Global Analysis of Influencing Forces of Fire Activity: the Threshold Relationships between Vegetation and Fire

Ruisen Luo[1, 2], Yingying Dong[1], Muye Gan[1], Dejun Li[2], Shuli Niu[3, 2], Amy Oliver[2], Ke Wang[1]*, Yiqi Luo[2]*

[1]College of Environmental & Resources Sciences, Zhejiang University, Hangzhou 310058, China
[2]Department of Botany and Microbiology, University of Oklahoma, Norman, Oklahoma 73019, USA
[3]Synthesis Research Center of CERN, Key Laboratory of Ecosystem Network Observation and Modeling, Institute of Geographic Sciences and Natural Resources Research, CAS, Beijing 100101, China
kwang@zju.edu.cn; yluo@ou.edu.

Abstract : Manylarge scale firestudies considered the relationships between fire and its influencing factors as smooth.However, the responses of fire activity to influencing factors could be abrupt on the global scale, because the hysteretic responses of vegetation to fire and vegetation types are discrete. This study examined the climatic, vegetation, anthropogenic, lightning, and topographic factorsdriving variations in global fire density, and discussedthe thresholds of vegetation on fire activity. Fire density was developed from 7 years of Moderate Resolution Imaging Spectroradiometer (MODIS) active fire data to represent global fire activity, and nine typical influencing variables were selected. The random forest regression tree method was used to identify the relative importance and relationships between fire and the influencing variables. The patterns of global fire density were captured well by the model (78.33% variance was explained), and the related thresholds were identified. Climatic factors played a primary role in determining global fire density. Agricultural land use and topographic roughness were not identified as the most important factors, probably due to the large scale we considered. Three intervals of tree density were identified to have distinct levels of fire density. Intermediate tree density (9%-53%) was related with the highest fire density, but both low and high percent of tree cover were associated with low fire density (7.0 vs. 1.3/0.9 counts per 100 km^2 per year). This study could provide further insights into understanding of the threshold effects of influencing factors on fire activity, and contribute to advances in fire modelingand vegetation distribution studies.

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1.Introduction

Fire influences global ecosystem patterns and processes, e.g., vegetation distribution and structure, the carbon cycle (Bowman *et al.* , 2009). Changing fire activity has been observed and predicted in the context of global change (Westerling *et al.* , 2006, IPCC, 2007, Flannigan *et al.* , 2009, Bradstock, 2010, Silvestrini *et al.* , 2011). An understanding of the drivers of such changes is beneficial to predict shift of fire patterns (Marlon *et al.* , 2008, Archibald *et al.* , 2009, Krawchuk *et al.* , 2009).

Most previous modeling studies assumed smooth response of vegetation to fire disturbance(Krawchuk and Moritz, 2011). However, therelationships between fire and vegetation could be abrupt (threshold responses), due to the hysteresis of vegetation responses to fire(Greve *et al.* , 2011, Hirota *et al.* , 2011, Staver *et al.* , 2011a, Staver *et al.* , 2011b, Loepfe *et al.* , 2012, Murphy and Bowman, 2012). In addition, the fire-climate-vegetation relationships were commonly investigated via continuous vegetation characteristics, e.g., Net Primary Production (NPP)(Krawchuk *et al.* , 2009), Normalized Difference Vegetation Index (NDVI)(Bastos *et al.* , 2011). However, the vegetation type itself could be an important trait in differencing fire activity. For instance, herbaceous materials are necessary for the connectivity of surface fuels, but forests oftenfunction as barriers to fire spread(Prober *et al.* , 2007, Bradstock, 2010). Vegetation types are not continuous, thus challenging the commonly used continuous relationships between vegetation and fire in biogeochemistry modeling. Non-parameter methods such as random forest and regression tree would be more suitable for quantifying thefire-climate-vegetation relationships, because theycould accommodate the abrupt changes and identify the thresholds (Flannigan *et al.* , 1998, Westerling and Bryant, 2008, Hoffmann *et al.* , 2012, Pausas and Paula, 2012). Also, the data of percent of tree cover (tree density) have been proved to be useful in identifying the three distinct attractors for vegetation states: treeless, savannas, and forests in recent studies (Hirota *et al.* , 2011, Staver *et al.* , 2011b), which might facilitate quantifying the non-smooth fire-vegetation relationships.

Ice core, tree ring and fire statistics data are commonly used to study local fire activity (Price and Rind, 1994, Buechling and Baker, 2004, Parisien and Moritz, 2009, Eichler *et al.* , 2011). Nevertheless, satellite is probably the most suitable data source for fire studies on the global scale (Ichoku *et al.* , 2012).Global fire patterns were delineated by several studies, e.g., via the Advanced Very High Resolution Radiometer (AVHRR) active fire data (Dwyer *et al.* , 2000), and Moderate Resolution Imaging Spectroradiometer (MODIS) active fire data (Giglio *et al.* , 2006a). In terms of influencing forces analysis, groups of fire were compared to factors on the global scale to explain the global fire groups(Chuvieco *et al.* , 2008). Krawchuk et al. (2009) identified the importance ranking of environmental drivers of vegetation fires distribution using statistical models (Krawchuk *et al.* , 2009). However, few studies consideratedthe threshold relationships between influencing factors and fire activity, let alone identified the thresholds trigger it.

Fire density is the counts of fire pixels (hot sources detected in satellite image grid pixels) in a unit area and a unit time (Giglio *et al.* , 2006a, Giglio, 2010). It has been validated in the previous studies as a general indicator for fire activity (Dwyer *et al.* , 2000, Csiszar *et al.* , 2005, Krawchuk *et al.* , 2009, Krawchuk and Moritz, 2011). Fire density is also useful for deriving other fire characteristics on the large scale, e.g., global burned area (Giglio *et al.* , 2006b) and length of fire season (Chuvieco *et al.* , 2008). Additionally, it is important for studies of biomass combustion (Chuvieco, 2008) and emissions (van der Werf *et al.* , 2010). Fire density is also critical to fire management, because management agencies could become overwhelmed and fail to take effective actions when a large amount of fires occur over a short time period. It is during such occasions that fires are mostly likely to escape and burn extensive regions (Flannigan *et al.* , 2009).

The objectives of the study are to: 1. Quantify the relative importance of typical climatic, vegetation, anthropogenic, lightning, and topographic factors forces in explainingglobal fire density. 2. Identify whether there are thresholds effects existed in modulating climate-vegetation-fire relationships on the global scale. 3. Explicitly quantify the thresholds, if they exist. Given there are few studies that explicitly explored the threshold of influencing forces on fire activity on the global scale, this study would be of general interest to the macro-ecology and biogeography community.

2. Materials

We used fire information from MODIS and selected nine variables to represent the climatic, ecological, and human influencing factors (Table 1). All data were adjusted into the same 0.5°×0.5° resolution and accurately registered, in the WGS-84 geographic coordinate system. Antarctica and Greenland were excluded from analysis.

Table 1.Influencing variables for global fire density.

Name	Variables (full name)	Units
Temperature	Mean annual temperature	℃
Precipitation	Annual precipitation	mm
Dry month	Annual length of dry period	months
Topo rough	Topographic roughness	m
Pop density	Population density	people km-^{2}
Per crop	Percent of cropland cover	%
Per pasture	Percent of cropland cover	%
Lig	Lightning density	flash km^{-2} year^{-1}
Tree cover	Percent of tree cover	%

Fire data

We calculated a metric, - Mean Annual Fire Density (MAFD, Formula 1) - to represent global fire density, following Giglio et al. (Giglio *et al.* , 2006a). The MAFD was calculated via averaging Terra MODIS Collection 5 Monthly Climate Modeling Grid (CMG) fire products (MOD14CMH) from January, 2001 to December, 2007. The MOD14CMH data represent gridded statistical summaries of fire information in every pixel, which is suitable for global environmental research. The spatial resolution is 0.5°×0.5°, and the temporal resolution is one calendar month (Giglio, 2010).

$$MAFD_i = \frac{\sum_{t=1}^{n} C_{i,t}}{A_i \times k}, \quad (1)$$

where,$C_{i,t}$is the monthly fire pixel frequency in the specific grid cell i, over a calendar month indexed by t, and there are n calendar months in k years, total. A_i is the area of the specific cell i. This can compensate the areal differences among cell areas along with latitude changes. The unit for fire density is counts per 100 km^2 per year. Chen et al. (2011) also developed a similar metric - fire season severity (annual counts in fire season) - to assess deforestation and degradation in South America (Chen *et al.* , 2011).

Influencing data

It is commonly assumed that fire activity depends on the coincidence of three elements: fuel structure (fuel amount and connectivity), flammable conditions, and ignition (Stott, 2000, Meyn *et al.* , 2007, Pausas and Paula, 2012).Tree density, annual rainfall, and topographic roughness were selected to stand for fuel structure. Annual rainfall is closely related to the growth of burning materials, thus determining accumulation of fuel load. Topographic roughness indicates how many natural barriers there are in the landscape reducing fuel connectivity (Archibald *et al.* , 2009). In terms of flammable conditions, temperature, rainfall, and the distribution of rainfall (the length of dry period) could combine to determine fuel moisture (Meyn *et al.* , 2007, Flannigan *et al.* , 2009, Krawchuk *et al.* , 2009). Finally, lightning density was used to capture the patterns of ignition. Population density and agricultural land use (croplands and pastures) were used to represent the suppressionof fire(Aldersley *et al.* , 2011).

1) Climatic variables. We used temperature and precipitation data from Center for Climatic Research, University of Delaware (Legates and Willmott, 1990b, a)..Dry season length is defined as the number of months, when the precipitation is lower than 30% of the average monthly rainfall of all the study period, following the previous study (Archibald *et al.* , 2009).

2) Tree cover.We used the Vegetation Continuous Fields data in 2004, which contains proportional estimates for three vegetative cover types: woody vegetation, herbaceous vegetation, and bare ground (Hansen *et al.* , 2003). The product is derived from the MODerate-resolution Imaging Spectroradiometer (MODIS) sensor onboard NASA's Terra satellite.

3) Biomes. Biomes are identified by dominant vegetation type and climatic conditions, e.g., temperature and precipitation. 13 terrestrial biomes were used in the study, based on Olson et al.'s (2001) classification (Olson *et al.* , 2001). The map ignores many community variations within each biome category due to the large scale. Mangroves were excluded due to the fact that fire is impossible there (Figure 1, Krawchuk *et al.* , 2011).

4) Lightning ignition. We assessed lightning density, expressed as flash rate density (flash km^{-2} $year^{-1}$), using the LIS/OTD 0.5 Degree High Resolution Full Climatology (HRFC) data (Christian *et al.* , 2003).

5) Topographic roughness. We used Global Multi-resolution Terrain Elevation Data 2010 available at the U.S. Geological Survey (USGS) and the National Geospatial-Intelligence Agency (NGA). We used the 30 arc-seconds resolution product, with Root Mean Square Error (RMSE) ranges between 25 and 42 meters (Danielson, 2011). We aggregated it into $0.5°\times0.5°$ data to maintain consistency among datasets. We calculated topographic roughness as the standard deviation within 8×8 block of the 30 arc-seconds resolution GMTED 2010 product.

6) Human activities. We used population densities grids in year 2000 of Gridded Population of the World Version 3 (GPWv3). The time period of data is close to fire data years, and we assume that the results would not be affected by the time difference due to the fact that population density usually changes gradually. The $0.5°\times0.5°$ spatial resolution data are from Center for International Earth Science Information Network (CIESIN), Columbia University, and Centro International de Agricultura Tropical (CIAT) (http://sedac.ciesin.columbia.edu/gpw). Data were adjusted to match United Nation totals.

We used percent of cropland and pasture in the year 2000 to study the agricultural land-use impacts on global fire activity. Data represents the global fraction of cropland cover in every $0.5°\times0.5°$ cell in the year 2000(Ramankutty *et al.* , 2008). We aggregated it into $0.5°\times0.5°$ via 6×6 block mean valve neighborhood statistics.

3. Methods

The correlations among influencing variables and the effects between influencing factor and fire activity are non-additive and non-smooth. Therefore, the regular linear model is not suitable for application to such type of relationships. Instead, we used a random forest regression tree procedure,which is shown to be suitable for modeling such abruptand non-additiverelationships(Archibald *et al.* , 2009, Aldersley *et al.* , 2011, Oliveira *et al.* , 2012). Influencingvariables were prepared in ArcGIS v.9.3 (ESRI, Redlands, CA, USA) and all analyseswere performed in R v. 2.15.1 (http://www.r-project.org/).

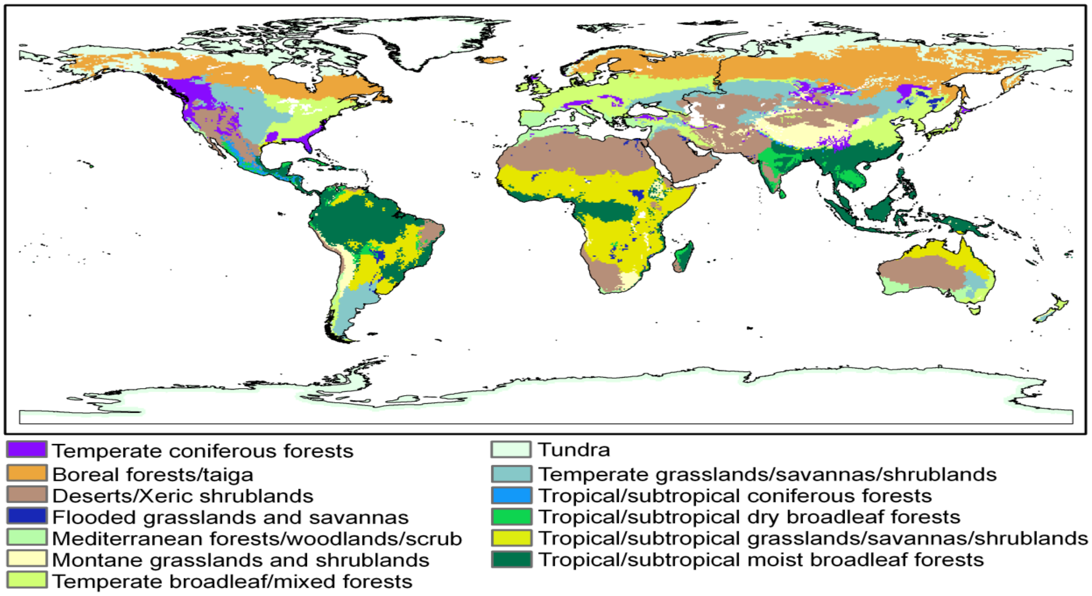

Figure 1.The 13 terrestrial biomes used in the study, based on Olson et al.'s (2001) classification (Olson *et al.* , 2001).

Random forest

Random forest algorithm can enhance the predictive ability and avoid over-fitting of standardregression models. There are two features in trees generating: bagging and random sub-setting ofvariables. Bagging is one of the ensemble learning methods, which generates many sub-models and aggregates their results. In addition, each node in random forest is split using the best among a random subset of predictors, instead of all variables. This ensures a high predictive power due to diversity among the trees, while keeping the correlation among trees to the minimum (Blanche *et al.* , 2001, Archibald *et al.* , 2009, Aldersley *et al.* , 2011).

The relative importance of variables was determined by random forest method. In the random forest,a large number of regression trees are grown. A different subset of predictor variables is selected randomly, and a certain percent of data is kept aside, i.e., reserved data. The final prediction for each data point is the mean of the predicted values from all the regression trees. This analysis was undertaken in R via the 'randomForest' package. The measure of relative importance is through the total decrease in node impurities from splitting on one specific variable, averaged over all trees. The node impurity is measured by the sum of squared errors of prediction (SSE, the residual sum of squares), which is ameasure of the discrepancy between data and the estimation model. A small SSE indicates a tight fit of the model to data. In terms of spatial dependence, tree density, and topographic roughness were all explicitly included as predictor variables that would account for the major geographical gradients. Data were subsampled (using 66% each time) in the random forest procedure to further reduce the spatial dependency of data (Archibald *et al.* , 2009, Aldersley *et al.* , 2011).

We constructed the random forest via 500 regression trees, because additional growth cannot improve prediction accuracy significantly. Three variables were randomly sampled as candidates at each split. The default minimum node size of five was used, meaning only nodes with cases more than five were split (Breiman, 2001, Archibald *et al.* , 2009,Aldersley *et al.* , 2011).

Regression tree

Because random forests do not allow the interpretation of forest structure, we ran a regression tree to get the explicit split conditions. Regression trees explain variations of a response variable by repeatedly partitioning data into more homogeneous subsets (nodes), using combinations of influencing variables. The criterion for splitting is the sum of squares (De'ath and Fabricius, 2000). This process is repeated until a satisfying tree is created or preset conditions are met. This analysis was undertaken in R via the "rpart" packages. The pre-defined standard is controlled by a parameter, "complexity parameter" (see R document 'rpart.control' for an explanation of this parameter). Regression trees make no prior assumptions concerning the statistical distribution of data, and do not require homoscedasticity of variances (Rejwan *et al.* , 1999). They can accommodate non-additive and threshold relationships between the dependent and independent variables. This allows us to explore the complex combinations of controlling factors for fire activity (Archibald *et al.* , 2009, Aldersley *et al.* , 2011).

We set the minimum size of terminal nodes to 1 and complexity parameter to 0.01,referring to previous studies (Archibald *et al.* , 2009, Aldersley *et al.* , 2011). The split conditions generated from regression trees are useful for exploring the influencing forces in fire activity variation and the specific thresholds between fire density and the influencing factors.

Table 2.Regression tree analysis of global fire density.

Split conditions*						Fire density	Node
Temperature<19.3						0.6	1
Temperature≥19.3	Tree cover<9					0.9	2
	Tree cover≥9	Dry month<3.2	Tree cover≥66			0.3	3
			Tree cover<66			1.7	4
		Dry month≥3.2	Pop density≥64			1.4	5
			Pop density<64	Lig<11.3	Precipitation<702	1.8	6
					Precipitation≥702	3.9	7
				Lig≥11.3	Tree cover≥53	1.3	8
					Tree cover<53	7.0	9

* See the Table 1 for meanings and units of variables.

4.Results

The observed global fire density pattern is shown in Figure 2A. The highest fire density was predominantly found in the savannas and shrublandsalong southern border of the Sahara desert and Zambia, Angola, Congo and Mozambique in Africa. It also concentrated in central South America and northern Australia.

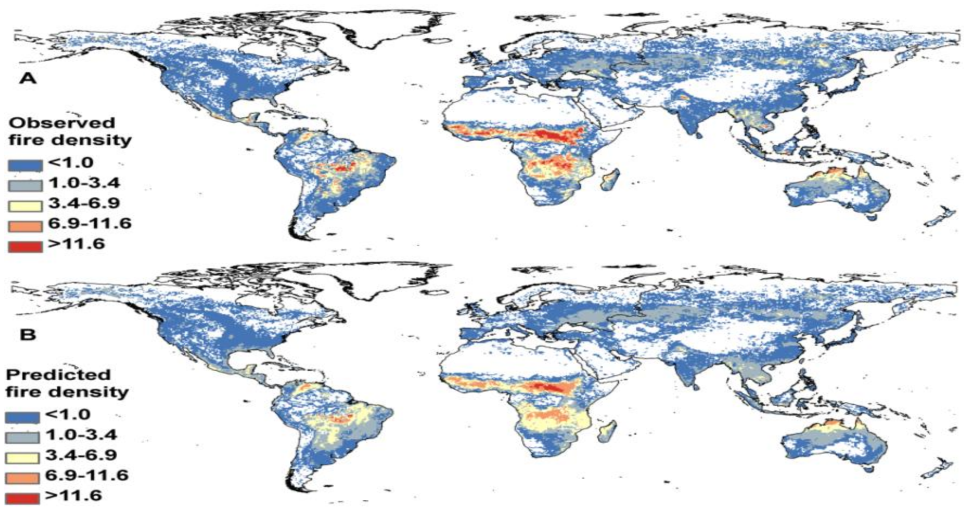

Figure 2. Observed global fire density (A) and predicted global fire density by the random forest model (B). Observed global fire density was represented by the metric, Mean Annual Fire Density (MAFD), which was derived from 7 years (Jan 2001 to Dec 2007) MODIS data of fire counts. The unit is counts per 100 km^2 per year. Antarctica and Greenland were excluded from the analysis. Predicted global fire density was generated from the random forest model.

Random forest analysis

The observed fire density patterns were predicted well by the random forest model, although with slightly underestimation in medium and highfire density regions (Figure 2Band 3). Validation via reserved samples showed that the variance explained by the random forest model was 78.33% (Figure 3). The relative importance of the influencing variables in fire density was shown in Figure 4. Temperature reduced the sum of squared errors (SSE) most in predicting global fire density, and its relative importance was taken as 1. The relative importance of other factors was compared with that of the most important factor.Precipitation, tree cover, lightning, and population density were also identified to be influential in explaining fire density pattern, with relative importance higher than 0.6.

Regression tree analysis

The conditions that resulted in different fire densities were identified by running a regression tree on the observed fire density and influencing data. Although the accuracy of regression tree prediction was lower than that of random forest (R^2=0.42, P<0.01), the available split conditions revealed additional insights of global fire density pattern (Table 2).

The regression trees results showed that climate conditions were important, consistent with the random forest analysis. Adequate temperature was the primary requirement for high fire density. Fire density value was below 1 counts per 100 km^2 per yearin zones where mean annual temperature were lower than 19.3℃ (node 1). Additional factors basically influenced fire density in areas where temperatures were sufficiently high (above 19.3℃). When fuel moisture was high (the annual length of dry period less than 3.2 months), fire density tended to remain less than 2 counts per 100 km^2 per year(node 3 and 4); however, if there was sufficient dry period (the period of dry months longer than 3.2 months), fire density could increase to 7 counts per 100 km^2 per year, interacting with other factors (node 9). It is consistent with the finding that the highest fire activity coincided with intermediate levels ofprecipitation(Figure 5).

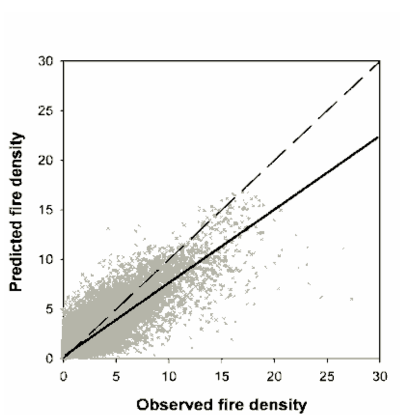

Figure 3. The relationship between observed fire density and fire density predicted by the random forest model. The solid line is the linear regression line of random forest model (variance explained was 78.33%). The dashed line indicates the 1:1 correspondence.

Ecological forces also played an important role in determining global fire density.In regions where temperature was not the limiting factor (mean annual temperature above 19.3℃), global fire density was associated with three classes of tree density, i.e., intervals of tree cover percent below 9%, between 9% and 53%, above 53% of the grid cells, respectively (node 2, 3 and node 8, 9). When the percent of tree cover was in the first or the last interval, fire density remained in a low level (approximately 1 count per 100 km^2 per year). Only with moderate tree density (9%-53%) can fire density exceed 7 counts per 100 km^2 per year (node 9). Because fire density around tree density of 66% is similar to that of 53%, the threshold of 66% was also included in the interval of high tree cover percent (above 53%, node 3 and 4 in Table 2). Furthermore, we calculated the distribution of fire counts in the three tree density intervals, accordingto the methods of Chuvieco et al. (2008) (Chuvieco *et al.* , 2008). We found the three regions were possibly in accordance with the biomes of deserts (53% of all the grid cells), tropical and subtropical savannas (53% of all the grid cells), and tropical and subtropical moist broadleaf forests (89% of all the grid cells), respectively (Table 3). In addition, there were significant differences between fire density in the intermediate and low/high tree density classes (Figure 6).

High human population (above 64 people per km^2) played a suppressing role in determining fire density at the global scale, overall. Fire density was lower than 1.5 per hectare per year, if population density was above 64 people per km^2 (node 5 in Table 2). Agricultural land uses and topographic roughness werenot identified in the regression tree analysis for the global fire density, consistent with the results of random forest (Figure 4).

5. Discussions

In this study, fire density is developed from 7 years of MODIS active fire data to represent global fire activity, following the previous studies (Giglio *et al.* , 2006a, Chuvieco *et al.* , 2008). The random forest and regression tree analysis capture global fire density pattern well. Temperature, precipitation, tree cover, lightning density, and population density are identified to be highly effective in explaining the observed fire density patterns. Agricultural land use and topographic roughness are not identified as the most important factors, probably due to the large scale we considered.

Table 3. Cross-tabulation of tree density categories (columns) and biomes (rows) in regions of temperature above 19.3 ℃. The numbers in the table are the counts of fire-prone grid cells.

Biome	**Percent of tree cover (%)**		
	<9.5	**9.5-52.5**	**>52.5**
Tropical/subtropical moist broadleaf forests	176	2341	1985
Tropical/subtropical dry broadleaf forests	139	766	86
Tropical/subtropical coniferous forests	2	96	7
Temperate broadleaf/mixed forests	32	47	9
Temperate coniferous forests	4	65	13
Tropical/subtropical grasslands/savannas/shrublands	1088	4627	127
Temperate grasslands/savannas/shrublands	67	78	0
Flooded grasslands/savannas	60	200	6
Montane grasslands/shrublands	19	62	3
Mediterranean forests/woodlands/scrub	38	17	0
Deserts/xeric Shrublands	1806	405	2
Total	3431	8704	2238

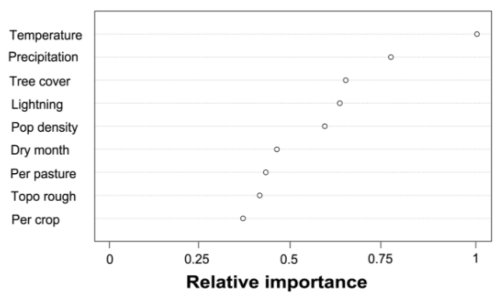

Figure 4.The relative importance of factors influencing variation in global fire density. Factors were ranked according to their contributions in explaining global fire density patterns. The importance of factor contributed most, temperature, was set to 1, and the relative importance of other factors werecompared with that of temperature.

There are significant differences among fire density in the three intervals of tree cover percent (Figure 6). The intermediate tree density is related with high fire density, but both low and high tree density are coincident with low fire density.The low fire density in the low tree density zones is likely related to few available burning resources in the deserts.The low fire density in the high tree density zonesis presumably due to the insufficient dryness of burning materials(Giglio *et al.* , 2006a, Chuvieco *et al.* , 2008, Bowman *et al.* , 2009, Bradstock, 2010, Staver *et al.* , 2011a).

In addition, the substantial differences between fire density of the medium and high/low tree cover zones (7.0 vs. 1.3/0.9 counts per 100 km^2 peryear) indicate that there might be severaldistinct stages of tree density(i.e., vegetation states)correlated with fire density.The three intervals of tree cover percent are mainly related with three biomes, i.e., deserts, tropical/subtropical savannas, and tropical/subtropical moist broadleaf forests (Table 3).Hirota et al. (2011) analyzed tree density in Africa, Australia, and South America, and also revealed the existence of three distinct attractors: forest, savanna,and a treeless state (Hirota *et al.* , 2011).It is suggested that alternative stable states (biome types) might exist due to influence of fire (Staver *et al.* , 2011). Since herbaceous plants tend to recover quicker than trees, fire constrains tree cover (Bond, 2008, Staver *et al.* , 2009) and promotes the openness of savanna, but once tree cover becomes sufficiently dense, fires might be kept out(Archibald*et al.* , 2009, Warman and Moles, 2009, Staver *et al.* 2011b, Murphy and Bowman, 2012). Therefore, it might be not appropriate to continue regarding the relationships between fire and vegetation as linear and smooth. It is necessary to take the catastrophic transition ofvegetation states into next generation fire model, and percent of tree cover data might serve as a good option(Murphy *et al.* , 2011, Murphy and Bowman, 2012, Pausas and Paula, 2012).

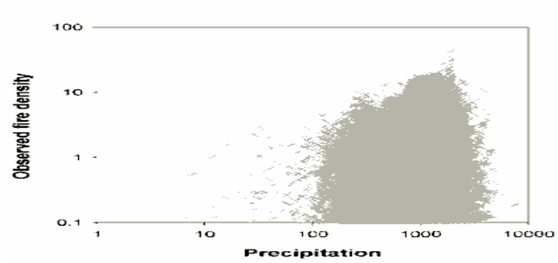

Figure 5.Effects of annual precipitation (mm) on global fire density (counts per 100 km^2 per year), displayed on log-log coordinates.

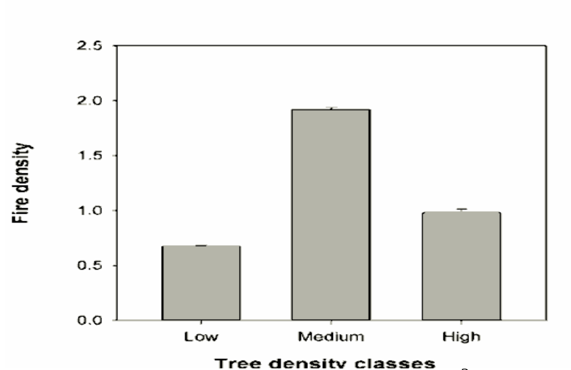

Figure 6. Fire density (counts per 100 km^2 per year) in the three tree density classes.Low tree density: below 9%, medium tree density: 9-53%, high tree density: above 53%. The thresholds were identified by the random forest regression tree method. The fire density in the medium tree density class was higher than that of the low/high tree density classes at the 1% significance level.

Mean annual temperature is found to be the primary factor in determining global fire density. High temperature (higher than 19.3 ℃) tends to favor high fire density. It is probably because warmer temperatures would increase evapotranspiration and lengthen the fire season (Westerling *et al.* , 2006). It is projected that temperature would rise by 2-7 ℃ and precipitation regimes would change tremendously across the globe at the end of this century (IPCC, 2007). This might shift future fire regime and transform the ecosystem processes substantially (Westerling *et al.* , 2006, Westerling *et al.* , 2011).

It is assumed that topographic roughness might result in different fuel connectivity, i.e., fragmented or continuous fuels (Archibald *et al.* , 2009). However, topographic roughness is not identified as an important influencing variable (Figure 3), probably due to the large scale we considered. The next step is to explore the effects of topographic roughness on fire density at regional scales and compare it across regions. In addition, population density and percent of agricultural land use (croplands and pastures) are not identified as the most influential factors in influencing global fire density (Figure 3).It is presumably because human activities only take effect in certain regions suitable for human livings, thus making its effects on fire density not obvious on the global scale (Aldersley *et al.* , 2011, Murphy *et al.* , 2011).There are underestimations in the high fire density zones (Figure 2). Because random forest and regression tree partition data into relatively homogeneous subsets, underestimation is predictable and has been reported before (Archibald *et al.* , 2009, Aldersley *et al.* , 2011). In addition, extreme weather conditions are shown to be related with catastrophic fire events (Moritz, 2003, Cochrane and Barber, 2009). The averaging of fire data across years can enhance the robustness of results we derived, although it is not suitable to incorporate cumulative precipitation data preceding fires (Archibald *et al.* , 2009, Aldersley *et al.* , 2011).

6. Conclusion

Previous studies mostly tookthe relationship between fire and vegetation as linear and continuous, neglecting the resilience of ecosystem and resultant non-linear relationships between fire and vegetation. This study explicitly quantified the abrupt relationships between global fire density and vegetation, demonstrating the feasibility of data of tree density and method of random forest in quantifying the thresholds in the climate-vegetation-fire relationships. The classes and thresholds of tree densityidentified in this studypresumably provide insights into next generation fire model and global biogeochemistry cycle model.

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Corresponding authors:
Ke Wang,
College of Environmental & Resource Sciences, Zhejiang University, Hangzhou, Zhejiang 310058, China,
Email: kwang@zju.edu.cn.

Yiqi Luo
Department of Botany and Microbiology
The University of Oklahoma
Norman, OK 73019, USA
Email: yluo@ou.edu

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