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Climate change and disruptions to global fire activity

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Abstract. Future disruptions to fire activity will threaten ecosystems and human well-being throughout the world, yet there are few fire projections at global scales and almost none from a broad range of global climate models (GCMs). Here we integrate global fire datasets and environmental covariates to build spatial statistical models of fire probability at a 0.5° resolution and examine environmental controls on fire activity. Fire models are driven by climate norms from 16 GCMs (A2 emissions scenario) to assess the magnitude and direction of change over two time periods, 2010–2039 and 2070–2099. From the ensemble results, we identify areas of consensus for increases or decreases in fire activity, as well as areas where GCMs disagree. Although certain biomes are sensitive to constraints on biomass productivity and others to atmospheric conditions promoting combustion, substantial and rapid shifts are projected for future fire activity across vast portions of the globe. In the near term, the most consistent increases in fire activity occur in biomes with already somewhat warm climates; decreases are less pronounced and concentrated primarily in a few tropical and subtropical biomes. However, models do not agree on the direction of near-term changes across more than 50% of terrestrial lands, highlighting major uncertainties in the next few decades. By the end of the century, the magnitude and the agreement in direction of change are projected to increase substantially. Most far-term model agreement on increasing fire probabilities (~62%) occurs at mid- to high-latitudes, while agreement on decreasing probabilities (~20%) is mainly in the tropics. Although our global models demonstrate that long-term environmental norms are very successful at capturing chronic fire probability patterns, future work is necessary to assess how much more explanatory power would be added through interannual variation in climate variables. This study provides a first examination of global disruptions to fire activity using an empirically based statistical framework and a multi-model ensemble of GCM projections, an important step toward assessing fire-related vulnerabilities to humans and the ecosystems upon which they depend.

Key words: climatic constraints; ensemble model uncertainty; flammability; global climate models (GCM); GCM agreement; global fire probabilities; resources to burn; spatial statistical models; species distribution models.

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INTRODUCTION

Fire's pervasive influence on human societies and ecosystem functions has motivated great interest in understanding its environmental drivers and effects, especially in the context of anthropogenic climate change (Bowman et al. 2009, Flannigan et al. 2009, Whitlock et al. 2010). Recent increases in fire activity in some parts of the world have been attributed to climate change (e.g., Piñol et al. 1998, Gillett et al. 2004, Kasischke and Turetsky 2006, Westerling et al. 2006), often overshadowing the potential range of future outcomes that may occur across the planet, including relative stability or decreases in fire activity. Even the latest IPCC AR4 chapter on ecosystem impacts focused almost exclusively on projected increases in fire (Fischlin et al. 2007), despite mixed results from Scholze et al. (2006), who predicted both increases and decreases in fire using a model of vegetation dynamics driven by projections from multiple global climate models (GCMs).

Given the strong linkage between fire and climate (e.g., Swetnam and Betancourt 1990, Marlon et al. 2008, Aldersley et al. 2011), there is little doubt that climate-induced disruptions to fire activity will occur in many areas. However, the projected magnitude of change, and even whether fire probabilities will increase or decrease, is hotly debated for many parts of the world. Ongoing fire activity requires biomass resources to burn, atmospheric conditions conducive to combustion (i.e., dry, hot, and/or windy periods), and ignitions (Bond and van Wilgen 1996, Moritz et al. 2005, Bradstock 2010). Climate can affect all three of these factors in complex ways and over multiple timescales. The relative importance of different controls on fire activity, as well as inherent sources of uncertainty in them, can be separated into short-term environmental fluctuations versus long-term norms (Fig. 1A). This approach has been used in analyses of climate averages versus interannual climate variability to explain habitat suitability patterns (Zimmermann et al. 2009), and a similar logic has been proposed for examining changes in mean climate values versus episodic events for ecology in general (Jentsch et al. 2007). Here, we focus on coarser, long-term climate norms as they affect fire occurrence across the planet.

Different modeling schools have emerged for capturing climate-vegetation-fire relationships at broad scales. Dynamic global vegetation models (DGVMs) simulate the climate-based processes controlling plant growth and death in different vegetation types, and many of these models have incorporated a fire module (e.g., Lenihan et al. 1998, Fosberg et al. 1999, Thonicke et al. 2001, Arora and Boer 2005). Recent advances in some DGVMs have improved their ability to represent historical patterns of burning (Thonicke et al. 2010, Prentice et al. 2011), and this remains an active area of research. An alternative approach has been to build statistical models of fire activity, based directly on correlating empirical observations of fire and the key environmental variables that control its occurrence (e.g., McKenzie et al. 2004, Archibald et al. 2009, Preisler et al. 2009, Littell et al. 2009, Balshi et al. 2009, Krawchuk et al. 2009, Parisien and Moritz 2009, Westerling et al. 2011). These empirical fire models are similar to species distribution models often used to project future shifts in habitat ranges (e.g., Guisan and Thuiller 2005, Elith et al. 2006, Hijmans and Graham 2006, Morin and Thuiller 2009, Engler et al. 2011) and thus share some of their strengths and weaknesses. Despite the basic differences between process-based and more correlative modeling approaches, it is encouraging that their predictions can often be similar (Morin and Thuiller 2009, Kearney et al. 2010).

Regardless of the modeling framework, future projections of fire at the global scale are relatively rare (Scholze et al. 2006, Krawchuk et al. 2009, Gonzalez et al. 2010, Liu et al. 2010, Pechony and Shindell 2010). Furthermore, because most of these global studies used different GCMs, there remains a lack of understanding about how variations among GCMs affect future fire projections versus differences in the modeling approaches themselves (Littell et al. 2011). This issue is not trivial because discrepancies among GCMs, especially with respect to precipitation, may be important in the context of fire. There is growing evidence that more precipitation in some warm grasslands and shrublands can lead to higher productivity and increased fire activity during the dry season, whereas in more mesic areas the same precipitation increase could diminish fire activity (Meyn et al. 2007, van der

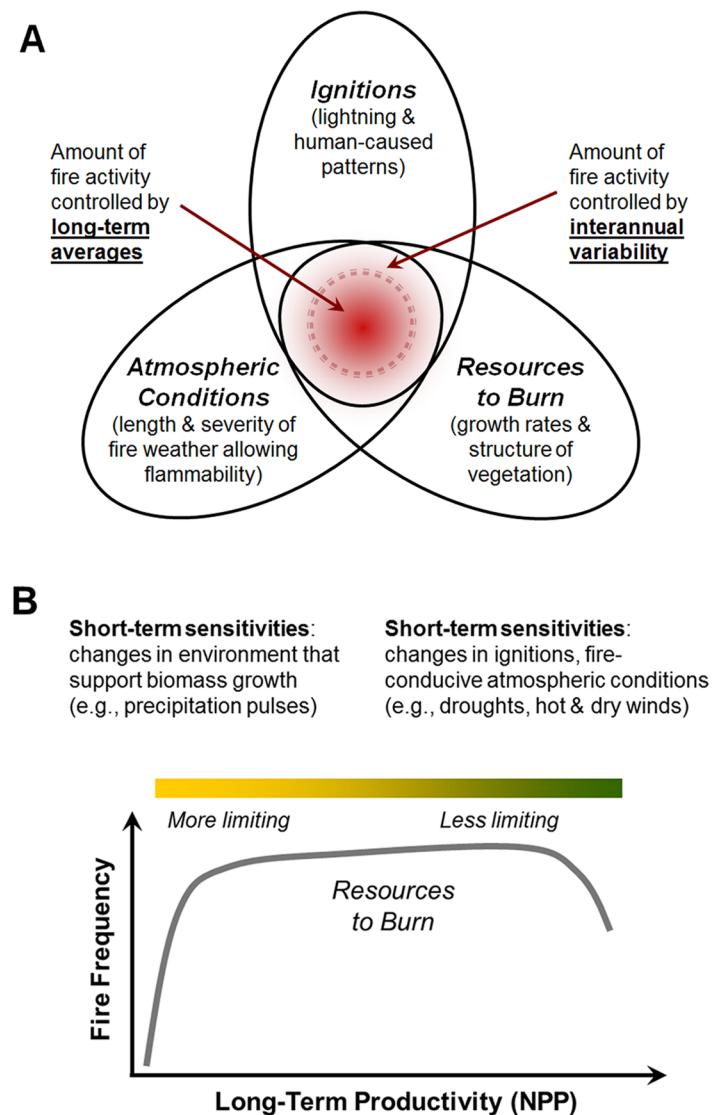


Fig. 1. Conceptual models of coarse-scale controls on fire activity. The fire regime triangle (A) reflects the three dominant factors influencing fire in different regions (vegetation characteristics, fire weather climatology, and ignition patterns), all of which vary in importance spatially and temporally. The darker center region represents a core level of fire activity, or gradients in chronic probabilities of fire, that are controlled by long-term environmental norms; the lighter outer circle represents additional spatial variation in probabilities controlled by interannual environmental fluctuations. Across a long-term global gradient in biomass productivity (B), fuel-limited areas will tend to experience more fire due to interannual pulses in precipitation; in contrast, areas with more abundant fuel will tend to experience more fire due to pulses of ignitions, combined with episodic drought and/or hot and dry winds. (After Krawchuk and Moritz 2011.)

Werf et al. 2008, Littell et al. 2009, Krawchuk and Moritz 2011). Warmer and drier weather may therefore increase fire activity in biomass-rich areas, but have the opposite effect in moisture-stressed biomes, as increased evaporative de-

mand decreases growth of biomass necessary to carry fire (Fig. 1B). Along with human behaviors, the continuum of varying constraints on fire are central to understanding responses to global change, and they lead to important questions

about GCM-based uncertainties. How well can global fire activity be modeled using long-term climate norms available from GCMs? Where do GCMs agree on the future of fire activity? What climate variables drive these changes, and will they be consistent through time?

Here we integrate empirically based statistical models of fire occurrence with an ensemble of GCM projections to derive a globally consistent analysis of future fire activity. Of the parameters important for characterizing fire regimes—fire sizes, frequencies, intensities, and seasonality—our models are designed to project fire probabilities over a given time period, results that are directly representative of fire frequencies. Our fire probability models are built from over a decade of remotely sensed fire observations and key environmental variables representing vegetation to burn and fire-conducive atmospheric conditions. The fire models are then driven by projected future climates from 16 different GCMs covering the 2010–2039 and 2070–2099 time periods, statistically downscaled to 0.5°, corresponding to the mid-high A2 emissions scenario. From these projected fire probability models, we assess the ensemble mean change in fire probability for the 16 GCMs, the degree of model agreement in projected increases and decreases in fire activity, and the long-term environmental controls contributing to these global changes.

DATA AND METHODS

The study region covers the terrestrial surface of the globe, with the exception of Antarctica and small islands. The area is gridded using 0.5° by 0.5° pixels; for a pixel to be included in the analysis, a land cover of at least 2/3 of its area is required. The climate- and vegetation-related variables, which are detailed below, are registered using the WGS 1984 geographic coordinate system, and statistical models are run using this system. Fire data are sampled using a Behrmann equal area projection and then transformed to WGS 1984. Though the WGS 1984 overestimates true area as one moves away from the Equator, equal area sampling of fire data minimizes bias in our statistical models. Supplemental comparisons of the change in probability of fire with altered climate using geographic and Behrmann equal area data showed that our geographic

sampling framework does not affect outcomes of the study.

Fire

This work combines two sources of remotely sensed global fire activity observations to develop models of fire probability: a screened version of the European Space Agency's Advanced and Along Track Scanning Radiometer (ATSR) World Fire Atlas (algorithm 2) for 1996–2006 (Mota et al. 2006), and the Moderate Resolution Imaging Spectroradiometer (MODIS) Collection 5 CMG corrected active fire data from 2001–2007 (Giglio et al. 2006). These two products document vegetation fires across the globe, and screening techniques are used to isolate and remove signals originating from other types of fire or non-fire processes. Both ATSR and MODIS satellite data include human- and lightning-caused fires. Note that not all fires are detected by these sensors; for example, smoldering fires in peatland soils may evade detection. Conversely, despite the screening, some non-vegetation fires are reported in the datasets.

To generate a global vegetation fire dataset representative of longer term fire probabilities, ATSR and MODIS data are sampled at 50-km spacing using a Behrmann equal area projection. ATSR data are aggregated to 50-km, and MODIS data are sampled from projections of their native 0.5° grids. We then use a consensus approach to develop a final fire occurrence map, such that fire-prone pixels are those where both MODIS and ATSR detected fire activity at least once over the 12-year period (Fig. 2A). Relatively few pixels are excluded due to lack of consensus between ATSR and MODIS at this coarse spatial and temporal resolution. Because multiple counts of fire observations often result from a single fire, we opted to classify the data into a binary surface of recorded fire and no fire (Fig. 2B). Although the 1996 to 2007 time period could be considered relatively short for fire observations, it is sufficient to build our fire probability models at the macroscopic scale of the study. Note that due to the presence-only modeling strategy (see below), outcomes from the study are relative probabilities of fire.

Climate

The climatic variables in our statistical models represent key environmental controls on global

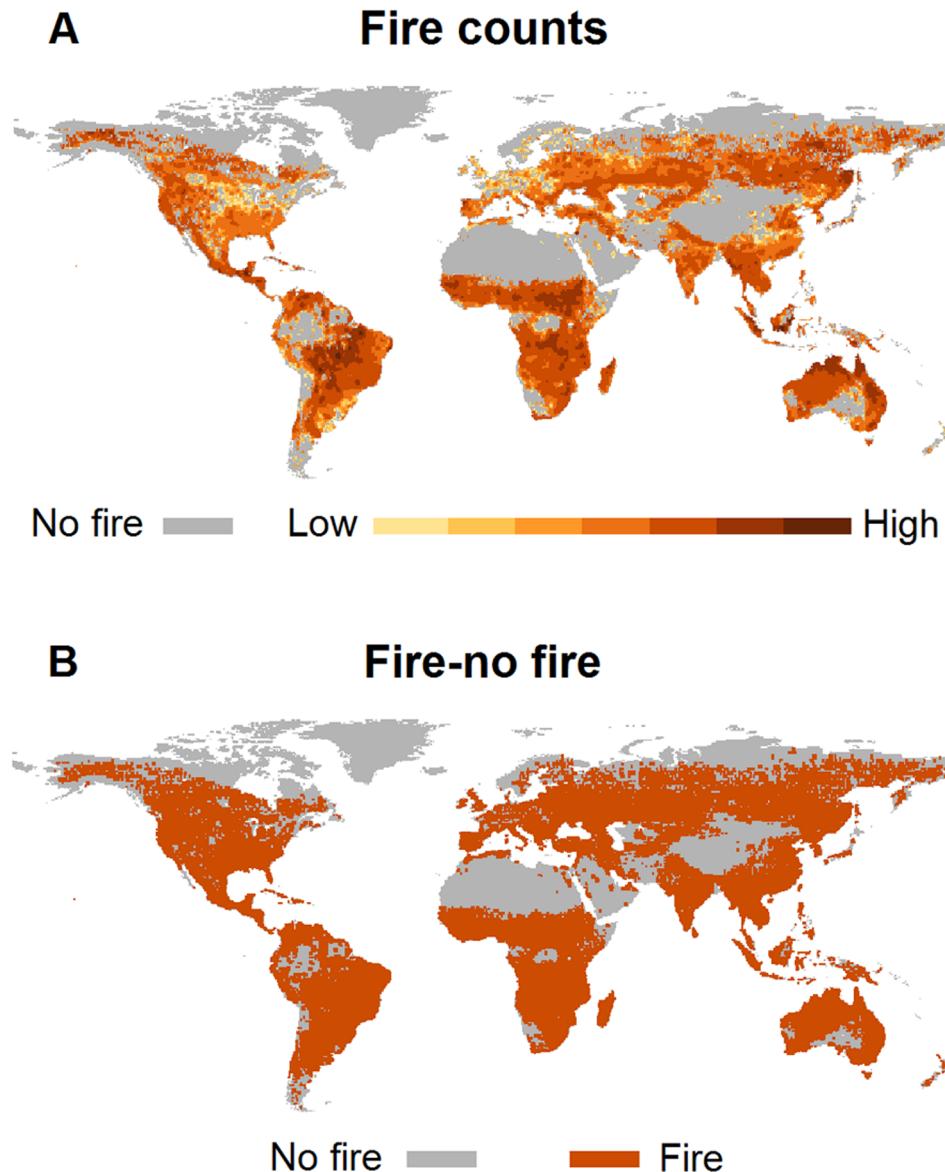


Fig. 2. Counts of observed fire occurrence readings from combined MODIS and ATSR remote sensing products from 1996 to 2007 (A) and its binary classification used in the fire probability models (B).

fire activity. While it is the interplay of weather, topography, and fuel that controls the ignition and behavior of a particular fire event, our focus is on the coarse-scale controls responsible for the longer-term likelihood of an area burning (Fig. 1A). These variables are calculated from averages of temperature and precipitation over a reference period of 1971–2000. A broad set of climate normals were initially examined due to their demonstrated importance in controlling global

fire activity in previous work (Krawchuk et al. 2009). Values were calculated from global climate model output from the World Climate Research Programme's (WCRP) Coupled Model Intercomparison Project phase 3 (CMIP3) multi-model dataset (Meehl et al. 2007). Data were down-scaled as described by Maurer et al. (2009) using the bias-correction/spatial downscaling method of Wood et al. (2004) to a 0.5° grid, based on the 1950–1999 gridded observations of Adam and

Lettenmaier (2003). This dataset included output from 16 GCMs, all of which are considered in this study.

For future projections of fire activity, we use values from the CMIP3 multi-model dataset for the time periods 2010–2039 and 2070–2099. For each of the 16 GCMs, we first considered two SRES emissions scenarios, the B1 and the A2. The B1 scenario represents a lower emissions future (Nakicenovic et al. 2000), wherein multi-model GCM projections show a median of roughly 1.8°C global surface warming from 2000 levels by 2100. The A2 scenario is a mid-to-high emissions future wherein projections show a median increase closer to 3.5°C. Only the A2 scenario results are presented here. Although the projected changes in fire probability are on the whole comparable among A2 and B1 scenarios, regional discrepancies will require additional analysis to discern their differences. Similarly, the additional explanatory power that interannual variability in climate variables may have in different parts of the world (Fig. 1B) will also need to be assessed in future work.

Vegetation patterns

An estimate of net primary productivity (NPP) acts as a coarse-scale surrogate for vegetation biomass (Fig. 1A) in a subset of our fire models; these are described in the next section. Although it may not fully capture the spatial variation in biomass available to burn, the approximately linear relationship between NPP and biomass (Kindermann et al. 2008) supports the use of NPP as a metric of vegetation. The NPP metric is based on data provided by Imhoff and Bounoua (2006) using the Carnegie-Ames-Stanford Approach (CASA) terrestrial carbon model (Potter et al. 1993). Measures of NPP represent the amount of solar energy converted to plant organic matter through photosynthesis, quantified as elemental units of carbon per unit time and area. These data were created using climatology, land cover data, solar radiation, soil texture and vegetation data (AVHRR from 1982–1998) (Imhoff and Bounoua 2006). The NPP data, which are provided at a resolution of 0.25°, are averaged for each of the 0.5° pixels. The purpose of including NPP as an input to projections of fire activity is to capture general differences in the generation of biomass and litter

and to constrain fire activity to areas with sufficient resources to burn (e.g., Archibald et al. 2009, Krawchuk et al. 2009, Bradstock 2010). Areas of persistent snow cover where no NPP data are available have a value of zero.

Statistical modeling of fire probability

We build baseline statistical models of fire probability from the recent historical GCM reference period (1971–2000; hereafter ‘baseline’) by relating recent global vegetation fires, as a dependent variable, to environmental variables depicting spatial patterns in resources to burn and atmospheric conditions conducive to fire activity. The fire dataset used in this study spans a shorter time period (1996–2007) than the GCM reference period and did not completely overlap. One might question whether the fire period of record reflects a process at equilibrium with its environment, an important assumption of this modeling approach. However, supplementary analyses using only fire data for 1996 to 2000 (the years of overlap with climate norms), as well as other subsets of the 12-year period, resulted in models with very similar response function shapes and fire probability surfaces to those estimated from the full fire data set. This consistent outcome strongly suggests that, at the temporal and spatial resolution of our study, the 12 years of fire observations provide a stable representation of fire in modern climates. To maximize the use of global data, we perform statistical analyses using the full 1996 to 2007 dataset.

The modeling framework, based on presence-only sampling, further alleviates potential issues related to temporal alignment between the fire and climate data. This is because a lack of fire observation in a given pixel is not considered a strict “absence” by the model and could still be predicted as fire-prone if the pixel shares environmental characteristics with other fire-prone areas. In our dataset, a lack of fire observations in a potentially fire-prone pixel may be due to a lack of detection (e.g., due to cloud cover), the fire return interval being longer than the observation period (e.g., as seen in much of the boreal biomes), or the prompt extinguishment of wildfires before they attain a detectable size (i.e., due to successful initial attack).

Fire models are built using the MaxEnt version

3.3.3e software (Phillips et al. 2006). This technique is well-suited to model fire probability in a presence-only framework, i.e., when fire records only exist for a limited number of years (Parisien et al. 2012, Renard et al. 2012). MaxEnt belongs to a class of models used extensively for predicting habitat suitability from observed species occurrence data. MaxEnt evaluates potential distribution from presence-only data by fitting the probability distribution of maximum entropy to the information provided at each observation. This approach attempts to capture how environmental gradients control relatively long-term potential occurrence patterns by quantifying the environmental space or envelope of observed fires. The modeling approach is thus not designed to evaluate specific sets of conditions that lead to a particular fire in a given year, but instead to evaluate the strength of chronic environmental constraints on fire's long-term geographic distribution. For example, climatic environments which exhibit strong inter-annual variation (e.g., due to climate oscillations) and may support fire activity relatively rarely will show up less often as fire-prone pixels in model estimation, and these areas (and their spatial analogues) would therefore be modeled as having relatively low probabilities of fire. In contrast, environments that experience frequent fires will be modeled as having relatively high fire probabilities.

MaxEnt has the flexibility to fit non-linear relationships between response variables (fire) and independent variables (climate and NPP), so that resulting models have the ability to encapsulate complex relationships. We included all feature types in the model: linear, quadratic, product, hinge and threshold, using the default Maxent settings for regularization values. In each run, we used 10 000 randomly selected points as background samples. These settings, in conjunction with the sampling scheme described below, produced models that represented the observed global fire patterns well but minimized overfitting of the data.

Two variants of the baseline fire probability model are developed from the recent historical data: one for projections to the upcoming 2010–2039 period and another for the end-of-century 2070–2099 period. The 2010–2039 models include existing NPP patterns as an environmental

control, in addition to climate variables. These “Climate + Baseline NPP” models explicitly specify the current distribution of biomass and are therefore more appropriate for near-term projections in which vegetation patterns are not likely to shift substantially across the 0.5° study cells. In contrast, we do not include NPP patterns in the 2070–2099 model projections. For these “Climate only” models, relationships to mapped biomass patterns are implicitly controlled by future climate variables (Beer et al. 2010). We propose that fire activity by the end of the 21st century is better represented by “Climate only” models, unconstrained by current vegetation patterns.

Environmental covariates representing ignition sources are not included in the modeling, because ignitions are assumed not to limit fire activity at the study's coarse spatial and temporal resolution, following Krawchuk et al. (2009). This implies that, where fuels are sufficient and atmospheric conditions are conducive to combustion, the potential for ignition during the period of record exists, either by lightning or human causes. The emphasis here is thus on disruptions to fire activity due to projected climate change.

Variable selection

From an initial set of 11 bioclimatic variables, we selected a subset of independent variables in order to build models with enough generality to be transferred among time periods. Removing highly correlated variables also greatly enhances the ability to interpret each variable's effect on fire probabilities. Winnowing was performed in a heuristic manner by first cross-correlating candidate climate variables and identifying those that were highly correlated (Spearman $r > 0.8$). Within each of these groups, we retained variables according to their importance in a MaxEnt model that included all variables. Finally, of the subset of variables, those that altered the response of other key variables to fire through interactions were also excluded.

The final set of five climate variables, which were used in both the “Climate + Baseline NPP” and “Climate only” models, consisted of the mean annual precipitation, the precipitation of the driest month, temperature seasonality, the mean temperature of the wettest month, and the

Table 1. Description of the independent variables used in the “Climate + Baseline NPP” and “Climate only” fire probability models and their relative contribution to the models (expressed as a percentage). Values for each variable are averages of the ensemble of models produced for each of the 16 GCMs.

| Variable name | Description (units) | Climate + Baseline NPP | Climate only |
|---------------|---|------------------------|--------------|
| NPP | Net primary productivity (g C/year) | 37.6 | ... |
| Pann | Annual precipitation (mm) | 6.9 | 24.0 |
| Pdry | Precipitation of driest month (mm) | 16.9 | 19.2 |
| Tseas | Temperature seasonality ($SD \times 100$) | 16.8 | 16.0 |
| Twet | Mean temperature of wettest month (°C) | 5.9 | 13.2 |
| Twarm | Mean temperature of warmest month (°C) | 15.9 | 27.6 |

mean temperature of the warmest month (Table 1). These climate metrics capture annual trends, seasonality and extreme environmental conditions that provide meaningful approximations of water and energy balances that determine the amount and dryness of biomass and thus fire occurrence. Note that the month in which some variables are anchored (e.g., wettest month, warmest month) may shift in the future, thereby entraining a change in the variable of interest, which would not be possible if variables were associated with actual calendar months. However, “cross-over” variables incorporating both temperature and precipitation can be difficult to interpret and should be used with caution. The coarse spatial scale of our analysis and the use of only one such variable (temperature of the wettest month) should minimize any challenges that future monthly shifts in this variable may pose. We examined the pixel-wise agreement among the 16 GCMs in increase and decrease of each of these climate variables to assess general trajectories from recent historical to the 2010–2039 and 2070–2099 periods (Fig. 3).

Subsampling of fire data and model building

To minimize the effect of inherent spatial autocorrelation in the fire data and environmental covariates and to minimize model overfitting, a small random fraction of the total pixel-wise fire observations are used to build individual MaxEnt models. The Ripley’s K-function is used to estimate the sampling fraction of fire-prone locations that exhibited a spatially independent pattern, based on five sampling fractions: 0.5%, 1%, 2.5%, 5%, and 10%. We first divide our point pattern analysis up into continents because of the spatial pattern associated with these landmasses, finding that fire data are spatially clustered at the 10% fraction and random below the 1–5%

fraction, with the value varying by continent. We therefore use the most conservative value of the range, the 1% fraction of total fire observations, for MaxEnt model building, although higher sampling fractions yield very similar probability surfaces.

Robust fire probability models are developed for each of the 16 GCMs based on 100 bootstrapped replicate MaxEnt models, each of which drew independent sample fractions from the fire data. A random subset (i.e., 1% fraction; 377 training points) of fire observations is used for training points in each model replicate, followed by model testing with the remaining 99% of the data (see *Model evaluation*). The output fire probabilities for the baseline period (1971–2000) are then averaged from the 100 replicates for each GCM. Using the same procedure, future fire probabilities are generated from averages of the 100 replicates for each GCM, by forcing the fire probability models with future climate data from the period in question. This entire process is performed separately for “Climate + Baseline NPP” and “Climate only” models. Future climate conditions that exceeded the range of historically observed values are “clamped” (i.e., held constant) at the maximum value of the range in order to provide a more conservative extrapolation.

Model evaluation

Each replicate of each GCM ensemble of MaxEnt models is evaluated using the area under the curve (AUC) statistic. The performance of the baseline fire probability models is assessed using AUC values of sensitivity (true positives) versus 1-specificity (in presence-only modeling, the fractional predicted area) using data locations withheld from model building (i.e., testing points). This is then computed and averaged for

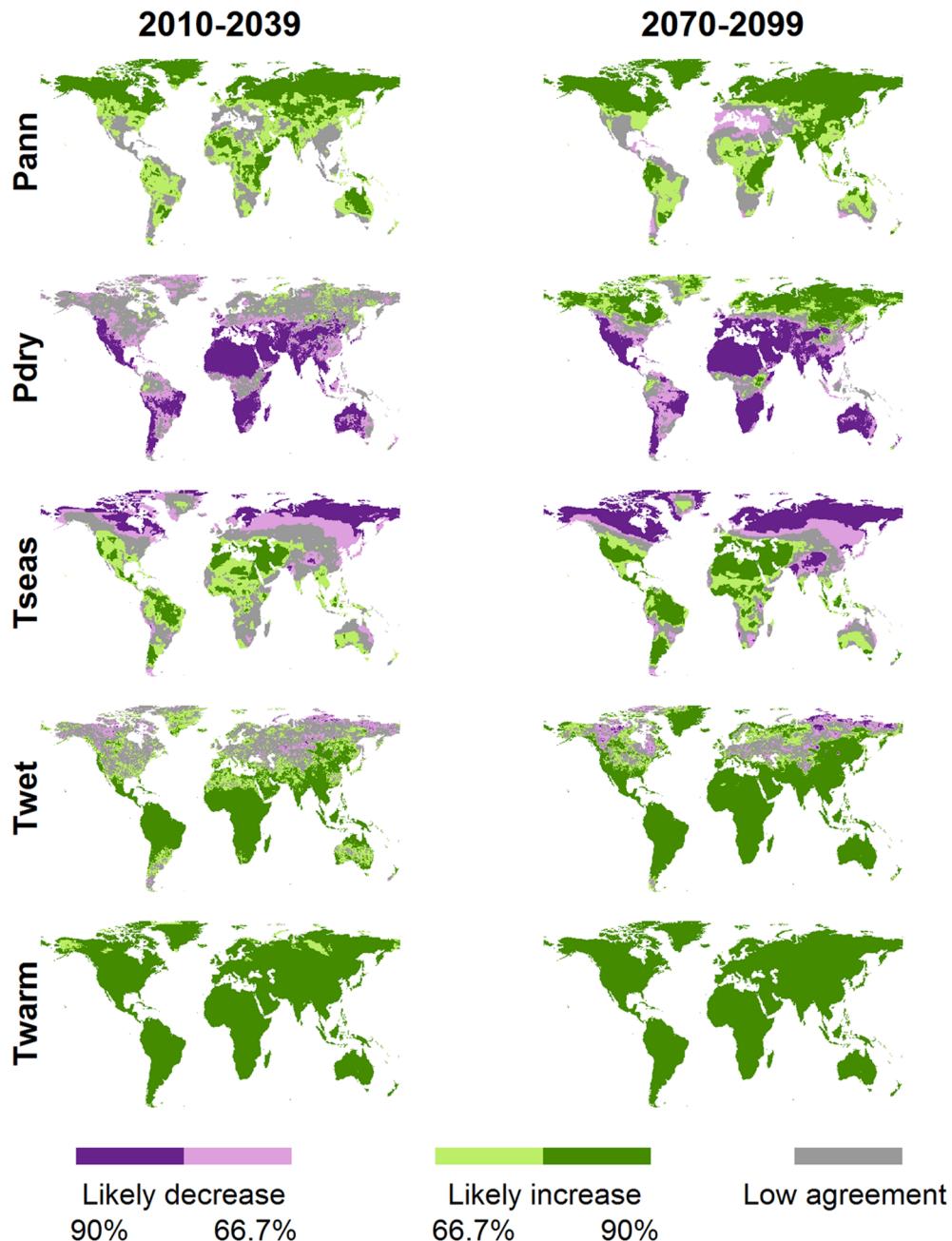


Fig. 3. The pixel-wise agreement among 16 GCMs of the projected values of five climate variables used for modeling fire probability for the 2010–2039 and 2070–2099 time periods.

each of the 100 model replicates by GCM. In a presence-absence modeling framework, the AUC typically ranges from 0.5, in which prediction accuracy is no better than if samples are picked at random, to 1, which indicates perfect classification accuracy. In contrast, in a presence-only

framework, as in this study, it is impossible to achieve unity in AUC because absences are unknown. However, when the prevalence is known, the maximum achievable AUC is equal to $1 - a/2$, where a is the fraction of the study area covered by true presences (Phillips et al. 2006).

Here, we consider a to be the percent of cells where fire was observed. Although this may be an underestimate, its value is a fair approximation of prevalence, given knowledge of global patterns and the fact that there may be some false positives from non-vegetation fires. Finally, the relative contribution of each independent variable to the fire probability models is assessed by estimating the change in model gain associated with each variable (Phillips and Dudík 2008).

Change in projected fire probability

The magnitude of change in future fire probability relative to baseline fire probabilities is assessed for each of the 16 GCMs by subtracting the model outputs for future probability of fire from those of baseline models. We then create maps of model means by averaging the pixel-wise estimates of change for the ensemble of 16 GCMs.

To complement the maps of ensemble mean change in fire probability, the agreement among models is evaluated by mapping the pixels where at least 2/3 (i.e., 66.7% or ≥ 11 out of 16) and 9/10 (i.e., 90% or ≥ 15 out of 16) of the GCMs predicted either a decrease or an increase in fire probability. The remaining pixels are those with high disagreement among GCMs in the direction of change. Model agreement is a very important component of these multi-model projections, given that the mean change in future fire probability does not provide an evaluation of the consistency in the predicted direction. Conversely, strong agreement may also be observed in pixels that have a very low mean change in the predicted fire probability. For this reason, maps of both agreement and mean change are complementary and must be interpreted together (Littell et al. 2011). The proportion of each agreement class is also broken down by terrestrial biome (Olson et al. 2001) to aid in interpreting geographic patterns of change.

To evaluate drivers of change, the shape of the relationship for each explanatory variable is examined using the MaxEnt model response functions. Variable influence is also characterized by producing “most limiting factor” (MLF) maps. The MLF at a given pixel corresponds to the variable whose value most influences model prediction at that point (Elith et al. 2010). This is achieved by changing the value of the variable of

interest to its mean value across the occurrence data; the most limiting factor is the variable that causes the largest change in fire probability (Elith et al. 2010). The most limiting factor results should be interpreted with caution, because identifying a single variable as dominant may mask a much stronger effect of two or more interacting variables.

RESULTS

Baseline models of fire probability

The modeled global fire probability for the baseline period of 1971–2000 shows complex spatial patterns of fire activity (Fig. 4) and is largely consistent with observed fire patterns (Fig. 2A). Some areas where fire is not observed in the fire dataset have high predicted fire probabilities, suggesting that they do in fact represent fire-prone environments. Both “Climate + Baseline NPP” and “Climate only” models predict low fire probabilities wherever biomass is very sparse, such as most deserts, arctic tundra, and ice caps. Although there are some minor and localized differences between the “Climate + Baseline NPP” and “Climate only” fire probabilities, the broad similarity between them suggests that the suite of climate variables used in “Climate only” models inherently capture the environmental space that controls NPP patterns.

All variables included in the models contribute relevant information on the distribution of fire (Table 1). In the “Climate + Baseline NPP” models, the NPP variable is by far the most important with a relative importance of 37.6%. As such, it largely constrains future fire probability to where sufficient biomass is currently found. Precipitation of the driest month (16.9%), temperature seasonality (16.8%), and the mean temperature of the warmest month (15.9%) are other important variables in these models. In the “Climate only” models, the mean temperature of the warmest month (27.6%) and annual precipitation (24.0%) are the dominant variables; however, all remaining climatic variables also play a significant role. The response curves describing the relationship between fire and each independent variable primarily show a unimodal response, especially in the data ranges where confidence intervals are narrowest (Fig. 5).

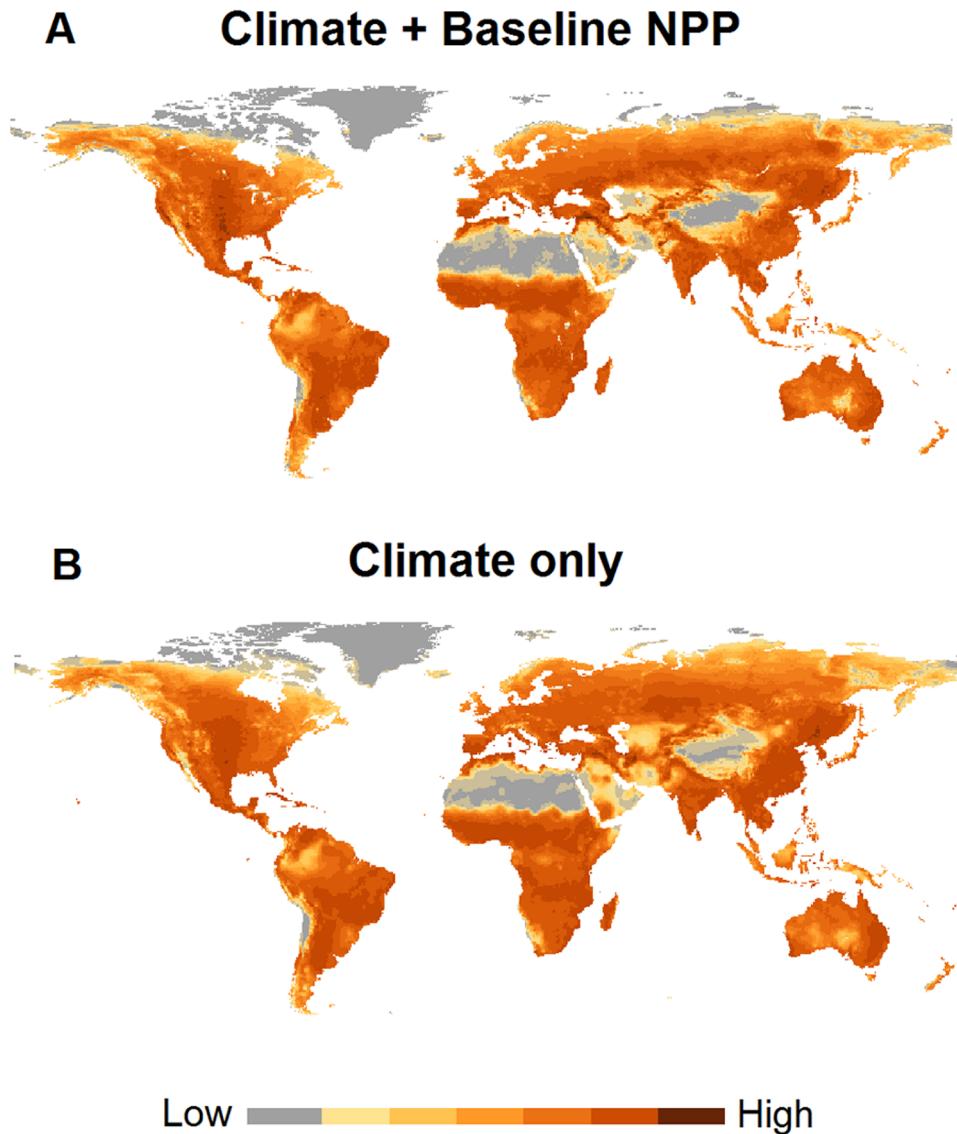


Fig. 4. Predicted baseline (1971–2000) fire probability averages for the 16 GCMs using climate variables and NPP (“Climate + Baseline NPP”) as independent variables (A) and using only climate variables (“Climate only”) (B).

Model evaluation metrics suggest that both “Climate + Baseline NPP” and “Climate only” models provide quite good discrimination of fire-prone areas. The uncorrected AUC, averaged for the 100 model replicates and then for the 16 climate models, is 0.67 for the “Climate + Baseline NPP” models and 0.66 for the “Climate only” models. The approximated prevalence of fire in this study is 0.56, which equates to a maximum achievable AUC of 0.72. When adjust-

ed for prevalence, the test AUC values are 0.93 and 0.92 for “Climate + Baseline NPP” and “Climate only” models, respectively.

Projected future fire probabilities

Departures from baseline (1971–2000) fire probabilities are computed from the 100-replicate ensembles of the 16 GCMs as mean change in fire probability for both the 2010–2039 and 2070–2099 time periods (Fig. 6). The ensemble mean

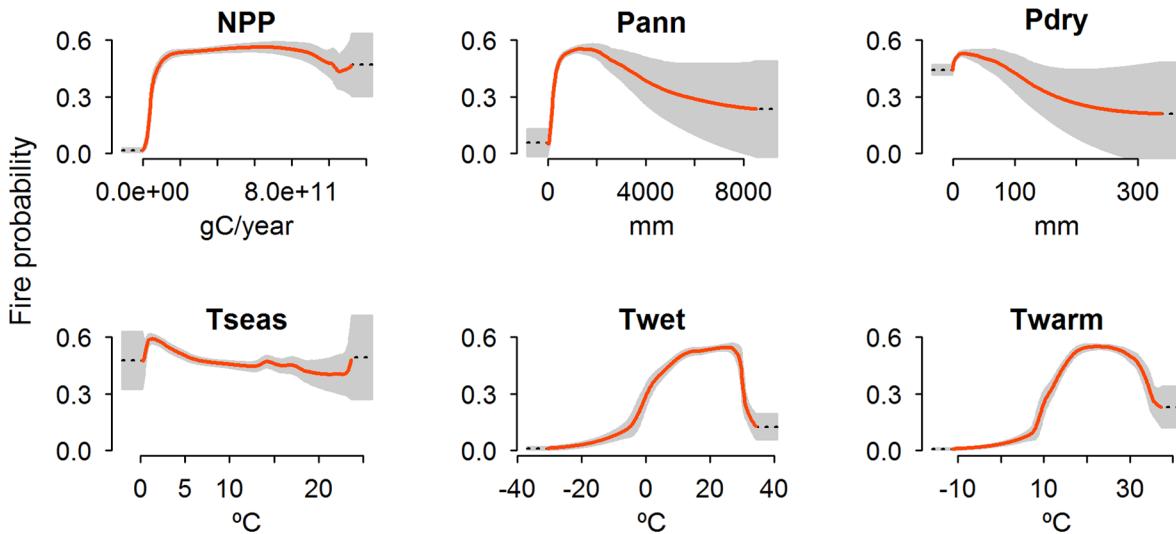


Fig. 5. Response curves for independent variables used in fire modeling, obtained by building MaxEnt models using only the single independent variable of interest. Red lines indicate the mean fire probability values, whereas the grey shading represents \pm SD, as calculated from model means from each of the 16 GCMs. Portions represented by dotted lines exceed the range of observed data; such values are “clamped” or held constant in order to prevent unrealistic fire probability projections. (Full variable names and descriptions are found in Table 1.)

changes in fire probability are highly variable, both spatially and temporally. Large areas of the globe are expected to experience relatively small near-term changes in fire probability (yellow areas in Fig. 6A), whereas predicted changes become much more pronounced in the 2070–2099 time period (Fig. 6C). Despite dramatic disruptions in fire activity illustrated by the model, supplementary analysis (not shown) indicated that the temperature of the warmest month is the only variable that consistently exceeds its current range of baseline observations. Furthermore, these out-of-range increases are confined to some of the warmest parts of the world in most GCMs (notably the Saharan and Arabian deserts and northern India).

Patterns of agreement for projected increases or decreases in fire probability (Fig. 6B and 6D) correspond to those of ensemble mean changes to a large degree, but not perfectly. Large tracts of the globe, especially the mid-latitudes of the northern hemisphere, show model agreement for increased fire probabilities in the 2010–2039 time period (37.8%); however, more than half of the world also shows low agreement in near-term changes (54.1%). Such areas of great uncertainty

tend to be prominent at higher latitudes. In contrast, far less area lacks consensus on increases or decreases in fire probability for the 2070–2099 time period. In fact, the 90% agreement threshold is met across very large regions. Although increases dominate (61.9%), almost one quarter of the terrestrial globe (20.2%) shows model agreement for projected decreases in fire by the end of the 21st century, largely in the tropics and sub-tropics. A similar fraction of terrestrial lands still shows low agreement among the models (17.9%), largely paralleling patterns of agreement in key climate variables (Fig. 3).

The analysis of model agreement patterns by biome (Fig. 7) indicates important differences among biomes and key shifts in predicted fire probability between near- and far-term fire projections. For the near- and far-term future, Mediterranean biomes, montane grasslands and shrublands, desert and xeric shrublands, and temperate coniferous forests show relative agreement for increased fire probability across most of their area. Many of the remaining biomes of the world also show model agreement for increased fire in 2010–2039 (e.g., tropical and subtropical

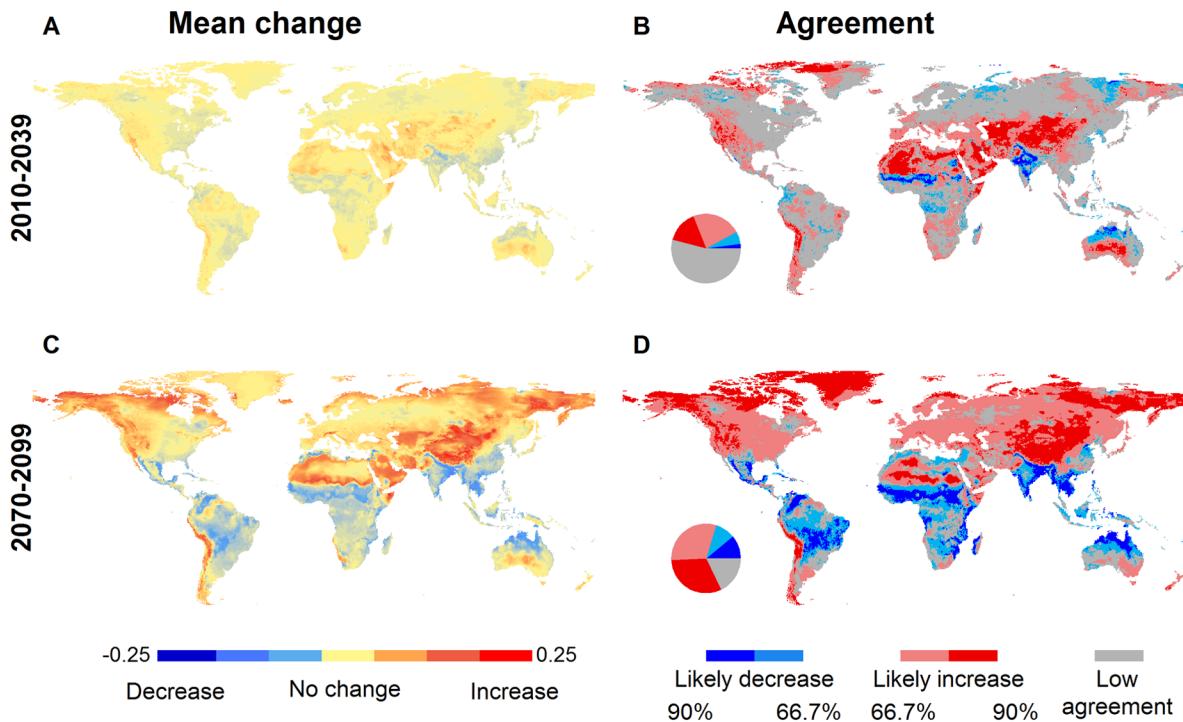


Fig. 6. Ensemble mean change (A, C) and degree of model agreement (B, D) in predicted fire probability among the 16 GCMs for 2010–2039 and 2070–2099 time periods (change assessed from baseline probabilities 1971–2000). Predictions for 2010–2039 are based on “Climate + Baseline NPP” models, and 2070–2099 are based on “Climate only” models. Pie charts indicate global proportions in each agreement class: Likely decrease, Likely increase, and Low agreement correspond to 8.1%, 37.8%, and 54.1% for the 2010–2039 period, and to 20.2%, 61.9%, and 17.9% for the 2070–2099 period.

coniferous forests, temperate grasslands/savannas/shrublands, and tundra), but these biomes also show substantial area (>50%) in the “low agreement” class. The most consistent projected fire decreases over the 2010–2039 period occur in some of the lower latitude biomes (e.g., tropical and subtropical grasslands/savannas/shrub and tropical and subtropical dry broadleaf forests). The trajectory of decreasing fire activity in these biomes strengthens over time, with most of their area showing greater agreement for fire decreases by the end of the 21st century. In contrast, the trajectory of biomes in the higher latitudes tends toward more agreement for increases in fire by 2070–2099. This trend is clear for temperate and northern regions of the world, and it is most striking for the boreal forests/taiga and tundra biomes.

The spatial pattern in variable importance is shown in the most limiting factor maps (Fig. 8).

Although this map represents a simplification, it does provide a general idea of the complexity of global fire–environmental relationships. In biomes where biomass productivity is typically limiting to fire activity, shifts in the most influential climate variable lead to vegetation growth; many high-latitude cold regions thus see long-term increases in fire probabilities associated with higher temperatures (especially in the warmest month), while mid-latitude desert and xeric regions tend to see increases due to more moisture (annual precipitation). In contrast, the vast savannas of the globe eventually experience decreased fire occurrence associated with increasing temperature seasonality, as well as warmer arid conditions overall. In the moist and biomass-rich tropical forests of the world, fire activity tends to be most limited by precipitation-related variables (largely decreasing with more annual precipitation, but increasing where

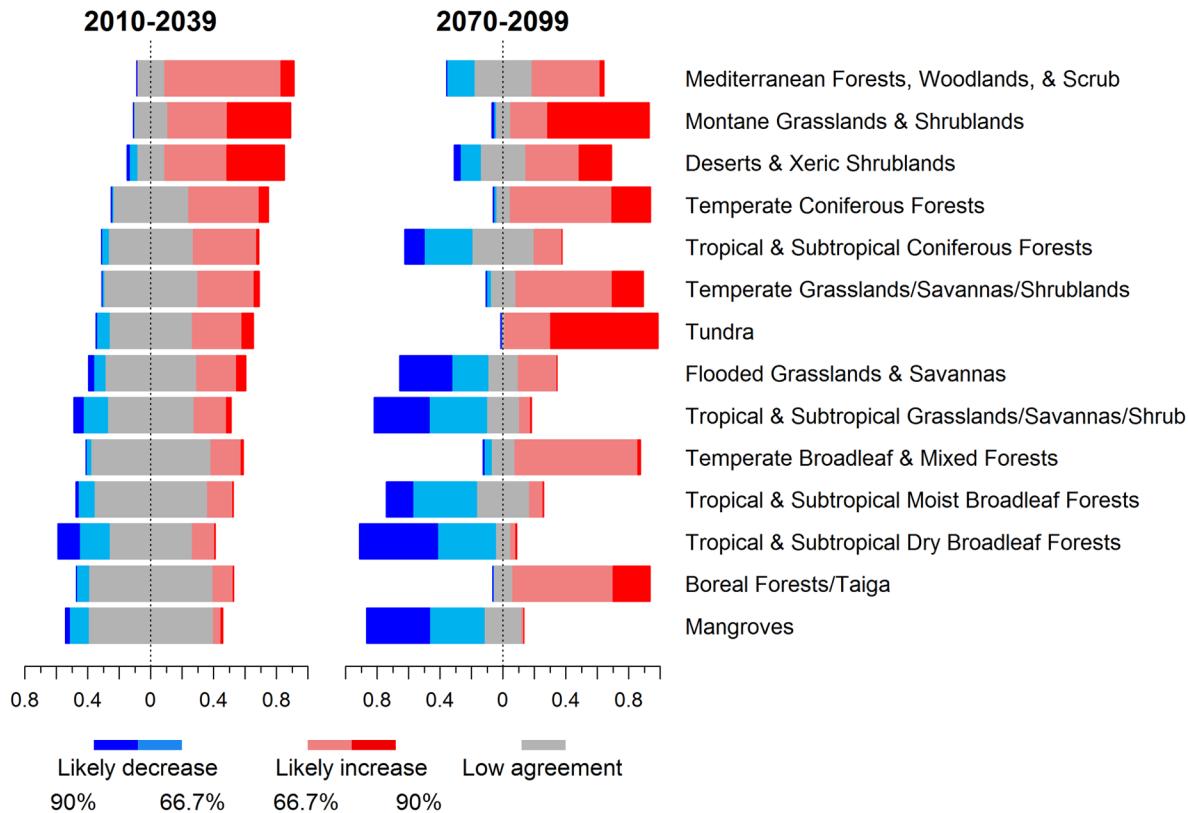


Fig. 7. The proportion of terrestrial biomes in each fire probability agreement class for 2010–2039 and 2070–2099 time periods, as shown in Fig. 6. Biomes are ordered by the proportion of lands in agreement for increased fire during 2010–2039.

there is less precipitation in the driest month). For temperate coniferous forests, higher temperatures in the warmest month appear to be occurring at a steeper portion of the response function, eventually resulting in increased fire occurrences; the same is true for broadleaf forests of North America and the forested portions of China, although the strength of specific climatic drivers is less clear.

DISCUSSION

Our projections, which are based on norms of key environmental controls on long-term fire probabilities, reveal tremendous heterogeneity in future fire patterns across the planet, as well as the variables driving expected changes. These results provide general support for regional studies that predict increases in fire activity over the next century. Although not as prevalent at a

global scale, many areas are also expected to experience decreased fire probabilities, particularly in the far term. This type of variability in disruptions to future fire patterns is not unexpected, as it is an outcome of nonlinear interactions between multiple temperature- and moisture-based climatic metrics that vary spatially (Fig. 1), which has been demonstrated in other recent global studies (Scholze et al. 2006, Gonzalez et al. 2010, Pechony and Shindell 2010). However, vast regions for which the models do not agree on the direction of future change are somewhat surprising. These uncertainties are due to inherent differences among GCMs (Meehl et al. 2007, Littell et al. 2011), illustrated in our climate agreement maps, and are a key motivation for global multi-model ensemble analyses such as those presented here. Although GCMs predict that temperatures will rise virtually everywhere on Earth over the next

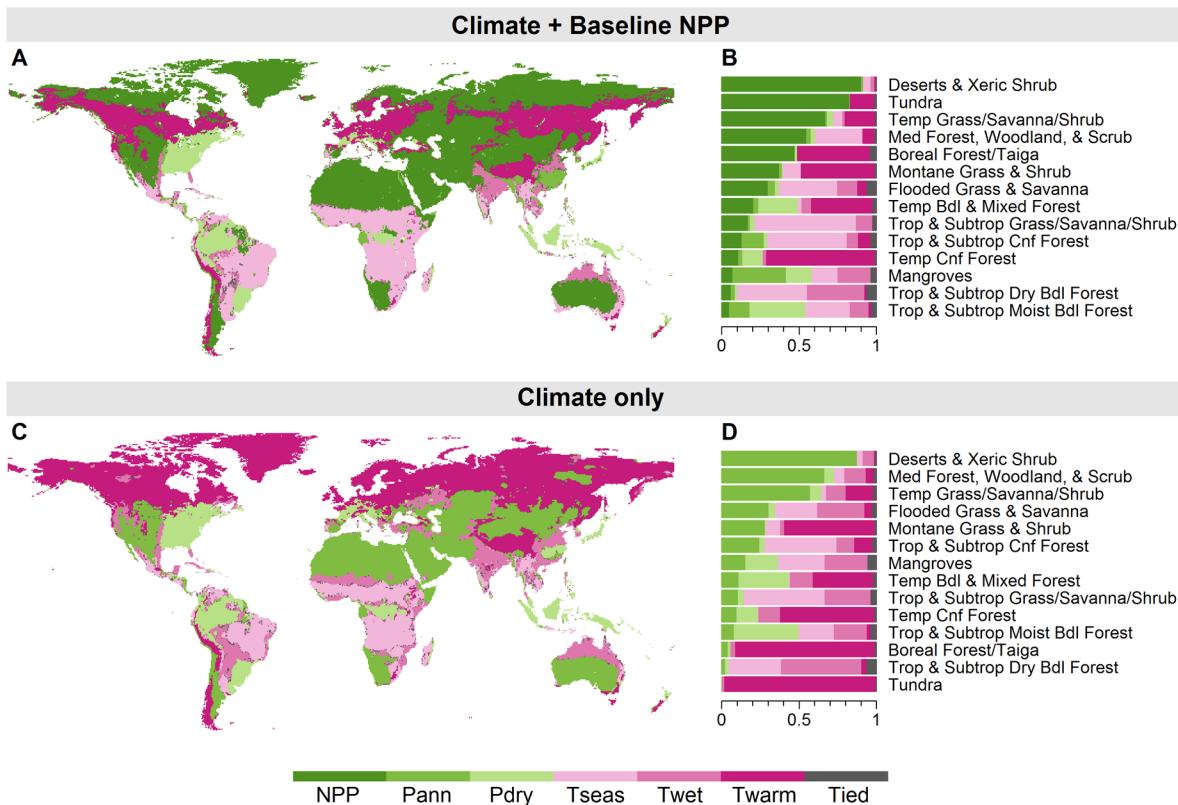


Fig. 8. Most limiting factor maps and proportions by biome for “Climate + Baseline NPP” (A, B) and “Climate only” (C, D) fire probability models. Maps are compiled from fire probability models of the 16 GCMs, by recording the variable most frequently identified as most limiting factor at each pixel (“tied” means no single variable dominated). Biomes are ordered by decreasing proportion limited by NPP for “Climate + Baseline NPP” models (B) and by Annual precipitation (Pann) for “Climate only” models (D).

century, future fire occurrence appears to primarily be a function of the available moisture in many areas. Due to such spatially varying constraints over fire among regions and biomes (Krawchuk and Moritz 2011), our results do not corroborate the notion that temperature will become the single dominant control on global wildfire during the next century (Pechony and Shindell 2010).

Global versus biome-specific changes

In the near term, despite consensus on key areas of increased and decreased fire activity, the majority of the globe (~55%) shows low agreement in the direction of projected change. Even so, the ensemble mean change in fire probabilities for many of these areas of low agreement may, in fact, be relatively small. Accordingly,

some of this uncertainty could equate to relative stability in fire activity over the next few decades. However, the magnitude of change and the degree of agreement among GCMs grows substantially through time. By the end of the century there is consensus that the vast majority of the globe (~82%) will experience disruptions in fire activity. Model agreement is strongest for fire increases in both the near and distant future (37.8% and 61.9% of terrestrial areas, respectively). Most of the predicted increase occurs in the higher northern latitudes, although in some regions of central Europe and central North America such changes are projected to be relatively minor. In contrast, the world’s decreasing fire activity is centered on the equatorial regions, a trend that is amplified through the end of the century.

Our global projections reflect the relative importance of resources to burn, as well as the length and severity of conditions affecting their flammability (Meyn et al. 2007, Krawchuk et al. 2009, Whitlock et al. 2010, Aldersley et al. 2011, Krawchuk and Moritz 2011). Not surprisingly, NPP is the most limiting factor in more arid areas, or those with a limited growing season, such as deserts and xeric shrublands, tundra, and temperate/grasslands/savannas/shrublands. In contrast, areas with higher fuel loads and limited climate seasonality, such as most tropical and subtropical biomes, appear to be more sensitive to temperature-related variables associated with conditions conducive to burning. However, biomass productivity is also a complex function of climate. Although productivity is mainly constrained by precipitation at a global scale, temperature is the dominant control on biomass in many parts of the world (Beer et al. 2010), a limitation that emerges when NPP is not included in our models.

Despite the observed within-biome heterogeneity in fire disruptions, our results are consistent with recent trends of increasing fire in some Mediterranean ecosystems (e.g., Piñol et al. 1998, Pausas and Fernández-Muñoz 2011) and temperate forests of the western US (Westerling et al. 2006). Our models suggest that this temperature-driven trend of increasing fire probability may continue into the future for some temperate forests (e.g., Westerling et al. 2011). The driest regions of the mid-latitudes and the Australian continent, which comprise most of the world's deserts, are projected to experience consistent and extensive increases in fire probabilities. Although most of these areas are biomass-poor ecosystems that may not become highly fire-prone, fire activity has been increasing in some deserts because of invasive herbaceous species (D'Antonio and Vitousek 1992, Brooks et al. 2004). It appears that any future increases in annual precipitation could exacerbate this trend, although some of these desert areas may also have novel climates in which temperature increases will outweigh precipitation increases, leading ultimately to lower productivity and less fire.

The near-term mixed changes projected for boreal ecosystems are consistent with reports on recent direction of change in fire activity (Gir-

ardin et al. 2009, Meyn et al. 2010). In fact, during the last century, different fire–environment relationships among areas within the boreal biome have led to divergent trajectories of change in fire regimes (Soja et al. 2007, Girardin et al. 2009), which may be reflected in certain parts of the biome being more limited by resources to burn than by fire-conducive weather. Our results suggest a striking increase in fire activity for boreal ecosystems in the more distant future, which is coherent with other temperature-driven projections (Stocks et al. 1998, Flannigan et al. 2005, Balshi et al. 2009). Despite the general lack of soils to support extensive flammable biomass in tundra of higher latitudes, parts of this biome are covered by peatlands that, under extreme conditions, will burn. Some studies suggest that recent warming is responsible for large fires in areas that have experienced very little (if any) fires over the last millennia (Higuera et al. 2008, Mack et al. 2011). With warmer temperatures, substantial tundra areas may become more conducive to plant growth within this next century, and thus fire could rapidly become a novel disturbance there.

Decreases in fire activity are most extensively projected for the tropical and subtropical savannas of the world, which eventually show agreement for higher temperatures in both warmest and wettest months, increasing temperature seasonality, and less precipitation in the driest month, likely causing greater water stress and lower biomass productivity. Interestingly, some of these relatively biomass-rich ecosystems are currently among the most fire-prone in the world. It is questionable, however, whether the single variable temperature seasonality is really “limiting” in the vast savannas of Africa, indicating that MaxEnt MLF results may somehow reflect a surrogate for more precipitation-related constraints there (e.g., Archibald et al. 2009). Although covering much less area, dry broadleaf forests also show consistent temperature-driven decreases in fire over the next few decades. This general trend is projected to strengthen by the end of the century, with agreement emerging for decreased fire in most other tropical and subtropical biomes. Our projected long-term decreases in fire for tropical rainforests, due to increasing precipitation, are notable given that concern in these regions tends

to be on future fire increases, particularly through intentional deforestation fires (e.g., Cochrane et al. 1999, van der Werf et al. 2008, Le Page et al. 2010).

Further work is needed to determine the degree to which long-term fire–climate relationships in many tropical and subtropical regions can be overpowered by local cultural practices, which can take advantage of short-term fluctuations in climate (Fig. 1B). To our knowledge, the potential for widespread climate-driven decreases in future tropical and subtropical fire probabilities is not reported in the published literature, although some studies (e.g., Scholze et al. 2006) have shown less extensive but still generally decreasing fire activity for many of these same regions. We nonetheless urge caution in application of our results, particularly with respect to Reducing Emissions from Deforestation and Degradation (REDD+) projects, despite model agreement for decreasing fire in many tropical biomes. It is also worth noting that fire in tropical peatlands is a major potential source of carbon emissions (van der Werf et al. 2009), and these events are not captured well in our vegetation fire datasets.

Assumptions and sources of uncertainty

The types of variables chosen for modeling future fire activity are affected by global data availability and constrained by the GCMs themselves. For example, our models use climate norms (i.e., means over multiple decades) for key variables, which can only indirectly capture short-term fluctuations in biomass resources and conditions affecting their flammability (Fig. 1A). However, the use of long-term climate norms may currently be the most stable and robust approach for predicting long-term, chronic fire probabilities across much of the globe. There is great uncertainty in the ability of GCMs to represent key modes of interannual variability (Stoner et al. 2009, Yeh et al. 2009), and even predicting future climate variability at decadal scales can pose substantial challenges (Solomon et al. 2011). Model agreement on disruptions to future fire is therefore no guarantee—the majority of GCMs could of course be wrong for any given location—but it is encouraging that these GCM-driven predictions show some consensus across large tracts of the globe.

Although our models achieve high classification accuracies, it has yet to be determined whether incorporating interannual variation would lead to large global improvements or marginal refinements in specific locations (e.g., Zimmermann et al. 2009). Greater climatic extremes, especially precipitation fluctuations, can promote increased fire activity in chronically wet locations (e.g., drought in tropical rainforests) and chronically dry locations (e.g., precipitation pulses in deserts) (Fig. 1B). Some tropical rainforests, however, appear to be less sensitive to such climate fluctuations than others (van der Werf et al. 2008). The degree to which long-term global fire projections would be improved by reliable projections of interannual variability is clearly an important area for future work.

Our model framework included NPP patterns in projections for 2010–2039 but not for 2070–2099 as a simple way to simulate potential changes in vegetation with global warming. Including NPP in the near term recognizes that most vegetation types are unable to track climate instantaneously, and thus holds vegetation constant while changing the climate conditions affecting flammability (i.e., fire weather). Not including NPP for the end-of-century models recognizes that vegetation patterns will likely have shifted by that time, and productivity may thus be more closely aligned or equilibrated with climate (especially annual precipitation). These assumptions must be considered in the interpretation of results. For example, the effects of using current NPP patterns may limit climate-related biomass depletion in some of the savannas and dry sub-tropical areas in the near term, which are then predicted to experience widespread fire decreases in the 2070–2099 time period. Conversely, including current NPP patterns may temper the direct effect of temperature and precipitation on biomass-rich areas in the near term, such as the temperate and boreal forests, whose fire probability is predicted to increase substantially by the end of the century.

The influence of localized human activities such as fire suppression and land development varies across the globe (Whitlock et al. 2010, Aldersley et al. 2011, Bowman et al. 2011), and these factors are not explicitly addressed in our study. We do not model “natural” global fire activity, but rather modern fire—with its many

human influences—as it currently occurs on Earth and how this may be altered by changing climates. Our models imply current levels of anthropogenic ignitions will continue into the future. Humans are not minor players with respect to global fire activity: their influence on global fire regimes is more than likely to increase in the future through population growth and more accelerated land cover change. However, detailed scenarios of future change in anthropogenic pressure are needed to assess the human contribution to future fire activity at the global scale.

Comparison with other global modeling studies

As one might expect, the spatial concordance of our projected future fire probabilities varies from those of other published global fire activity predictions. Our results are most similar to Krawchuk et al. (2009), especially when comparing patterns for the single GCM in their study, which used a different statistical approach but functionally similar variables. In contrast, Liu et al. (2010) used four GCMs and characterized drought-driven effects on the severity of the fire season, predicting almost opposite fire patterns to those reported here. In the only study that used a sizeable ensemble of GCMs to estimate future fire probabilities, the DGVM-based models of Scholze et al. (2006) yielded some predictions (e.g., decreasing fire in some tropical areas) that broadly concur with ours and other patterns (e.g., decreasing fire in boreal regions) that differ considerably. Another DGVM-based study by Gonzalez et al. (2010) used three GCMs and showed yet another outcome: increasing fire across much of the tropics and decreasing fire in many higher latitudes. Interestingly, the predicted future fire activity from Pechony and Shindell (2010), who used one GCM and a process-based fire module suitable for use in a DGVM, broadly agree with those of our study.

Based on the few global projections published to date, it is difficult to attribute differences among future fire predictions primarily to modeling strategies, variable types, prediction resolution, or choice of GCMs. A key difference in DGVMs is their bottom-up generation of global fire patterns by iteratively simulating fire–climate–vegetation feedbacks that may occur as climates change. Unlike more complex

DGVM approaches, our top-down statistical approach includes vegetation and biomass productivity patterns in a simpler but still functionally based framework. Our results could thus differ from a feedback-enabled DGVM, but we assume that the relatively rapid climatic changes being observed now should overwhelm any vegetation feedbacks that might dampen disruptions in fire under slower climatic shifts (e.g., Higuera et al., 2009). It remains unknown, however, how much or where future fire activity will be dampened or amplified by vegetation feedbacks alone, or how much invasive species might contribute to such changes. Divergent projections may also be due to differences in the environmental variables chosen to drive fire activity now and in the future.

CONCLUSION

Projections reported here highlight the potential for rapid disruptions in future fire activity, and consensus on such alterations strengthens through time. In addition to impacting terrestrial carbon stocks and human livelihoods, abrupt changes in fire will stress native flora and fauna as they adjust to climate change (Loarie et al. 2009) and threaten biodiversity in many conservation areas (Myers 2006, Nelson and Chomitz 2009). The ecological severity of projected changes will depend on the degree to which organisms are fire-sensitive or fire-adapted. This will be especially important in marginal or “trailing edge” habitats (Davis and Shaw 2001, Hampe and Petit 2005), which may be vulnerable to relatively sudden, fire-punctuated range contractions instead of more gradual, climate-driven transitions. Conversely, future fire may also act as a disturbance that frees up space and resources more quickly than would otherwise occur, facilitating establishment of “leading edge” populations (Landhäusser et al. 2010). Although sharp decreases in fire activity are less likely to capture our attention, reductions in this key ecological disturbance may have important trickle-down effects in many fire-prone regions (Bond and van Wilgen 1996, Krawchuk et al. 2009), and longer fire intervals could conceivably make some areas more vulnerable to catastrophic wildfires over time. Linking fire probabilities to fire intensities and area burned are thus important next steps. A

better quantification of interactions between climate change and fire is crucial for a complete global assessment of vulnerabilities for humans and the ecosystems upon which they depend.

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