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Causal relationships vs. emergent patterns in the global controls of fire frequency

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Abstract

Global controls on month-by-month fractional burnt area (2000–2005) were investigated by fitting a generalized linear model to Global Fire Emissions Database data with 11 predictor variables representing vegetation, climate, land use and potential ignition sources. Burnt area is shown to increase with annual net primary production (NPP), number of dry days, maximum temperature, grazing-land area, grass/shrub cover and diurnal temperature range, and to decrease with soil moisture, cropland area and population density. Lightning showed an apparent (weak) negative influence, but this disappeared when pure seasonal-cycle effects were taken into account. The model predicts observed geographic and seasonal patterns, and the emergent relationships seen when burnt area is plotted against each variable separately. Unimodal relationships to mean annual temperature and precipitation, population density and gross domestic product (GDP) are reproduced too, and thus shown to be secondary consequences of correlations among different controls (e.g. high NPP with high precipitation; low NPP with low population density and GDP). These findings have major implications for the design of global fire models, as several assumptions in current models – most notably, the widely assumed dependence of fire frequency on ignition rates – are evidently incorrect.

1 Introduction

Fire is a natural, recurring episodic event in almost all ecosystems, although most prevalent in savannas, Mediterranean evergreen woodlands, and boreal forests (Bond and Wilgren, 1996; Bowman et al., 2009). It is generally understood that fire occurrence is closely linked to climate, vegetation and human activities. But it has proved difficult to disentangle these various controls, in part because of their multiplicity, and in part because fire was impossible to observe and analyze as a global phenomenon until well into the satellite era (Lavorel et al., 2007; Bowman et al., 2009; Harrison et al.,

2010). Recent studies have suggested that the relative importance of the different controls may change with spatial and temporal scale (Parisien and Moritz, 2009; Falk et al., 2011), and moreover, that climate, vegetation properties and human activities can have different effects on different aspects of the fire regime – the timing of the fire season, the
5 prevalent fire type (crown vs. ground fires), the number of fires, and the area burnt (Lavorel et al., 2007; Archibald et al., 2009). Understanding global controls on fire regimes is practically important because the incidence of wildfire is already increasing in response to climate change (e.g. Running, 2006; Westerling et al., 2006; Baltzer et al., 2007; European Environmental Agency, 2012). There is a need to predict how fire haz-
10 ards may continue to develop in the future, so that appropriate management strategies and land-use policies can be developed (e.g. Moritz et al., 2012; Amatulli et al., 2013).

The availability of remotely sensed data on numbers of active fires (Giglio et al., 2006; Bartlein et al., 2008) and burnt area (Giglio et al., 2010) during the past decade makes it possible now to analyse the controls on wildfire at a global scale (Krawchuk
15 et al., 2009; Aldersley et al., 2011; Daniau et al., 2012; Moritz et al., 2012; Knorr et al., 2013). Each of these studies considered different sets of potential controls and used different methods. Krawchuk et al. (2009) (updated by Moritz et al., 2013) used Generalized Additive Models (GAMs) to explore relationships between burnt area and 17 climate variables, net primary production and two measures of human impact. Differ-
20 ent subsets of variables were selected by individual GAMs, but the availability of fuel (quantified by net primary production, NPP) was the strongest single predictor in all cases. Aldersley et al. (2011) used a regression-tree and random-forest approach to examine the influence of climate, vegetation and human impact on burnt area. Climate and climate-determined vegetation properties were the most important controls. Knorr
25 et al. (2013) examined human impact on annual burnt area using non-linear models (GAM), which show that the dominant influence of humans on global scale is to reduce fire frequency. Statistical models have been used to predict the potential consequences of future climate change for fire regimes (Krawchuk et al., 2009; Moritz et al., 2012).

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We suggest that the reliability of these predictions depends on the degree to which the fitted statistical relationships reflect underlying processes.

"Process-based" fire modules have also been developed, and included in dynamic global vegetation models (DGVMs). But current DGVMs differ greatly in the processes they consider and how they are represented. Some models (e.g. LPJ-SPITFIRE: Thonicke et al., 2010; LPJ-LMfire (v1.0): Pfeiffer et al., 2013) have include human ignitions as a right-skewed unimodal function of population density, with ignitions increasing up to an "optimum" (low) population density and decreasing thereafter. In contrast, the LPX model (Prentice et al., 2011; Kelley et al., 2014) considers only ignitions caused by lightning. Some models include the effects of land use by suppressing fire in cropland areas (e.g. LPX) and/or reducing fuel loads in grazing lands (e.g. ORCHIDEE: Krinner, 2005; Chang et al., 2013). None of these treatments is based on extensive data analysis.

Both the global consequences and the regional predictions of future fire hazards vary considerably among models and different types of models (Harrison et al., 2010). Krawchuk et al. (2009) showed increased future fire in boreal forests, while simulations with fire-enabled dynamic global vegetation models (DGVMs) have shown a decrease (Scholze et al., 2006) or no change (Harrison et al., 2010). We infer that the present level of scientific understanding of fire, as embodied in current models, is low.

Here we adopt a hybrid approach that is observationally based, but with the choice of environmental predictor variables guided by explicit hypotheses about the potential controls of burnt area. We focus on burnt area as (a) it is a general measure of the ecological and human importance of fire – equivalent to fire frequency, i.e. the probability of fire per unit time at a randomly chosen point in space (Knorr et al., 2013) – and (b) it is a key determinant (along with biomass) of the emissions of atmospheric constituents that influence climate, including greenhouse gases, volatile organic compounds and black carbon (Arneth et al., 2010). We use a generalized linear model to relate the fractional burnt area to a series of predictors representing the potential vegetation, climatic and human controls on fire ignition and spread.

A key point in our analysis is the distinction between "underlying" relationships (fitted using statistical methods making the simplest possible assumptions about their form, and displayed using partial residual plots) and "emergent" patterns, which are observed when plotting burnt area against each variable by itself. Built-in partial correlations among the predictor variables ensure that the two kinds of plots appear very different, and that the single-variable plots are not a reliable guide to the underlying relationships. To take one example that is already well understood (van der Werf et al., 2008; Harrison et al., 2010; Prentice et al., 2011), the emergent global relationship between burnt area and precipitation is unimodal because fire is limited by fuel availability in dry climates, and by fuel moisture in wet climates. In other words, the underlying causes can be represented as a monotonically increasing relationship of fire probability with primary production, and a monotonically decreasing relationship with climatic moisture. The emergent unimodal pattern results from the combination of two different mechanisms by which precipitation controls vegetation and fuel properties. We will demonstrate further examples where emergent unimodal responses of burnt area arise through the combined effects of different causal factors.

2 Data and methods

2.1 Generalized linear modelling

Our analysis is based on the principle of multiple regressions, which enables underlying relationships with several predictor variables to be teased out even in the presence of (moderate) correlations among the predictors. The finding that a given predictor has a statistically significant effect on the predictand means there is a relationship that remains after the effects of the other predictors have been taken into account. The form of the burnt-area data – lying between 0 and 1, but over-dispersed and with many ($\sim 90\%$) zero values – rules out the use of ordinary least-squares regression, and calls for the use of a generalized linear model (GLM), of which ordinary least-squares

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regression is a special case. There is no standard method for handling quantitative data of this particular type in a GLM context. However, the GLM variant known as logistic regression gives highly interpretable results with this kind of data (Wang et al., 2013). Logistic regression fits an underlying relationship between logit-transformed probability (y) and a linear combination of predictors:

$$\ln\left[y/(1-y)\right] = b_0 + b_1 x_1 + b_2 x_2 + \ldots \tag{1}$$

Where b_0 is the intercept and b_i are the slope coefficients for each variable i. In classical logistic regression the data consist of ones and zeroes, and it is assumed that the data are binomially distributed. The use of fractional data implies maximization of a quasi-likelihood function instead of a true likelihood (Papke and Wooldringe, 1996). Implicitly, the burnt area data are treated as estimates of an underlying probability. The logarithm on the left-hand side of Eq. (1) implies that the predictors are assumed to combine multiplicatively, so the model is "linear" only in the sense that the terms on the right-hand side are added together.

Logistic regression was implemented using the glm package in R. Goodness-of-fit of the complete model was quantified using the proportion of explained deviance, also known as MacFadden's R^2 (McFadden, 1974). This is a so-called pseudo-R^2 that can be interpreted analogously to the coefficient of determination in ordinary regression. Partial residual plots were used to display the fitted underlying relationship between each variable and the predicted probabilities. These plots are analogous to x-y plots in bivariate regression, except that the y-coordinate of each data point in each plot is shifted so as to remove the fitted partial effects of all the other predictors (Larsen et al., 1972). Z values (slope coefficients normalized by their respective standard errors) were used to quantify the importance of each partial relationship. Z values are the most appropriate statistics for this purpose because they express the strength of the signal relative to noise, and are independent of the units of measurement. We did not include any interactions among predictors, nor did we add quadratic terms or use the more flexible functions represented by GAMs. Instead, we set out to discover whether key

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features of the burnt area data could be adequately described by a combination of independent, monotonically increasing (or decreasing) functions of the predictors.

2.2 Burnt area data

Global fractional burnt area data, on the standard 0.5° grid, were obtained for each
5 month from January 2000 through December 2005, from the third version of the Global Fire Emissions Database (GFED3: Giglio et al., 2010). We confined our attention to the post-2000 period, for which the GFED data were derived by combining MODIS satellite observations with biome-dependent modelling of the relationship between burnt area and observed fires.

10 ## 2.3 Environmental predictor variables

We selected 11 variables representing vegetation, land use, climate and potential ignition rates (Table 1). Not every variable has a unique entry for each grid cell and month. We categorize the variables as static (spatial pattern only); annually varying (not varying between months); seasonally varying (not varying between years); and dynamic
15 (varying between months and years).

Tree cover and grass/shrub cover. The division into forested and non-forested vegetation types is fundamental, distinguishing ecosystem types (e.g. forest vs. savannas) and layers (canopy, subcanopy, ground cover) that can possess very different fire regimes (Lavorel et al., 2007). Brovkin et al. (2012) showed that woody litter decays an
20 order of magnitude more slowly than grass litter. Fractional cover data (static) for trees and non-trees (defined as plants < 5 m tall, whether shrubby or herbaceous) were obtained from the remotely sensed Vegetation Continuous Fraction data set derived from MODIS (DeFries and Hansen, 2009). The two variables are not mutually redundant because the data set also includes fractional bare ground.
25 Net primary production. Fuel limitation is a major constraint on burnt area (van der Werf et al., 2008). We used annual net primary production (NPP) (annually varying) as

an index of the potential natural fuel load. NPP was included as annually varying be-cause litter mass accumulates over a year or longer; it does not vary with monthly NPP. Annual NPP was estimated using the Simple Diagnostic Biosphere Model (SDBM, Knorr et al., 1995), driven by remotely sensed "greenness" (fractional absorbed pho-tosynthetically active radiation) from the SeaWiFS data set (Gobron et al., 2006). The SDBM is an implementation of the general light-use efficiency model for primary pro-duction. It provides the most accurate available gridded NPP data, as shown by its ability to predict observed seasonal cycles of CO_2 concentration at different locations, so far unmatched by any other model (Kelley et al., 2012), as well as field-based NPP where this has been measured.

Land use. Human activities have greatly modified the natural vegetation in much of the world (Sanderson et al., 2002). Intensive agriculture leads to landscape frag-mentation (Guyette et al., 2002; Syphard et al., 2002), which inhibits fire spread by disrupting fuel continuity. Grazing also removes fuel. But fire has been used as part of the management of both croplands and grazing lands (Pyne, 2012; Fernandes et al., 2013). Fractional cover data for crops and grazing land (static) were obtained from the Vegetation Continuous Fields data set MOD44B (DiMiceli et al., 2011).

Climate. Fuel dryness determines whether ignition events lead to spreading fires, and also the rate of spread and thus the area burnt. The Nesterov Index (Nesterov, 1949) is one of the measures used to assess the risk of fire, takes into account fac-tors that control drying rate. We selected climatic predictors based on the logic of the simplified Nesterov Index used in the LPJ-SPITFIRE (Thonicke et al., 2010) and LPX (Prentice et al., 2011) models:

$$NI = \sum T_{max} \cdot (T_{max} - T_{dew}) \tag{2}$$

where NI is the simplified Nesterov index, T_{max} is the daily maximum temperature, T_{dew} is the dewpoint temperature (approximated by the daily minimum temperature) and summation is over each period of consecutive dry days, conventionally defined as days with 3 mm precipitation or less. The predictors used here are: the monthly mean diurnal

temperature range (a proxy for vapour pressure deficit); monthly mean daily maximum temperature; and the number of dry days in the month (ndry). Vapour pressure deficit is the main environmental control on the drying rate of dead fuel. Maximum temperature determines whether an ignition event will heat the fuel enough to start a fire. Diurnal temperature range and maximum daily temperature determine flammability on a given day, but the time since rain is crucial for the evolution of fuel moisture. Dry days were entered as the ratio ndry/(1-ndry), which is proportional to the expected time since a rainfall event. These three predictors are combined multiplicatively in the model, as they are in the Index. Climate data were obtained from the Climate Research Unit (CRU) TS 3.1 time-series data set.

Soil moisture. The moisture content of live fuel depends on soil moisture, which varies much more slowly through the season than either vapour pressure deficit or fuel moisture because the water-holding capacity of soil allows moisture to be retained for several months. In the absence of a global data set for soil moisture, we used as a surrogate a standard estimate for the ratio of actual to equilibrium evapotranspiration (α) (dynamic) calculated as described in Gallego-Sala et al. (2010) from CRU TS3.1 climate data. Equilibrium evapotranspiration refers to the water loss from a large homogeneous area under constant atmospheric conditions. Estimated actual evapotranspiration depends on the rate of supply of moisture from the soil, which declines in proportion to soil water content.

Ignition sources. Fires can be started by lightning or (accidentally or deliberately) by people. There is no global data set of the frequency of effective ground strikes, but this is approximately proportional to the total number of lightning flashes (Kelley et al. 2014) We used remotely sensed, gridded data on total flashes at 0.5° spatial resolution (seasonally varying) to describe the potential natural ignition rate. These data are only available globally as a fixed seasonal cycle combining Optical Transient Detector (OTD) and Lightning Imaging Sensor (LIS) (Cecil et al., 2014).

As it has been widely assumed that the number of human-set fires increases as human activities increase (see e.g. Aldersley et al., 2011) we used population density

(static) as a general index of human influence. Data were obtained from GRUMP v1.0 (CIESIN, 2005).

Some predictors used in previous analyses are not included in ours. Wind speed influences the rate of fire spread (Rothermel, 1972; Wiese and Biging, 1997) and is an important control on the area burnt by any particular fire. We do not expect it to be important for monthly data at 0.5o resolution. In any case there is no reliable global data set for wind speed near the surface. Reanalysis products underestimate diurnal variability in wind speed, and gustiness (Sheridan, 2011), both of which are critical for fire spread. Gross domestic product (GDP) has been used as an index of cultural influences on the use of fire (Aldersley et al., 2011). The only available global dataset (http://sedac.ciesin.org/wdc/index.jsp) expresses GDP per unit area (rather than per capita) and is dominated by patterns in population density. The primary data appear to have been collected either at a country level or from variably-sized administrative units. When population density is factored out (in order to estimate GDP per capita) the resulting mapped patterns are grossly unrealistic.

Many additional climate variables have been used in fire studies (see e.g. Krawchuk et al., 2009). These are expected to be highly correlated with other climate predictors, and less easy to relate mechanistically to fire properties. We wished to avoid inclusion of redundant variables to avoid multicollinearity. We examined our set of predictor variables (Table 1) for independence using cross-correlation analysis. No pairwise correlation exceeded 0.5. Correlation among predictor variables increases the sample size required to achieve statistical significance (Maxwell, 2000), but does not compromise the validity of the regression coefficients or their estimated significance levels. By defining the combinations of predictors a priori we avoided the bias towards significance that is characteristic of stepwise methods (Cohen et al., 2003). The great majority of fires are much smaller than a grid cell, so there is effectively no contagion. Spatial autocorrelation is thus not a problem for this analysis as the data points can be considered as independent realizations of the underlying process.

Many of the predictor variables have highly skewed distributions. We transformed the data prior to analysis to reduce their skewness (Table 1). We used logarithmic transformation in cases where logically we expect there to be no fire when the predictor variable takes the value zero; and square-root transformation where this is not the case. If a log-transformed variable appears as one of the x_i terms on the right-hand side of Eq. (1), this is equivalent to fitting a power function (x_i raised to power b_i) in the multiplicative model.

We carried out a further analysis in which pure seasonal-cycle effects were included. Two (seasonally varying) predictors were added, namely $\sin\theta$ and $\cos\theta$ where January (in the Northern Hemisphere) or July (in the Southern Hemisphere) is coded as $\theta = 0$ and subsequent months in increments of $\pi/6$. Positive (negative) values of $\sin\theta$ represent proximity to spring (autumn) and positive (negative) values of $\cos\theta$ represent proximity to winter (summer). Each month possesses a unique combination of values of these two variables.

We applied the GLM to predict seasonal burnt areas for 2005 as an example to demonstrate the realism of its spatial patterns, in comparison with maps based directly on the data. We also show the predicted emergent relationships of modelled burnt area to each predictor, one by one, for comparison with similar plots derived directly from the data.

The GLM can be used to predict emergent relationships with variables other than the selected predictors (i.e. differently transformed, or even variables that were not included in the model). We examined the predicted and observed emergent relationships with mean annual temperature, mean annual precipitation, and the logarithms of population density and GDP.

3 Results

The fitted GLM attained a pseudo-R^2 of 0.74. All the predictor variables except tree cover were significant predictors of burnt area (Table 2). The strongest effects were an

increase of burnt area with NPP ($z = 56.8$), and a decrease of burnt area with soil moisture ($z = -58.9$). In addition, dry days ($z = 32.9$), maximum temperature ($z = 19.6$), grazing-land area ($z = 17.9$), grass/shrub cover ($z = 16.2$) and diurnal temperature range ($z = 11.1$) increased burnt area; human population ($z = -22.5$) and cropland area ($z = -22.0$) decreased burnt area. These relationships were highly significant ($P < 0.001$). Partial residual plots (Fig. 1) show the fidelity of the data to the fitted relationships for these variables. A general finding, however, is that some grid cells and months have exceptionally high burnt areas, not accounted for by the GLM, and thus appearing as a spread of large residuals above the fitted partial relationships.

Lightning showed a weak negative effect on burnt area. However, when pure seasonal cycle effects were added in the second analysis (Table 2), this paradoxical effect became non-significant. The negative signs on the coefficients for the seasonal variables indicate a global tendency for fires to occur in summer and autumn in both hemispheres. We infer that some strongly seasonal effects (possibly associated with vegetation phenology) were not captured by the other environmental predictors, and became associated with lightning in the GLM because (a) it has an extremely strong seasonal cycle, and (b) its values were unavoidably fixed from year to year. The z values for other predictors were not materially altered by the inclusion of seasonal cycle effects. A third analysis (Table 2) excluded both tree cover (being non-significant) and lightning. The relationships of burnt area to the remaining predictors were closely similar in all three models.

The fitted GLM (Table 2, first column) was used to predict monthly burnt area for 2005, and totals mapped for the four meteorological seasons (Fig. 2). The predicted probabilities have been truncated below so that values < 0.004166 fraction of cell area are shown as zero. This threshold is equal to the minimum (nominal 500 m) pixel size of the MODIS data on which GFED is based. Thus, the data do not record burnt areas smaller than this value. A general (and expected) feature is that fire in the real world is patchy, with more absences and some very high values, in comparison with the fitted values (which are strictly speaking probabilities, and by definition are smooth func-

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tions of the predictors). Nevertheless, the visual impression given by this comparison is satisfactory. We use R^2 in order to assess this visual agreement as it gives a good geometrical interpretation as the cosine of the angle between observed and calculated. We achieve R^2 values of 0.65 (DJF), 0.25 (MAM), 0.52 (JJA) and 0.43 (SON).

5 The broad geographic and seasonal patterns are captured well by the GLM.

Emergent relationships between predictor variables and burnt area are shown in Fig. 3. The y-axis scales used for the paired graphs (observation vs. prediction) differ because their visual impact is dominated by the highest values. (The highest observed burnt area values are typically 3–4 times higher than the predicted probabilities of burn-

10 ing, while the many counterbalancing zero values in the data are obscured.) We focus on comparing the forms of the relationships. The key point is that they are rarely the same as the underlying partial relationships as fitted by the GLM, and yet they are successfully predicted post hoc by the GLM. For example, although the underlying relationship between burnt area and NPP is monotonically increasing, the emergent

15 pattern is unimodal with a peak at $38\,\mathrm{g\,C\,m^{-2}\,a^{-1}}$. This unimodal pattern is nonetheless correctly predicted by the GLM (Fig. 3). Low NPP results in fuel limitation, and the initial increase in burnt area with NPP is a consequence of the removal of this limitation. The apparent decrease in burnt area at high values of NPP occurs because high rainfall is necessary to sustain high NPP. Similar logic explains why despite the strongly neg-

20 ative underlying relationship between burnt area and monthly dry days, the emergent relationship is unimodal. The apparent relationship between burnt area and diurnal temperature range is also unimodal. This relationship emerges because small diurnal ranges are characteristic of wet environments and large diurnal ranges of deserts (Dai et al., 1999), so that either the fuel is too wet or NPP too low to allow fires to burn.

25 A number of variables outside our set of predictors have been shown to correlate with burnt area. Our GLM can also predict the emergent relationships with these variables. Daniau et al. (2012), for example, from an analysis of remotely-sensed burnt area and the charcoal palaeorecord of biomass burning, showed that fire increases monotonically with mean annual temperature (MAT). We predict the same steeply positive

emergent response (Fig. 3) but also an extremely steep decline at the very highest temperatures, which are encountered only in exceptionally dry environments where there is little or no fuel to burn. Van der Werf et al. (2008) showed a unimodal relationship between fire in the tropics and subtropics and mean annual precipitation (MAP) and this response has been replicated in a process-based model (Prentice et al., 2011). Our GLM also predicts a unimodal relationship between burnt area and MAP. This relationship emerges because fuel availability (through NPP) is strongly controlled by MAP while the fuel is too wet to burn in climates with high MAP (van der Werf et al., 2008; Archibald et al., 2009).

A number of studies have shown a unimodal relationship between burnt area and human population density, when log-transformed to emphasize the form of the relationship at very low population densities (Archibald et al., 2009; Aldersley et al., 2011; Bistinas et al., 2013). We also predict this unimodal response, even though the underlying fitted relationship is monotonically decreasing. The emergent relationship is therefore an accurate representation of how population affects fire frequency with other factors held constant. It emerges simply because regions with very low NPP generally support low population densities. Similarly, the emergent unimodal relationship between fire and gross domestic product (GDP), shown by Aldersley et al. (2011), is an artefact caused by the automatic correlation of GDP (expressed per unit area) with population density.

4 Discussion

We have focused on plausible mechanistic controls of burnt area. The controls on burnt area are not necessarily the same as the controls on other aspects of the fire regime, especially fire numbers. Confusion about this distinction is rife. Knowing that people start fires, some model developers have focused on human ignitions as a supposed determinant of burnt area (e.g. Thonicke et al., 2010). Fire size however is extremely skewed, and burnt area is dominated by large fires that can only occur under weather

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conditions suitable to their rapid spread. Part of the confusion may stem from the fact that remotely sensed data on active fire counts have been available for longer than burnt area products. Indeed, pre-2000 burnt area products (including the early years covered by GFED) strongly depend on active fire counts (Giglio et al., 2010). This is

5 why we have only used data from 2000 onwards.

We have shown that NPP is a key control on burnt area, not surprisingly as NPP determines the amount of fuel available to burn. The importance of NPP has been one of the most consistent results emerging from previous studies (e.g. Krawchuk et al., 2009; Aldersley et al., 2011; Moritz et al., 2012). Fire is limited in regions of low NPP

10 because of lack of fuel or the discontinuous nature of the fuel. Regions of high NPP however are always associated with high precipitation. As a result, burnt area declines at high NPP; but high NPP is not the cause of this decline. We can simulate this pattern, because our GLM includes the relevant climatic predictors as well as NPP.

Given the importance of NPP, it might be expected that other aspects of vegetation

15 – influencing the flammability of fuel – would influence burnt area. There is indeed a strong relationship between burnt area and grass/shrub cover. This is probably due to the predominance of fast-drying fine fuels in grasslands and shrublands, compared to the coarser woody fuels that comprise much of the litter in forests.

We have shown that burnt area declines with soil moisture while increasing with all

20 three components of the Nesterov Index (and other fire danger indices: see Alexander et al., 1996; Noble et al., 1980; Hardy and Hardy, 2007), representing time since rain, maximum temperature, and vapour pressure deficit, respectively. Our analysis implies that each one of these components is independently necessary for a realistic prediction of burnt area. However, the strong relationship to α indicates that these three are not

25 sufficient: soil moisture, with a much longer "memory" than litter moisture, is of major importance as well. We suggest that this is because soil moisture (a) controls the moisture content of live fuels, and (b) influences the rate at which foliage in highly seasonal climates (e.g. grass leaves in tropical savannas) "cures" i.e. transitions from living, turgid leaves into highly flammable fine litter.

Our analysis confirms the importance of human agency in influencing burnt area – but not always in the ways commonly envisaged. Cropland area, as expected, has a negative relationship to burnt area. The steep negative relationship between croplands and fire provides support for the idea that landscape fragmentation associated with intensive agriculture limits burnt area (see e.g. Marlon et al., 2008; Archibald et al., 2013) by reducing fuel connectivity. Grazing-land area however has a positive relationship to burnt area: suggesting that the effect of grazing in reducing fuel load (implemented as an effect reducing fire in some models) is outweighed by other factors, which may include the increase in fine fuel promoted by forest conversion and continuing rangeland management. Many rangelands are in areas that would otherwise be dominated by natural grasslands, so the amount of grazed land is unlikely to reduce landscape connectivity.

Human population density shows a strong and consistently negative relationship to burnt area, which is significant despite the separate inclusion of cropland and grazing-land area. This implies that the net effect of human population is to suppress fires, and thus limit the area and biomass burnt. It is likely that the mechanisms are different at different levels of population density (Bistinas et al., 2013; Knorr et al., 2013). Possible mechanisms include the removal of wood for heating and cooking, roads and clearings creating barriers to fire spread, and urbanization.

It is implausible that burnt area decreases as lightning ignitions increase, and our second analysis showed that the initially fitted negative relationship of lightning to burnt area must be an artefact of other, yet-to-be-determined processes with a strong seasonal cycle – such as day length effects on phenology in seasonal climates. Pre-emptive burning before weather conditions become most suitable for large wildfires (Le Page et al., 2010) may also be a factor in synchronizing the timing of fires with the seasonal cycle, and would also be expected to contribute to the human-induced reduction in burnt area.

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Our results question some widely held assumptions about what controls fire. These assumptions underpin both the selection of variables included in statistical models, and the treatment of fire in DGVMs:

Many fire models reduce fire in agricultural areas. But no DGVM allows for the full impact of landscape fragmentation on fire spread, implied by the strength of the negative influence of cropland on burnt area.

DGVMs have assumed that burnt area increases in proportion to ignitions by lightning and/or people. Our results show that any effect of increased ignition on burnt area at higher human population density is more than counteracted by other effects that reduce burnt area. Lightning has no significant effect, indicating that lightning strikes are not a limiting factor. These conclusions support the suggestion of Knorr et al. (2013) that ignition sources rarely or never limit fire frequency.

Unimodal relationships between burnt area and climate variables, which have been used in some statistical models, have no mechanistic basis and are therefore likely to mis-predict burnt area when global conditions change, for example due to decoupled changes in temperature and precipitation, or to increasing CO_2 concentration.

The increasing availability and quality control of global data sets on fire provides an opportunity for further data-driven analyses of fire to inform model development. We anticipate that this will lead to major changes in the way fire is represented in models.

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Table 1. Sources of data.

	Initial analysis	Including pure seasonal cycle effects	Excluding non-significant predictiors
Tree cover	(0.2)	(−0.1)	–
Grass/shrub cover	16.2	16.3	22.9
Cropland area	−20.4	−19.8	−20.7
Grazing land area	17.9	16.6	17.9
Number of dry days per month	32.9	25.2	36.9
Diurnal temperature range	11.1	11.9	11.3
Maximum monthly temperature	19.6	19.5	20.7
Lightning counts	−2.9	(0.6)	–
Net primary productivity	56.8	49.3	74.3
Population density	−22.5	−22.6	−23.1
Alpha	−58.9	−46.1	−66.0
$\cos\theta$	–	−8.5	–

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Table 2. Regression coefficients from each of the three models. Non-significant values ($P >$ 0.05) in parentheses.

	Data source	Transformation
Trees	Vegetation continuous fields	Cell fraction
Non-Trees	Vegetation continuous fields	Cell fraction
Croplands	HYDES	Cell fraction
Grazing lands	HYDES	Cell fraction
Number of dry days per month	CRU	Log-transformed
Diurnal temperature range	CRU	Log-transformed
Maximum monthly temperature	CRU	Log-transformed
Lightning counts	LIS/OTD	Square-root transformed
Net primary productivity	SDBM, Knorr et al. (1995)	Log-transformed
Population density	GRUMP v1.0	Square-root transformed
Alpha	Gallego-Sala et al. (2010)	–

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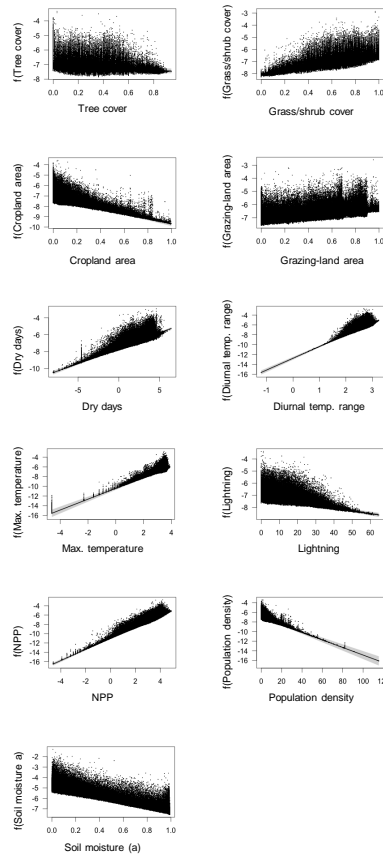
Fig. 1. Partial residual plots for the main analysis (Table 2, first column). The lines and grey-shaded areas shows the fitted partial relationships (with standard errors) between the logit-transformed probability of fire in a given month ($f(y)$), and the predictor variables. The points show similarly transformed burnt area data, adjusted on the y-axis for the fitted partial effects of all the other predictors.

DJF

MAM

JJA

SON

Burnt area fraction

<0.01   0.01 - 0.1   0.1 - 0.2   >0.2
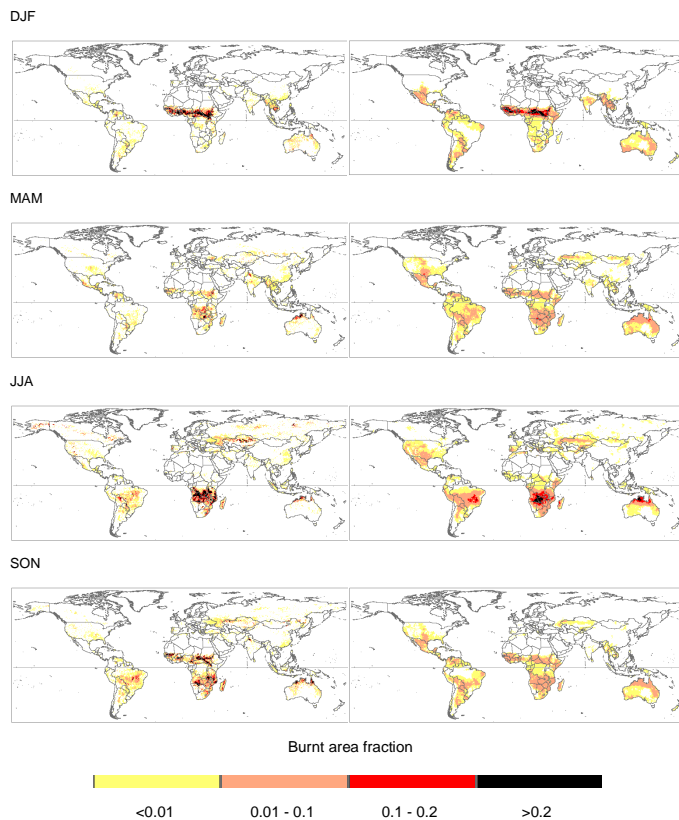
Fig. 2. Predicted probability of fire (right panel) and observed burnt area (left panel) for December-January-February (DJF), March-April-May (MAM), June-July-August (JJA) and September-October-November (SON) of 2005. Predicted probabilities < 0.004 are shown as zero. Global R^2 values are 0.65, 0.25, 0.52 and 0.43 respectively.
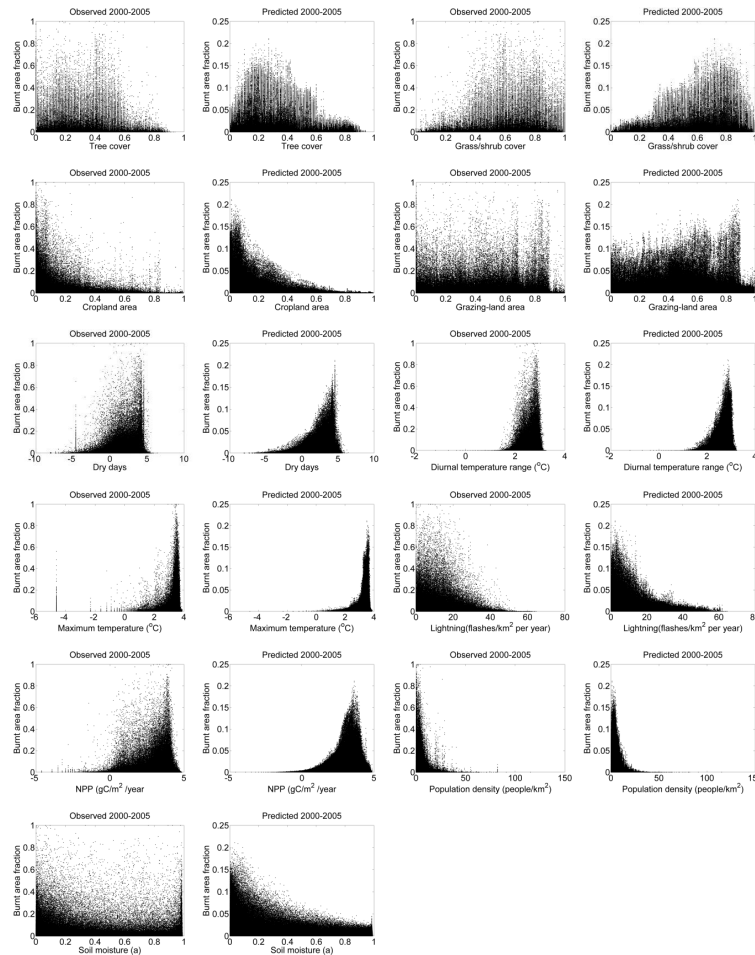
Fig. 3. Emergent patterns: predicted probabilities and observed burnt area plotted against each predictor variable in turn.
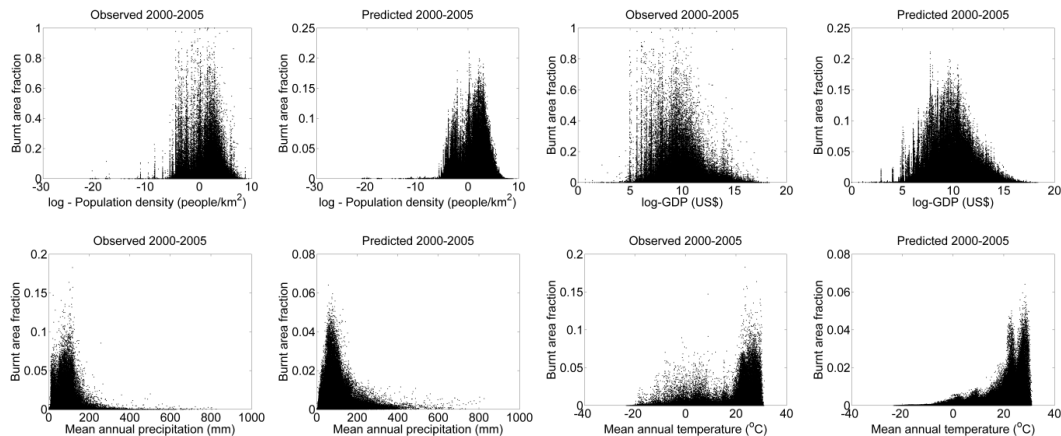
Fig. 4. Emergent patterns: predicted probabilities against mean annual temperature (MAT), mean annual precipitation (MAP), ln (population density) and ln (GDP per unit area).