter-ecoregion variability in CWD-fire correlations for the two vegetation classes. Similar patterns were seen with NPP (not shown). CWD-burned area correlations became increasingly positive with increased tree density up to around 30,000 trees per square kilometer. By contrast, positive CWD-burned area correlations weakened in forests with higher anthropogenic influences, whereas no effect was seen for non-forests. No significant patterns were seen with mean lightning frequency (not shown).

Positive correlations between antecedent precipitation and non-forest burned area strengthened in ecoregions with higher climatological CWD. These relationships were also realized with NPP (not shown), with productivity-limited regions showing stronger positive correlations with antecedent precipitation characteristic of water-limited, fuel-limited fire regimes. Antecedent precipitation-burned area relationships in non-forest environments also showed a tendency for stronger positive correlations in ecoregions with sparse tree coverage and low anthropogenic influence. By contrast, weak and non-significant patterns were evident for forest burned area.

### c. Explained variance in interannual burned area

Climate variability explained approximately a third of interannual variability in burned area across ecoregions (Fig. 4; Fig S3 for MODIS), with slightly more variance explained for forest burned area (ecoregion average of 35% explained) than non-forest (32%) burned area. Stemming from the strong interannual correlations between concurrent fuel aridity and burned area, the simple linear model explains more than 40% of the interannual variability in forest burned area during 1997–2016 across many boreal and tropical ecoregions. Likewise, the strong and positive correlations between burned area and antecedent precipitation in non-forest parts of interior Australia and southern Africa account for much of the explained variance for these ecoregions. By contrast, the climate variables evaluated explain relatively little variance in interannual burned area across portions of central Africa, southeast Asia, and parts of western Europe.

## 4. Discussion

Interannual climate-fire relationships exhibited patterns similar to those seen in regional studies (e.g., Littell *et al.* 2009) characterizing fuel-limited to flammability-limited fire regimes spanning broad biogeographic gradients. Interannual variability in forest burned area positively correlated with fire season fuel aridity (FWI, CWD) in a majority of ecoregions, with the strongest relationships in mesic environments where moisture often limits landscape flammability (Bradstock, 2010; Krawchuk et al., 2009). This was particularly evident in the boreal and evergreen temperate forests of western North America where lightning-ignited fires account for a majority of the burned area (Stocks et al., 2002; Westerling, 2016), as well in tropical forests in Oceania and the Brazilian Amazon, where human ignitions for agricultural land clearing dominate fire activity (Cochrane, 2003). The stronger and more widespread correlations between forest burned area and fuel aridity compared to those with fire-season precipitation emphasizes the added value of accounting for atmospheric moisture demand in enabling fire activity in flammability-limited fire regimes (Ray, Nepstad, & Moutinho, 2005; Sedano & Randerson, 2014; Williams et al., 2015).

Antecedent precipitation 14–25 months prior to the fire season was strongly and positively correlated with non-forest burned area in semi-arid regions with the strongest correlations found in ecoregions with high mean CWD. This is consistent with fuel-limited fire regimes in dry regions and has been highlighted by previous research (e.g., van der Werf *et al.* 2008; Abatzoglou and Kolden 2013) and the intermediate productivity hypothesis (Krawchuk et al., 2009; Pausas & Ribeiro, 2013), which assumes fuel abundance, not flammability or ignitions, limit fire activity in such environments. Precipitation 2–13 months prior to the onset of the fire season showed positive correlations with non-forested burned area in subtropical regions where drying of fine fuels following anomalous wet conditions immediately prior to the fire season have been shown to promote fire activity (Andela et al., 2017; Archibald et al., 2009). Precipitation 2–13 months prior to the onset of the fire season was negatively correlated with forest burned area in regions with low CWD such as the tropical forests of Oceania and Indonesia. Human-ignited fire for land clearing in these regions spikes in years when water tables descend and tropical rain forests desiccate due to low rainfall (Field, Van Der Werf, & Shen, 2009). Prolonged drought that persists into the fire season, as demonstrated by strong positive fuel aridity-area burned correlations, facilitates increased intentional biomass burning.

The strength of the interannual fuel aridity-fire relationships waned in ecoregions with higher climatological moisture deficits where flammability is less limiting during the fire season. Weaker aridity-fire correlations were found in resource-poor/low-productivity environments and for non-forests when fuel abundance limitations exert a stronger constraint on fire activity. These findings extend prior global analyses of climatic constraints of pyrogeography (e.g., Krawchuk & Moritz, 2011) to interannual timescales and regional studies (e.g., McKenzie & Littell, 2017) to global scales. Likewise, interannual aridity-burned area correlations were stronger in ecoregions with higher average tree density up to approximately 30,000 trees/$km^2$. Aridity-burned area relationships are likely weaker in regions of sparse tree coverage both because fire in these regions is carried by understory grasses and shrubs, mimicking the fuel-limited fire regime, and also because many woody savanna ecoregions are dominated by human ignitions for pastoral burning on an annual basis (Archibald et al., 2013; Cahoon Jr, Stocks, Levine, Cofer III, & O’Neill, 1992). We note that the strong collinearity between mean climatic conditions and tree density precludes a complete separation of these factors. Finally, differences in vegetation characteristics as well as negative fire-feedbacks, both not considered in this study, may further help elucidate how climate variability shapes global fire activity (Archibald et al., 2018).

Positive aridity-forest burned area correlations were strongest in regions with a low anthropogenic footprint. This finding supports the notion that fire suppression, conversion to agricultural lands and greater land fragmentation, and landscapes where intentional burning occurs, tend to reduce the influence of climate variability on fire activity (Syphard, Keeley, Pfaff, & Ferschweiler, 2017; Taylor et al., 2016). Paradoxically, fire suppression in regions where fuels are available may amplify climate-fire relationships as suppression activities may be successful when fire danger is moderate (e.g., Abatzoglou *et al.*, 2018), thereby allowing large wildland fires to preferentially occur with anomalous fuel aridity and fire weather conditions (Barbero et al., 2014; Stephens et al., 2014). By contrast, non-forested ecoregions did not demonstrate strong relationships along a gradient of anthropogenic influence. At the global scale this likely represents the dissimilarities between landscapes that are sparsely populated where extreme climatic conditions dominate (e.g., high latitude tundra) and landscapes that are sparsely populated but where pastoral burning is widely practiced (e.g., savannas).

Our simple linear models suggest that approximately a third of the interannual variability in burned area across global ecoregions is explained by climate variability. Consistent with the increased strength of positive fuel aridity-burned area correlations along a productivity gradient, climate explained more variability in forest burned area in wetter climates, including tropical rainforests in Indonesia and Oceania, much of the Amazon and boreal forests, and many temperate forests than in more arid ecoregions and for non-forest burned area. Likewise, climate explained more than 40% of the interannual variability in non-forested burned area in many semi-arid regions including across central Australia, African savannas, and portions of the semi-arid United States through the strong positive links with antecedent moisture as seen in previous regional studies (e.g., Archibald et al., 2009). These results may be instructive for contextualizing biophysical drivers of recent changes in regional fire activity (e.g., Abatzoglou & Williams, 2016), and highlighting regions with strong climate-fire relationships that may exhibit substantial changes in the coming decades (Pechony & Shindell, 2010; Westerling, Turner, Smithwick, Romme, & Ryan, 2011).

By contrast, climate explained less of the interannual variability in burned area in other regions including central African rainforest and the semi-arid and arid steppe of central and eastern Asia. The weak climate-fire relationships may be associated with a variety of factors tied to anthropogenic controls, sub-geographic variability in biophysical constraints on fire activity, and potentially poor quality of climate data in these regions. Anthropogenic factors can effectively decouple climate and fire in some regions due to extensive and regular intentional human ignitions and biomass burning across landscapes (Le Page, Oom, Silva, Jönsson, & Pereira, 2010), land use and landscape fragmentation (Pausas & Keeley, 2014), and suppression (Turco et al., 2016). Pertinent lessons may be learned for living with fire and mitigating fire-related hazards (Smith et al., 2016) from regions where fire activity is largely decoupled from climate.

Alternatively, weak interannual climate-fire relationships may arise due to environmental conditions often being conducive to fire activity (i.e., intermediate productivity region with sufficient ignitions, Krawchuk et al., (2009), Pausas & Paula, (2012)), in regions where annual burned area is strongly determined by episodic wind-driven fires (Keeley, Safford, Fotheringham, Franklin, & Moritz, 2009), and where fire activity is ignition-limited (e.g., Abatzoglou, Kolden, Balch, & Bradley, 2016; Syphard et al., 2007). Additional analysis decomposing bottom-up anthropogenic factors from macroscale climate variability is needed to better elucidate fire regimes that are relatively insensitive to climate variability.

The relatively short record of global fire observations from satellites is not optimal for understanding interannual relationships, and worse still for understanding drivers of lower frequency variability in fire activity, yet the general relationships gleaned in our study are broadly consistent with longer-term regional climate-fire relationships (e.g., Littell et al., 2009). Our supplemental analysis using the shorter fire record from MODIS Burned Area Product (MDC64A1) shows somewhat stronger relationships, potentially due to known data issues in GFED4, but generally supports the results of Figure 2. Inadequate climate data may also obfuscate relationships in some regions. A single modern reanalysis (ERA-Interim) paired with a high-quality global gridded precipitation dataset (MSWEP) was used in this study. However, structural uncertainty in climate data, namely precipitation, is a likely source of uncertainty in relationships identified here, particularly in the tropics (Beck, Vergopolan, et al., 2017).

Previous analyses performed at the native resolution of the fire data (e.g., Bedia et al., 2015) have showed weaker overall relationships than those shown here. We demonstrate more coherent climate-fire relationships by stratifying burned area by primary land-cover classes (forest and non-forest excluding cropland burning) and aggregating to broader ecologically relevant spatial units. We do not suggest that ecoregions are the optimal spatial unit for conducting climate-fire analyses. Ecoregions vary substantially in size and there can be spatial mismatches between burned area within an ecoregion and climatic features aggregated over the extent of the ecoregion. Analyses performed at different resolutions may reveal alternative strength and patterns in relationships (Parisien & Moritz, 2009; Urbieta et al., 2015).

Nonstationarity in climate-fire relationships (Higuera, Abatzoglou, Littell, & Morgan, 2015; McKenzie & Littell, 2017; Taylor et al., 2016) is likely to occur due to changing underlying climate, vegetation, and anthropogenic factors (e.g., settlement, fire-suppression technology). This study provides a modern-day estimate of these relationships, but the degree to which these relationships hold under future climatic conditions is questionable. Increased fuel aridity projected by the mid 21$^{st}$ century in most regions (Flannigan, Krawchuk, de Groot, Wotton, & Gowman, 2009) would engender increased burned area, particularly in relatively wet forests, based on the results of this study. Increases in mean state aridity (e.g., mean CWD) may temper increases in fire activity based on weaker interannual aridity-burned area correlations due to negative feedbacks between fire and subsequent fuel available to support fire (McKenzie & Littell, 2017; Parks et al., 2016). However, disequilibrium vegetation composition and loads (e.g., based on past climates and management) under changing climatic conditions (e.g., transition to higher aridity) may result in substantial increases in burned area prior before negative feedbacks are effective (Williams & Abatzoglou, 2016). As fire is a coupled earth system process, dynamic global vegetation models such as those used for the Fire Model Intercomparison Project (Hantson et al., 2016) are, in theory, well suited to help us better understand how fire activity is likely to change in the future amidst complex interactions among climatic, vegetation, and human factors. Process-based global fire models are still in a stage of rapid development and empirical relationships between fire, climate, and land-cover characteristics such as those presented here are essential for benchmarking global models and identifying needed improvements.

## Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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## References

Abatzoglou JT, Balch JK, Bradley BA, & Kolden CA (2018). Human-related ignitions concurrent with high winds promote large wildfires across the USA. International Journal of Wildland Fire, 27, 377–386.

Abatzoglou JT, & Kolden CA (2013). Relationships between climate and macroscale area burned in the western United States. International Journal of Wildland Fire, 22(7), 1003–1020.

Abatzoglou JT, Kolden CA, Balch JK, & Bradley BA (2016). Controls on interannual variability in lightning-caused fire activity in the western US. Environmental Research Letters, 11(4), 45005.

Abatzoglou JT, & Williams AP (2016). Impact of anthropogenic climate change on wildfire across western US forests. Proceedings of the National Academy of Sciences, 113(42), 11770–11775.

Aldersley A, Murray SJ, & Cornell SE (2011). Global and regional analysis of climate and human drivers of wildfire. Science of the Total Environment, 409(18), 3472–3481. [PubMed: 21689843]

Andela N, Morton DC, Giglio L, Chen Y, van der Werf GR, Kasibhatla PS, … Kloster S (2017). A human-driven decline in global burned area. Science, 356(6345), 1356–1362. [PubMed: 28663495]

Archibald S, Lehmann CER, Belcher CM, Bond WJ, Bradstock RA, Daniau AL, … He T (2018). Biological and geophysical feedbacks with fire in the Earth system. Environmental Research Letters, 13(3), 33003.

Archibald S, Lehmann CER, Gómez-Dans JL, & Bradstock RA (2013). Defining pyromes and global syndromes of fire regimes. Proceedings of the National Academy of Sciences, 110(16), 6442–6447.

Archibald S, Nickless A, Govender N, Scholes RJ, & Lehsten V (2010). Climate and the inter-annual variability of fire in southern Africa: a meta-analysis using long-term field data and satellite-derived burnt area data. Global Ecology and Biogeography, 19(6), 794–809.

Archibald S, Roy DP, Wilgen V, Brian W, & Scholes RJ (2009). What limits fire? An examination of drivers of burnt area in Southern Africa. Global Change Biology, 15(3), 613–630.

Balch JK, Bradley BA, Abatzoglou JT, Nagy RC, Fusco EJ, Mahood AL, & Chelsea Nagy R (2017). Human-started wildfires expand the fire niche across the United States. Proceedings of the National Academy of Sciences, 114(11), 2946–2951.

Barbero R, Abatzoglou JT, Steel EA, & Larkin NK (2014). Modeling very large-fire occurrences over the continental United States from weather and climate forcing. Environmental Research Letters, 9(12), 124009.

Beck HE, van Dijk AIJM, Levizzani V, Schellekens J, Miralles DG, Martens B, & de Roo A (2017). MSWEP: 3-hourly 0.25 global gridded precipitation (1979–2015) by merging gauge, satellite, and reanalysis data. Hydrology and Earth System Sciences, 21(1), 589.

Beck HE, Vergopolan N, Pan M, Levizzani V, van Dijk AI, Weedon G, … Wood EF (2017). Global-scale evaluation of 23 precipitation datasets using gauge observations and hydrological modeling. Hydrol. Earth Syst. Sci, 21, 6201–6217

Bedia J, Herrera S, Gutiérrez JM, Benali A, Brands S, Mota B, & Moreno JM (2015). Global patterns in the sensitivity of burned area to fire-weather: Implications for climate change. Agricultural and Forest Meteorology, 214–215, 369–379.

Bistinas I, Harrison SP, Prentice IC, & Pereira JMC (2014). Causal relationships versus emergent patterns in the global controls of fire frequency. Biogeosciences, 11(18), 5087–5101.

Boer MM, Nolan RH, Resco De Dios V, Clarke H, Price OF, & Bradstock RA (2017). Changing Weather Extremes Call for Early Warning of Potential for Catastrophic Fire. Earth's Future, 5(12), 1196–1202.

Bond WJ, & Keeley JE (2005). Fire as a global 'herbivore': the ecology and evolution of flammable ecosystems. Trends in Ecology & Evolution, 20(7), 387–394. [PubMed: 16701401]

Boschetti L, Flasse SP, & Brivio PA (2004). Analysis of the conflict between omission and commission in low spatial resolution dichotomic thematic products: The Pareto Boundary. Remote Sensing of Environment, 91(3–4), 280–292.

Boschetti L, & Roy DP (2008). Defining a fire year for reporting and analysis of global interannual fire variability. Journal of Geophysical Research: Biogeosciences, 113(G3).

Bowman DMJS, Balch JK, Artaxo P, Bond WJ, Carlson JM, Cochrane MA, … Harrison SP (2009). Fire in the Earth system. Science, 324(5926), 481–484. [PubMed: 19390038]

Bowman DMJS, Williamson GJG, Abatzoglou JT, Kolden CA, Cochrane MA, & Smith AMS (2017). Human exposure and sensitivity to globally extreme wildfire events. Nature Ecology & Evolution, 1(3), 58. [PubMed: 28812737]

Bradstock RA (2010). A biogeographic model of fire regimes in Australia: current and future implications. Global Ecology and Biogeography, 19(2), 145–158.

Cahoon DR Jr, Stocks BJ, Levine JS, Cofer III WR, & O'Neill KP (1992). Seasonal distribution of African savanna fires. Nature, 359(6398), 812.

Cecil DJ, Buechler DE, & Blakeslee RJ (2014). Gridded lightning climatology from TRMM-LIS and OTD: Dataset description. Atmospheric Research, 135, 404–414.

Cochrane MA (2003). Fire science for rainforests. Nature, 421(6926), 913. [PubMed: 12606992]

Crowther TW, Glick HB, Covey KR, Bettigole C, Maynard DS, Thomas SM, … Bradford MA (2015). Mapping tree density at a global scale. Nature, 525, 201. [PubMed: 26331545]

Cruz MG, Sullivan AL, Gould JS, Sims NC, Bannister AJ, Hollis JJ, & Hurley RJ (2012). Anatomy of a catastrophic wildfire: The Black Saturday Kilmore East fire in Victoria, Australia. Forest Ecology and Management, 284, 269–285.

Dobrowski SZ, Abatzoglou J, Swanson AK, Greenberg JA, Mynsberge AR, Holden ZA, & Schwartz MK (2013). The climate velocity of the contiguous United States during the 20th century. Global Change Biology, 19(1), 241–251. [PubMed: 23504735]

Field RD, Van Der Werf GR, Fanin T, Fetzer EJ, Fuller R, Jethva H, … Torres O (2016). Indonesian fire activity and smoke pollution in 2015 show persistent nonlinear sensitivity to El Niño-induced drought. Proceedings of the National Academy of Sciences, 113(33), 9204–9209.

Field RD, Van Der Werf GR, & Shen SSP (2009). Human amplification of drought-induced biomass burning in Indonesia since 1960. Nature Geoscience, 2(3), 185.

Flannigan MD, Krawchuk MA, de Groot WJ, Wotton BM, & Gowman LM (2009). Implications of changing climate for global wildland fire. International Journal of Wildland Fire, 18(5), 483–507.

Friedl MA, Sulla-Menashe D, Tan B, Schneider A, Ramankutty N, Sibley A, & Huang X (2010). MODIS Collection 5 global land cover: Algorithm refinements and characterization of new datasets. Remote Sensing of Environment, 114(1), 168–182.

Giglio L, Descloitres J, Justice CO, & Kaufman YJ (2003). An enhanced contextual fire detection algorithm for MODIS. Remote Sensing of Environment, 87(2–3), 273–282.

Giglio L, Loboda T, Roy DP, Quayle B, & Justice CO (2009). An active-fire based burned area mapping algorithm for the MODIS sensor. Remote Sensing of Environment, 113(2), 408–420.

Giglio L, Randerson JT, & Werf GR (2013). Analysis of daily, monthly, and annual burned area using the fourth-generation global fire emissions database (GFED4). Journal of Geophysical Research: Biogeosciences, 118(1), 317–328.

Giglio L, Boschetti L, Humber M, Justice C (2018) The Collection 6 MODIS Burned Area Mapping Algorithm and Burned Area Product, Remote Sensing of Environment*, revised* 6 *2018*

Hall JV, Loboda TV, Giglio L, & McCarty GW (2016). A MODIS-based burned area assessment for Russian croplands: Mapping requirements and challenges. Remote Sensing of Environment, 184, 506–521.

Hantson S, Arneth A, Harrison SP, Kelley DI, Prentice IC, Rabin SS, … Yue C (2016). The status and challenge of global fire modelling. Biogeosciences, 13(11), 3359–3375.

Higuera PE, Abatzoglou JT, Littell JS, & Morgan P (2015). The Changing Strength and Nature of Fire-Climate Relationships in the Northern Rocky Mountains, USA, 1902–2008. PloS One, 10(6), e0127563. [PubMed: 26114580]

Holz A, Paritsis J, Mundo IA, Veblen TT, Kitzberger T, Williamson GJ, … Grau HR (2017). Southern Annular Mode drives multicentury wildfire activity in southern South America. Proceedings of the National Academy of Sciences, 114(36), 9552–9557.

Johnston FH, Henderson SB, Chen Y, Randerson JT, Marlier M, DeFries RS, … Brauer M (2012). Estimated global mortality attributable to smoke from landscape fires. Environmental Health Perspectives, 120(5), 695. [PubMed: 22456494]

Jolly W, Cochrane M, Freeborn P, Holden ZA, Brown T, Williamson GJ, & Bowman DMJS (2015). Climate-induced variations in global wildfire danger from 1979 to 2013. Nature Communications, 6, 7537.

Kasischke ES, & Turetsky MR (2006). Recent changes in the fire regime across the North American boreal region - Spatial and temporal patterns of burning across Canada and Alaska. Geophysical Research Letters, 33(9).

Keeley JE, Safford H, Fotheringham CJ, Franklin J, & Moritz M (2009). The 2007 southern California wildfires: lessons in complexity. Journal of Forestry, 107(6), 287–296.

Knorr W, Jiang L, & Arneth A (2016). Climate, CO 2 and human population impacts on global wildfire emissions. Biogeosciences, 13(1), 267–282.

Knorr W, Kaminski T, Arneth A, & Weber U (2014). Impact of human population density on fire frequency at the global scale. Biogeosciences, 11, 1085–1102.

Kolden CA, Lutz JA, Key CH, Kane JT, & van Wagtendonk JW (2012). Mapped versus actual burned area within wildfire perimeters: characterizing the unburned. Forest Ecology and Management, 286, 38–47.

Korontzi S, McCarty J, Loboda T, Kumar S, & Justice C (2006). Global distribution of agricultural fires in croplands from 3 years of Moderate Resolution Imaging Spectroradiometer (MODIS) data. Global Biogeochemical Cycles, 20(2), GB2021.

Krawchuk MA, & Moritz MA (2014). Burning issues: statistical analyses of global fire data to inform assessments of environmental change. Environmetrics, 25(6), 472–481.

Krawchuk M, & Moritz M (2011). Constraints on global fire activity vary across a resource gradient. Ecology, 92(1), 121–132. [PubMed: 21560682]

Krawchuk M, Moritz MA, Parisien M-A, Van Dorn J, Hayhoe K, & others. (2009). Global pyrogeography: the current and future distribution of wildfire. PloS One, 4(4), e5102. [PubMed: 19352494]

Le Page Y, Oom D, Silva JMN, Jönsson P, & Pereira JMC (2010). Seasonality of vegetation fires as modified by human action: observing the deviation from eco-climatic fire regimes. Global Ecology and Biogeography, 19(4), 575–588.

Littell JS, McKenzie D, Peterson DL, & Westerling AL (2009). Climate and wildfire area burned in western US ecoprovinces, 1916–2003. Ecological Applications, 19(4), 1003–1021. [PubMed: 19544740]

Littell JS, Peterson DL, Riley KL, Liu Y, & Luce CH (2016). A review of the relationships between drought and forest fire in the United States. Global Change Biology, 22(7), 2352–2369.

Marlon JR, Bartlein PJ, Gavin DG, Long CJ, Anderson RS, Briles CE, … Walsh MK (2012). Long-term perspective on wildfires in the western USA. Proceedings of the National Academy of Sciences, 109(9), E535–E543.

McCarty JL, Korontzi S, Justice CO, & Loboda T (2009). The spatial and temporal distribution of crop residue burning in the contiguous United States. Science of the Total Environment, 407(21), 5701–5712. [PubMed: 19647857]

McKenzie D, & Littell JS (2017). Climate change and the eco-hydrology of fire: will area burned increase in a warming western U.S.? Ecological Applications, 27(1), 26–36. [PubMed: 28001335]

Moritz MA, Parisien M-A, Batllori E, Krawchuk MA, Van Dorn J, Ganz DJ, & Hayhoe K (2012). Climate change and disruptions to global fire activity. Ecosphere, 3(6), 1–22.

Olson DM, Dinerstein E, Wikramanayake ED, Burgess ND, Powell GVN, Underwood EC, … Morrison JC (2001). Terrestrial Ecoregions of the World: A New Map of Life on Earth: A new global map of terrestrial ecoregions provides an innovative tool for conserving biodiversity. BioScience, 51(11), 933–938.

Parisien M-A, Miller C, Parks SA, DeLancey ER, Robinne F-N, & Flannigan MD (2016). The spatially varying influence of humans on fire probability in North America. Environmental Research Letters, 11(7), 75005.

Parisien M-A, & Moritz MA (2009). Environmental controls on the distribution of wildfire at multiple spatial scales. Ecological Monographs, 79(1), 127–154.

Parisien M-A, Snetsinger S, Greenberg JA, Nelson CR, Schoennagel T, Dobrowski SZ, & Moritz MA (2012). Spatial variability in wildfire probability across the western United States. International Journal of Wildland Fire, 21(4), 313–327.

Parks SA, Miller C, Abatzoglou JT, Holsinger LM, Parisien M-A, & Dobrowski SZ (2016). How will climate change affect wildland fire severity in the western US? Environmental Research Letters, 11(3), 35002.

Parks SA, Miller C, Parisien M-A, Holsinger LM, Dobrowski SZ, & Abatzoglou J (2015). Wildland fire deficit and surplus in the western United States, 1984–2012. Ecosphere, 6(12), 1–13.

Pausas JG, & Bradstock RA (2006). Fire persistence traits of plants along a productivity and disturbance gradient in mediterranean shrublands of south-east Australia. Global Ecology and Biogeography, 16(3), 330–340.

Pausas JG, & Keeley JE (2014). Abrupt climate-independent fire regime changes. Ecosystems, 17(6), 1109–1120.

Pausas JG, & Paula S (2012). Fuel shapes the fire–climate relationship: evidence from Mediterranean ecosystems. Global Ecology and Biogeography, 21(11), 1074–1082.

Pausas JG, & Ribeiro E (2013). The global fire–productivity relationship. Global Ecology and Biogeography, 22(6), 728–736.

Pechony O, & Shindell DT (2010). Driving forces of global wildfires over the past millennium and the forthcoming century. Proceedings of the National Academy of Sciences of the United States of America, 107(45), 19167–19170. [PubMed: 20974914]

Randerson JT, Van der Werf GR, Collatz GJ, Giglio L, Still CJ, Kasibhatla P, … Kasischke ES (2005). Fire emissions from C3 and C4 vegetation and their influence on interannual variability of atmospheric CO2 and δ13CO2. Global Biogeochemical Cycles, 19(2).

Ray D, Nepstad D, & Moutinho P (2005). Micrometeorological and Canopy Controls of Fire Susceptibility in a Forested Amazon Landscape. Ecological Applications, 15(5), 1664–1678.

Reid CE, Brauer M, Johnston FH, Jerrett M, Balmes JR, & Elliott CT (2016). Critical review of health impacts of wildfire smoke exposure. Environmental Health Perspectives, 124(9), 1334. [PubMed: 27082891]

Roy DP, Boschetti L, Justice CO, & Ju J (2008). The collection 5 MODIS burned area product—Global evaluation by comparison with the MODIS active fire product. Remote Sensing of Environment, 112(9), 3690–3707.

Running SW, Nemani RR, Heinsch FA, Zhao M, Reeves M, & Hashimoto H (2004). A continuous satellite-derived measure of global terrestrial primary production. Bioscience, 54(6), 547–560.

Sedano F, & Randerson JT (2014). Multi-scale influence of vapor pressure deficit on fire ignition and spread in boreal forest ecosystems. Biogeosciences, 11(14), 3739–3755.

Smith AMS, Kolden CA, Paveglio TB, Cochrane MA, Bowman DMJS, Moritz MA, … Abatzoglou JT (2016). The Science of Firescapes: Achieving Fire-Resilient Communities. BioScience, 66(2), 130–146. [PubMed: 29593361]

Stephens SL, Burrows N, Buyantuyev A, Gray RW, Keane RE, Kubian R, … Tolhurst KG (2014). Temperate and boreal forest mega-fires: characteristics and challenges. Frontiers in Ecology and the Environment, 12(2), 115–122.

Stocks BJ, Mason JA, Todd JB, Bosch EM, Wotton BM, Amiro BD, … Skinner WR (2002). Large forest fires in Canada, 1959–1997. Journal of Geophysical Research: Atmospheres, 107(D1)

Swetnam TW, & Betancourt JL (1998). Mesoscale disturbance and ecological response to decadal climatic variability in the American Southwest. Journal of Climate, 11(12), 3128–3147.

Syphard AD, Keeley JE, Pfaff AH, & Ferschweiler K (2017). Human presence diminishes the importance of climate in driving fire activity across the United States. Proceedings of the National Academy of Sciences, 114(52), 13750–13755.

Syphard AD, Radeloff VC, Keeley JE, Hawbaker TJ, Clayton MK, Stewart SI, & Hammer RB (2007). Human influence on California fire regimes. Ecological Applications, 17(5), 1388–1402. [PubMed: 17708216]

Taylor AH, Trouet V, Skinner CN, & Stephens S (2016). Socioecological transitions trigger fire regime shifts and modulate fire–climate interactions in the Sierra Nevada, USA, 1600–2015 CE. Proceedings of the National Academy of Sciences, 113(48), 13684–13689.

Team RC (2017). R language definition. Vienna, Austria: R Foundation for Statistical Computing.

Turco M, Bedia J, Di Liberto F, Fiorucci P, von Hardenberg J, Koutsias N, … Provenzale A (2016). Decreasing Fires in Mediterranean Europe. PLOS ONE, 11(3), e0150663. [PubMed: 26982584]

Turetsky MR, Benscoter B, Page S, Rein G, Van Der Werf GR, & Watts A (2015). Global vulnerability of peatlands to fire and carbon loss. Nature Geoscience, 8(1), 11.

Urbieta I, Zavala G, Bedia J, Gutiérrez J, San Miguel-Ayanz J, Camia A, … Moreno J (2015). Fire activity as a function of fire–weather seasonal severity and antecedent climate across spatial scales in southern Europe and Pacific western USA. Environmental Research Letters, 10(11), 114013.

van der Werf GR, Randerson JT, Giglio L, Gobron N, & Dolman AJ (2008). Climate controls on the variability of fires in the tropics and subtropics. Global Biogeochemical Cycles, 22(3), GB3028.

Van Der Werf GR, Randerson JT, Giglio L, Van Leeuwen TT, Chen Y, Rogers BM, … Collatz GJ (2017). Global fire emissions estimates during 1997–2016. Earth System Science Data, 9(2), 697.

Westerling AL (2016). Increasing western US forest wildfire activity: sensitivity to changes in the timing of spring. Philosophical Transactions of the Royal Society B: Biological Sciences, 371(1696), 20150178.

Westerling AL, Turner MG, Smithwick EAH, Romme WH, & Ryan MG (2011). Continued warming could transform Greater Yellowstone fire regimes by mid-21st century. Proceedings of the National Academy of Sciences of the United States of America, 108(32), 13165–13170. [PubMed: 21788495]

Williams AP, & Abatzoglou JT (2016). Recent advances and remaining uncertainties in resolving past and future climate effects on global fire activity. Current Climate Change Reports, 2, 1–14.

Williams AP, Seager R, Macalady AK, Berkelhammer M, Crimmins MA, Swetnam TW, … Rahn T (2015). Correlations between components of the water balance and burned area reveal new insights for predicting forest fire area in the southwest United States. International Journal of Wildland Fire, 24(1), 14–26.

Willmott CJ, Rowe CM, & Mintz Y (1985). Climatology of the terrestrial seasonal water cycle. Journal of Climatology, 5(6), 589–606.

Wood S, & Wood MS (2017). Package ‘mgcv.’ R Package Version, 1–7.

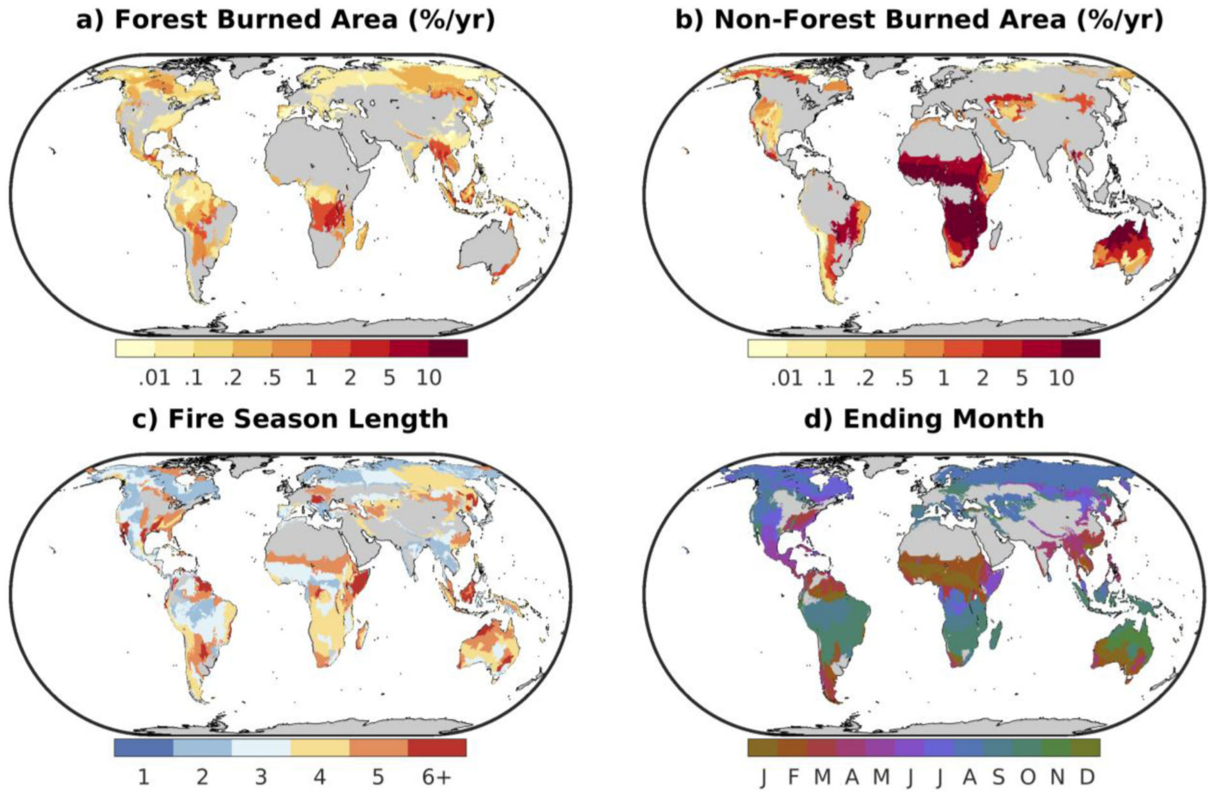


**Figure 1:**

Average ecoregion burned area fraction per year from 1997–2016 for (a) forests, and (b) non-forests. The duration of the fire season (in months) is shown in panel (c) and ending month of the fire season shown in panel (d). Grayed out are ecoregions that comprised <0.001% of either forest or non-forested burned area or where land cover was <20% forest or non-forest. Maps are provided in an Eckert IV equal-area projection.

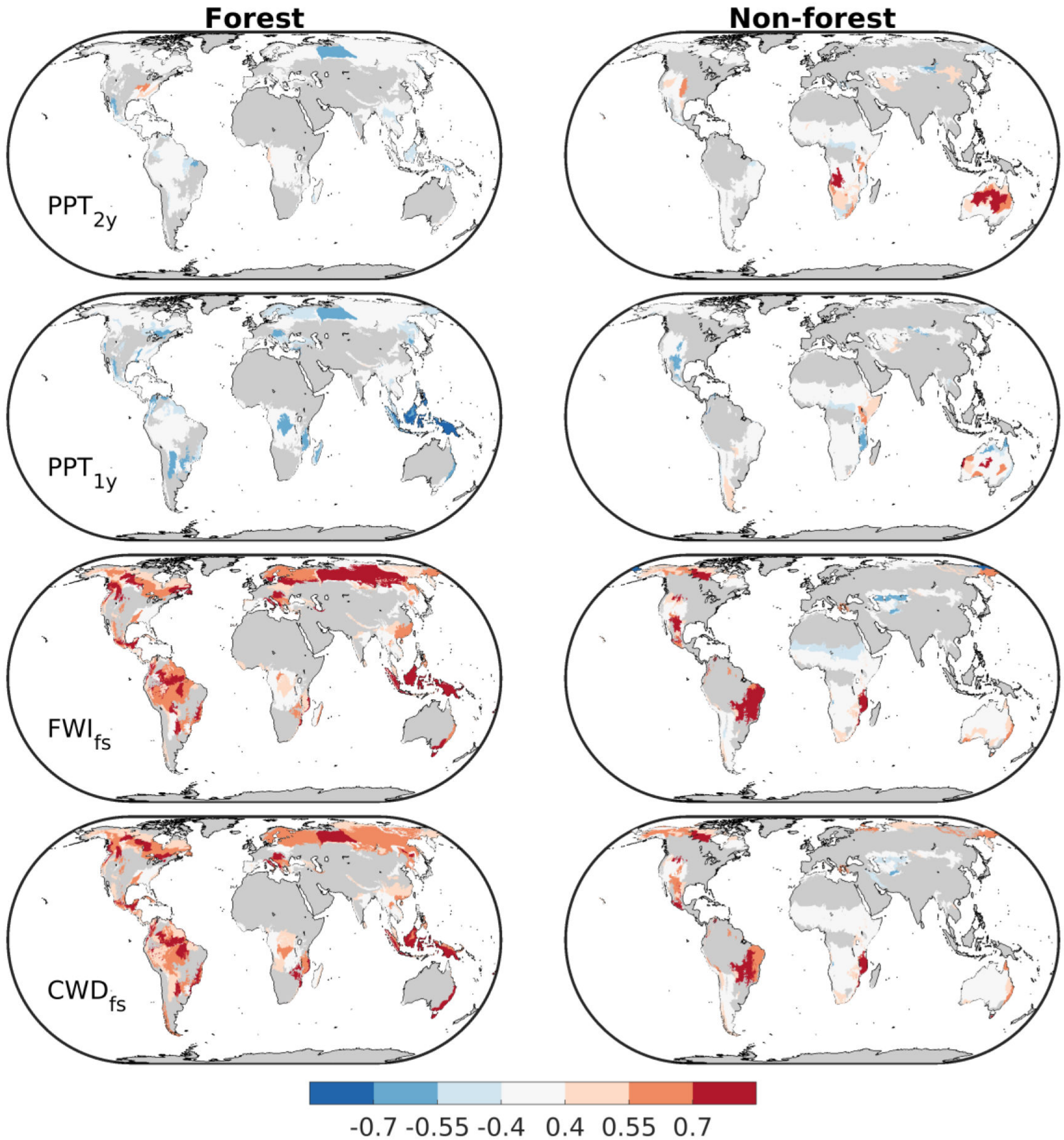


**Figure 2:**

Linear Pearson's correlation between the base-10 logarithm of fire year burned area and 12-month accumulated precipitation ending 14-months prior to the fire season ($PPT_{2y}$), 12-month accumulated precipitation ending 2-months prior to the fire season ($PPT_{1y}$), and the Fire Weather Index ($FWI_{fs}$), and climatic water deficit ($CWD_{fs}$) over the fire season. Only statistically significant correlations ($|r|>0.4$) are colored. Ecoregions with less than 20% land cover for each vegetation class are shaded darker gray.

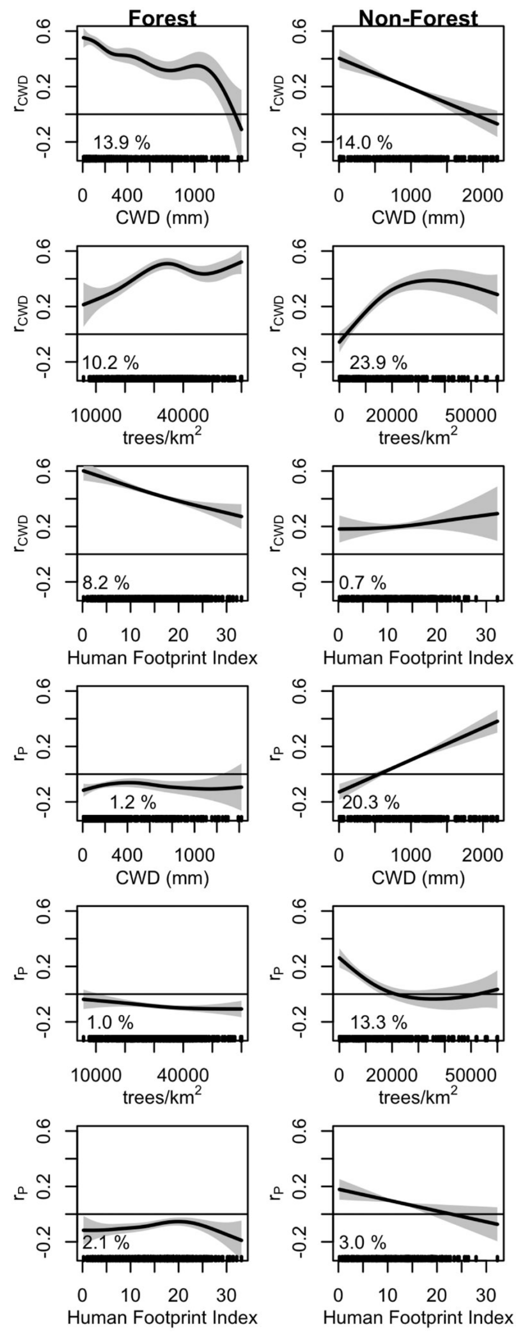


**Figure 3:**

Model generalized additive model (GAM) fit of climate correlations to burned area across global ecoregions for (left) forests and (right) non-forests as functions of spatial gradients in (top to bottom) annual average climatic water deficit (CWD), average tree density, and the Human Footprint Index. The top three panels show GAMs for correlations with concurrent CWD ($r_{CWD}$), while the bottom three panels show GAMs for correlations with antecedent precipitation (14–25 months prior to the fire season, $r_P$). The grey shading shows the 95% CI, black stripes along the x-axis denote the distribution of data from ecoregions, and values reported above x-axes show the percent of geographic variance explained by each GAM.

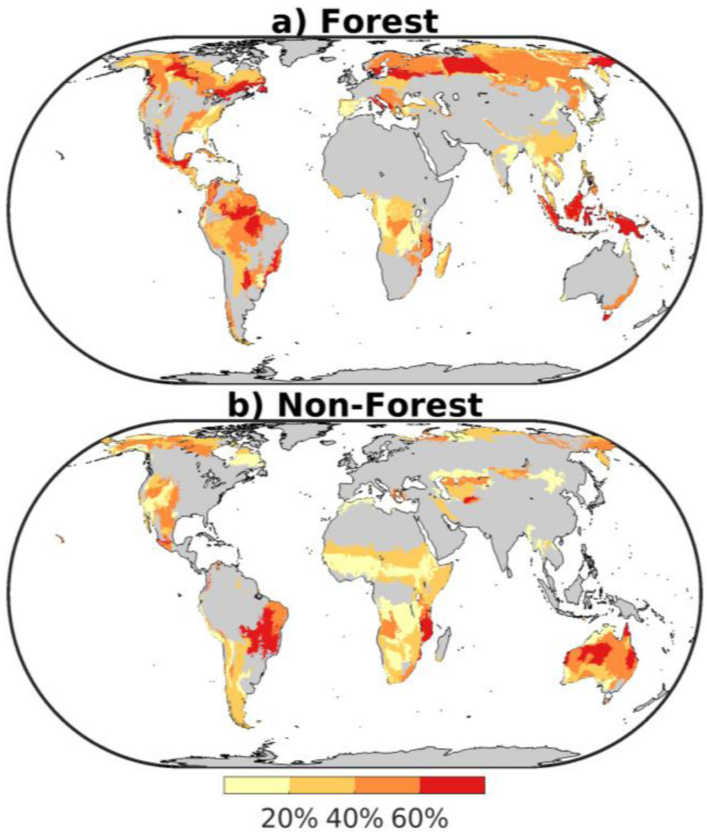


**Figure 4:**

Percent of interannual variability in the base-10 logarithm of fire season burned area accounted for using a linear model that includes one measure of antecedent precipitation and one measure of concurrent fuel aridity as depicted in Figure 2.