Analysis of critical transitions at the Global Forest

Abstract

One of the most important changes produced in the biosphere is the replacement of forest areas with human dominated landscapes. These areas contain much less species that the natural ecosystem they replaced, and are one the main drivers of extinctions in the anthropocene. The forest cover is also coupled to atmospheric dynamics and the balance of gases in the atmosphere. The dynamics of forest fragments or patches is central to its function as ecosystem. In different kinds of vegetation including forests the patch size distributions follow power laws or approximate power law, but all these patterns have been observed at relatively small scales. Here we studied the distribution of forest patch sizes at a global level and its changes in the last fourteen years. We hypothesize that the global forest patches should follow a power law distribution. Power laws are a signal of critical phase transitions, where the system changes suddenly of state at a critical point, in the case of forest patches this change implies an abrupt change in the connectivity that pose a risk on the functioning of forest as an habitat and as an ecosystem. Thus we estimate the closeness of forest at the continental level to a possible critical transition as an early warning indicator.

Introduction

Forest is one of the most important ecosystems on earth providing habitat for a large proportion of species and contributing extensively to global biodiversity [1]. In the previous century human activities have reached the global scale changing influencing the bio-geochemical cycles [2]. One of the most dramatic human induced changes is the replacement of 40% of Earth's formerly biodiverse land areas with landscapes that contain only a few species of crop plants, domestic animals and humans [3]. These changes have been happening locally but they have been accumulated over time and have reached a global scale that constitutes a global forcing [4]. That means a force that can induce changes at the level of the whole biosphere. Another global scale forcing that is tied to habitat destruction is fragmentation. Fragmentation is defined as the division of a continuous habitat into separated portions that are smaller and more isolated, this produces multiple interwoven effects: reductions of biodiversity between 13% and 75%, decreasing forest biomass and changes in nutrient cycling [5].

Complex interaction between species and feedbacks at different levels of organization [6] can produce abrupt changes called critical transitions [7]. These abrupt state shifts can not be linearly forecasted from past changes so they are difficult to predict and manage [7]. Critical transitions had been detected mostly at local

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scales [8,9], but the accumulation of changes in local communities that overlap geographically can propagate and cause an abrupt change of the entire system [4], this is coupled with the existence of global scale forcings implies the possibility that a critical transition occurs at a global scale [10,11].

There are two general classes of critical transitions: one where the sudden shift between states is mostly irreversible showing the presence of two stable states. These show hysteresis that is a catastrophic regime shift [12], also called first order transitions. This could be the result of a positive feedback mechanisms [13], for example the growth of forest in a site is more probable if it is surrounded by forest than if it is surrounded cultivated or degraded land [14]. This is observed in semiarid regions where the transition from a vegetated state to a desertic one occurs as a result of human pressures and climatic change [15], in biological invasions [16], and biology and social sciences in general [17].

The second are continuous critical transitions [18], or second order transitions. In this case there is a narrow region where the system changes from one domain to another, besides the change is also sudden it is continuous and theoretically reversible. These transitions are linked to spatial patterns: at the critical point we can observe scale invariant fractal structures characterized by power law patch distributions [19]. The simplest model where we can observe this kind of transitions is a random map: each site has an independent probability p of being occupied. Even in this simple setting, starting with $p = 0$, when p reaches a certain value the landscape changes from fragmented to a connected state. Another more relevant model is about forest fires, the key factor in this case is the existence of an ecological memory: after a fire biomass is consumed so there must be some time to build up fuel before a recurring fire [20].

The spatial phenomena studied by percolation theory is related to the concept of connection, in a very general way we can find a path between the objects that belongs to a system [17], thus connectivity is a fundamental property of general systems and also, ecosystems from forests [21] to marine ecosystems [22] and the whole biosphere [23]. Percolation is characterized by two domains or phases. One dominated by short range interactions where information can not spread and another where long range interactions are possible and information can spread over the whole area. In this context information is taken in a broad sense and can represent species dispersal or movement. Thus, there is a critical point that defines a threshold boundary between the two phases and the system could be driven close or far of the critical point by an external force. Climate change and deforestation are the main forces that could be the drivers of a phase change in forests [5,24].

Percolation thresholds are important to understand forest growth dynamics: when the system is above the critical point is in a connected state and the dispersal of species inside the forest is enhanced. Dispersal

strategies are influenced by percolation thresholds in three-dimensional forest structure [25]. Recently has been show that not only the patches but species distributions also have percolation thresholds [26]. If we push the system below the percolation threshold the system will be in an unconnected state, which could produce a biodiversity collapse [27,28]. In an opposite direction being in a connected state could produce the acceleration of an invasion of forest into a prairie [29,30].

One of the problems with critical transitions is that the value of the critical threshold is not known in advance, and near that point a small change can precipitate a state shift of the system, thus they are very difficult to anticipate. Several methods were developed to detect the closeness of the critical point such as a deceleration in recovery from perturbations, an increase in variance in the spatial or temporal pattern. Besides some of these methods have been experimentally tested [8,31], still there is a debate about the its reliability [32,33].

In most real systems where spatial dynamics is important we could observe processes like: demographic fluctuations, spatial heterogeneities and/or dispersal limitation. This processes that introduce stochasticity can convert a catastrophic transition to a second order transitions [13]. Forest is a system where these three processes are ubiquitous so continuous transitions should be more probable than catastrophic transitions, moreover some evidence of a second order critical transition related to drought and fire has been found in tropical forest [34].

From the point of view of percolation theory, the necessary condition we need to be near a critical transition is that the patch size distribution follows a power-law. But this is not a sufficient condition because power-law distributions are present in a wide range of conditions in vegetation of arid ecosystems [35,36] and ant colonies [37] and attached microalgae [38,39]. The origin of these power-laws is attributed to a facilitation mechanisms [40,41], that is likely to be present in forest [42].

Our objectives were to evaluate what models best describe forest patch distribution at a continental scale; examine how patch size and connectivity change between regions and across time; and look for evidence that forests are near critical fragmentation thresholds. The advantage of using data at a continental scale is that for very large systems the transitions are very sharp thus much easier to detect than at smaller scales, where noise can mask the signals of the transition.

Methods

Area definition

We choose mainland zones at a continental scale to analyze based in the possibility of connection, close patches of continuous forest must connect the region, big islands of more than XXXX km^2 like Madagascar were included as a separate regions, smaller islands where not included, we considered big islands connected to the mainland when they are at one km or less distance away. With this criteria we defined three regions in America, one corresponding to South America temperate forest (SAT), another to subtropical and tropical forest up to Mexico (SAST), and the last covering USA and Canada forest (NA). Europe and north Asia were all connected and they are included in one region (EUAS), the other regions are south Asia (SEAS), Africa (AF), and Australia and islands (OC) (Supplementary figure S1-S6). Each regions have subregions that correspond to nearby islands (Table 1).

To define patches we use the MODerate-resolution Imaging Spectroradiometer (MODIS) Vegetation Continuous Fields (VCF) Tree Cover dataset. This dataset is produced at 250-meters resolution, globally from 2000 to 2014, we used the version 051 [43]. There are several definition of forest [44], but we choose a 30% threshold to convert the percentage tree cover to a binary image of forest and non-forest pixels. This was the definition used by the United Nations' International Geosphere-Biosphere Programme [45], and studies of global fragmentation [5]. Patches of contiguous forest were determined in the binary image by grouping connected pixels using a neighborhood of 8 forest units (Moore neighborhood). To fit the patch size distributions we set a minimal patch size (X_{min}) at nine pixels to avoid artifacts at patch edges due to discretization [46].

Percolation theory

A more indeep introduction of percolation theory can be found elsewhere [19] and a review from an ecological point of view is available [47]. Here to explain the basic elements of percolation theory we formulate a simple model: we represent our area of interest by a square lattice and each site of the lattice can be occupied—e.g. by forest—with a probability p. The lattice will be more occupied when p is greater, but the sites are randomly distributed. We are interested in the connection between sites so we have to establish a neighborhood, for this example we define the eight sites surrounding the focal site as neighbors. The sites that are neighbors define a patch. When there is a patch that connects the lattice from opposite sides it is said that the system percolates. The percolating patch suddenly appears at some value of p called the critical point p_c.

Thus percolation is characterized by two well defined phases: the unconnected phase (called subcritical in

physics) when $p < p_c$, a individual of a species cannot travel far away inside the forest, the forest is fragmented, or in a general sense information cannot spread. The second is the connected phase (supercritical) when $p > p_c$, species can move inside a forest patch from side to side of the area, information can spread over the whole area. Near the critical point several scaling laws arise: the structure of the patch that spans the area is fractal, the size distribution of the patches is power-law, and other quantities also follow power-law scaling [19].

The value of the critical point p_c depends on the geometry of the lattice and on the definition of the neighborhood, but other power-law exponents only depend on the lattice dimension. Close to criticality is found that the distribution of patch sizes is:

(1) $n_s(p_c) \propto s^{-\alpha}$

where $n_s(p)$ is the number of patches of size s. The exponent α does not depend on the details of the model and it is called universal [19]. These scaling laws can be applied for landscape structures that are approximately random, with correlations if the forest sites are correlated over short distances [48]. This called in physics isotropic percolation universality class, and corresponds to an exponent $\alpha = 2.05495$, if we observe that the patch size distribution has another exponent it will not belong to this universality class and other kind of mechanisms should be invoked. Percolation thresholds can also be generated by models that have some kind of memory [49,50]: a patch that has been exploited for many years will recover different than a recently deforested forest patch. In this case the system can belongs to a different universality class or in some cases there is no universality and the value of α will depend on the parameters and details of the model [51].

Patch size distributions

We fitted the empirical distribution of forest patch areas to four distributions using maximum likelihood estimation [52,53]. The distributions were: power-law, power-law with exponential cut-off, log-normal, and exponential distributions. We assume that the patch size distribution is a continuous variable that was discretized by remote sensing data acquisition procedure.

Besides the hard X_{min} limit we set due to discretization, the power-law distribution needs a lower bound for its scaling behaviour. This lower bound is also estimated from the data by maximizing the Kolmogorov-Smirnov (KS) statistic comparing empirical to fitted cumulative distribution function [53]. We also calculate the uncertainty of the parameters using a non-parametric bootstrap method [54].

The corrected Akaike Information Criteria (AIC_c) and the Akaike weights were computed for each model [55]. Akaike weights (w_i) are the weight of evidence in favor of model i being the actual best model for the situation at hand given that one of the N models must be the best model for that set of N models.

Additionally, we computed the goodness of fit of the power-law model following the bootstrap approach described by Clauset et. al [53], where simulated data sets following the fitted model are generated, and a p-value equal to the proportion of simulated data sets that has a KS statistic less extreme than empirical data. The criterion to reject the power law model was $p \leq 0.1$ but as we have a very large n negligible small deviations could produce a rejection [56], thus we chose a $p \leq 0.05$ to reject the power law model.

To test for differences between the fitted power law exponent for regions and subregions we used a weighted linear regression with a residual auto-correlation structure. For this we use a generalized least squares procedures: function gls from package nlme [57]. The weights were the bootstraped 95% confidence intervals and we added an auto-regressive model of order 1 to the residuals to account for temporal autocorrelation.

Image processing were done in MATLAB (Version??). All statistical analyses were done using the GNU R version 3.3.0 [58], using code provided by Cosma R. Shalizi for power law with exponential cutoff model and the poweRlaw package [59] for fitting the other distributions. The complete source code for the processing of images and analysis, the patch size data and the figures with each fit (year by region by subregion) are available at figshare http://dx.doi.org/10.6084/m9.figshare.XXXXX.

Largest patch dynamics

The largest patch is the one that connects the highest number of sites in the area, it has been used extensively to indicate fragmentation [21,60]. The relation of the size of the largest patch S_{max} with critical transitions has been extensively studied in relation to percolation phenomena [19], but seldom used in ecological studies (but see [48]). When we are in a connected state ($p > p_c$) the landscape is almost insensitive to the loss of a small fraction of forest, but close to the critical point the same loss can have an important effects [18,47]. At this point the largest patch will have a filamentary structure, extended forest areas will be connected by thin threads, thus small losses could produce big fluctuations.

One way to evaluate the fragmentation of the forest is to calculate the proportion of the largest patch against the total area [61], as is very difficult to evaluate the total area that the forest could potentially occupy we use the total forest area. Thus we calculate the proportion of the largest patch for each year, dividing S_{max} by the total forest area of the same year: $RS_{max} = S_{max}/\sum_i S_i$. This has the effect of eliminate the fluctuations produced S_{max} due to environmental or climatic changes affecting all the region considered.

When the proportion RS_{max} is big (more than 60%) the largest patch contains most of the forest so there are less small forest patches and the system is probably in connected phase. When this proportion is low, 20% or less there are a greater quantity of forest patches and we are probably at the fragmented phase. But it is possible that with a high RS_{max} the system is near a percolation threshold, this has to be evaluated using the temporal fluctuations.

We calculate the fluctuations around the mean with the absolute values $\Delta S_{max} = S_{max}(t) - \langle S_{max} \rangle$, and also using the proportions of RS_{max}. To characterize the fluctuations we fitted three empirical distributions: power-law, log-normal, and exponential; using the same methods described previously. We expect that large fluctuation near a critical point have heavy tails (log-normal or power-law) and that fluctuations far from a critical point have exponential tails, corresponds to Gaussian processes. As the data set spans 15 years we have do not have enough power to reliably detect which distribution is better [53]. To improve this we performed the goodness of fit test described above for all the distributions. We generated animated maps showing the fluctuations of the 2 largest patches to aid in the interpretations of the results.

A robust way to detect if the system is near a critical transition is to analyze the increase of variance of the forest's density [62], the problem is that the variance increase appears when we are very close to the transition [51]. An alternative is to analyze the variance of the fluctuations of the largest patch ΔS_{max}, a maximum is attained at the critical point but a significant increase occurs well before the system reach the threshold [51]. Also before the critical fragmentation the skewness of the distribution of $\Delta_S max$ should be negative, this implies that the fluctuations below the average are more frequent. We characterized the increase in the variance using quantile regression: if variance is increasing the slopes of upper or/and lower quartiles should be positive or negative.

Results

The power law distribution was selected as the best model in most of the cases (Supplementary Figure S7). In a small number of cases (4 of 300) the power law with exponential cutoff was selected but the value of the parameter α was similar by ± 0.02 to the pure power law. Moreover the patch size where the exponential tail begins is very large (determined by the inverse of the exponential decay parameter), thus we use the power law parameters (See Supplementary data, region EUAS3). In finite-size systems the favored model should be the power law with exponential cutoff, because the power-law tails are truncated to the size of the system [19]. Here the regions are so large that the cutoff is practically not observed.

There is only one region that does not follow a power law: Eurasia mainland, and it follows a log-normal

distribution. The log-normal and power law are both heavy tailed distributions and they are difficult to distinguish. In our case Akaike weights have very high values for log-normal (near 1), meaning that this is the only possible model. Additionally the goodness of fit tests clearly rejected the power law model in all cases for this region (Supplementary table S1, region EUAS1). In general the goodness of fit test rejects the power law model in less than 10% of cases. In large forest areas like Africa mainland (AF1) or South America tropical-subtropical (SAST1), larger deviations are expected and the rejections rates are higher so the proportion is 30% or less (Supplementary Table S1).

Taking into account the bootstrapped confidence intervals of each power law exponent (α) and the temporal autocorrelation, there is no significant differences between α for the regions with biggest forest areas—greater than 10^7 km^2 (Figure 1 and Supplementary figure S8). And also there is no differences between these regions and the ones with forest areas smaller than 10^7 km^2(Supplementary Table S2 & S3), and all the slopes of α are not different from 0. Thus we can talk about global average $\alpha = 1.908$ with a bootstrapped 95% confidence interval between 1.898 and 1.920.

The proportion of the largest patch relative to total forest area RS_{max} for regions with more than 10^7 km^2 of forest is showed in figure 2. South America tropical and subtropical (SAST1) and North America (NA1) have a higher RS_{max} of more than 60%, the other big regions have 40% or less. For regions with less total forest area (Supplementary figure S9 & Table 1), United Kingdom (EUAS3) has a very low proportion near 1%, and other regions have a very high proportion like New Guinea (OC2) and Malaysia/Kalimantan (OC3).

We analyzed the distributions of relative fluctuations of the largest ΔRS_{max} and absolute fluctuations ΔS_{max}. The model selection for ΔS_{max} results in power laws distributions for all regions (Supplementary table S6). The goodness of fit test (GOF) did not reject power laws in any case, but either can not reject the other models except in few cases, this is due to the small number of observation we have for this analysis. When we analyzed ΔRS_{max} we found some differences: Eurasia mainland (EUAS1), New Guinea (OC2), Malaysia (OC3), New Zealand (OC6, OC8) and Java (OC7) all follow an exponential distribution (Supplementary Table S7). We only considered that fluctuations follows a power law when this distribution is selected for both absolute and relative fluctuations.

The results of quantile regressions are identical for ΔRS_{max} and ΔS_{max} (supplementary table S4). In the biggest regions, Africa (AF1) have the upper and lower quantiles significant with negative slopes, but the lower quantile slope is lower so we conclude that negative fluctuations and variance are increasing (Figure 3). Eurasia mainland (EUAS1) have only the upper quantile significant with a positive slope so it presents an increase of the variance. North America mainland (NA1) have only the lower quantile is significant with
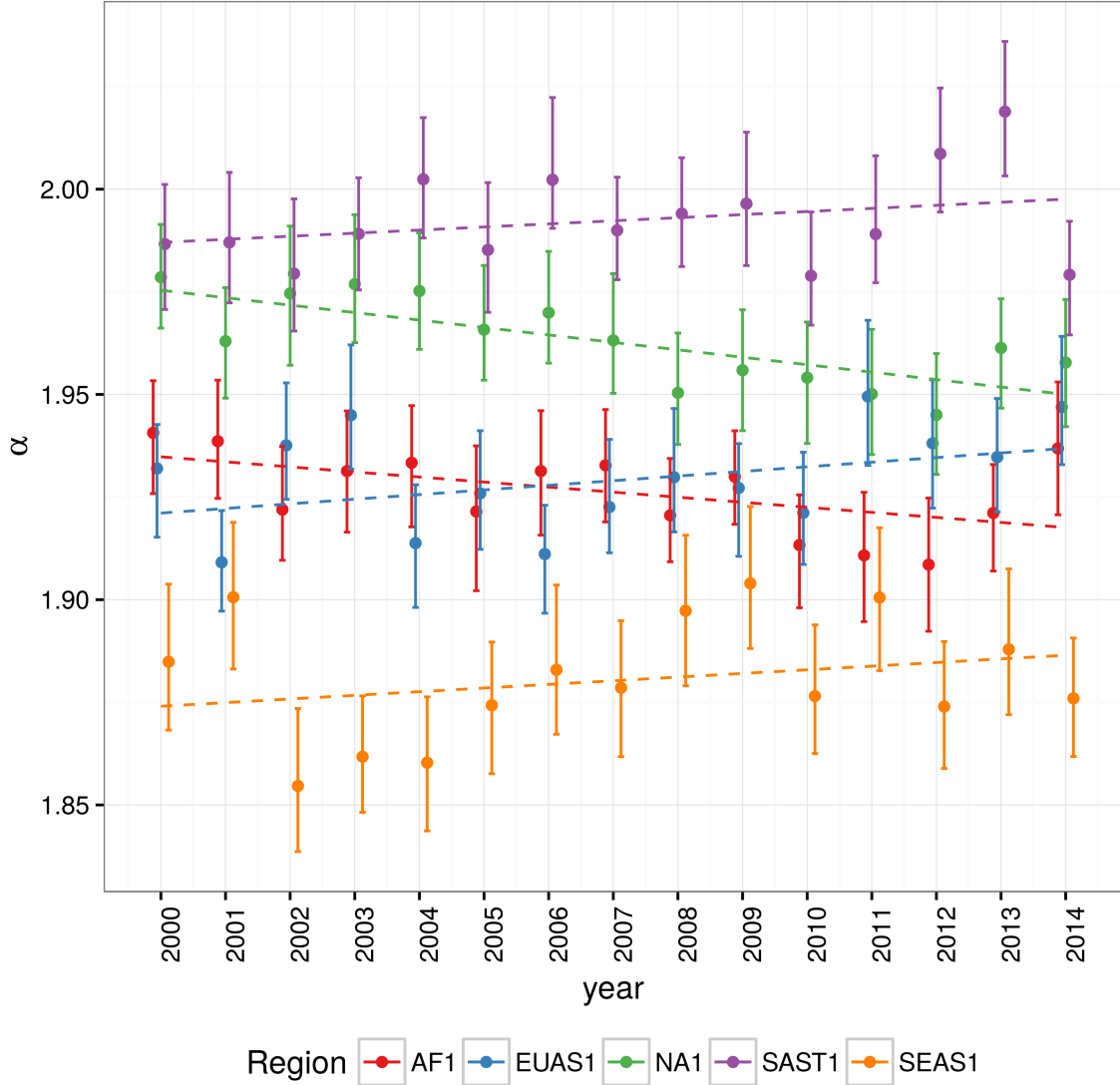
Figure 1: Power law exponents (α) of forest patch distributions for regions with total forest area $> 10^7$ km^2. Dashed horizontal lines are the fitted generalized least squares linear model, error bars are 95% confidence intervals estimated by bootstrap resampling. The regions are AF1: Africa mainland, EUAS1: Eurasia mainland, NA1: North America mainland, SAST1: South America subtropical and tropical, SEAS1: Southeast Asia mainland. For EUAS1 the best model is log-normal but the exponents are included here for comparison.
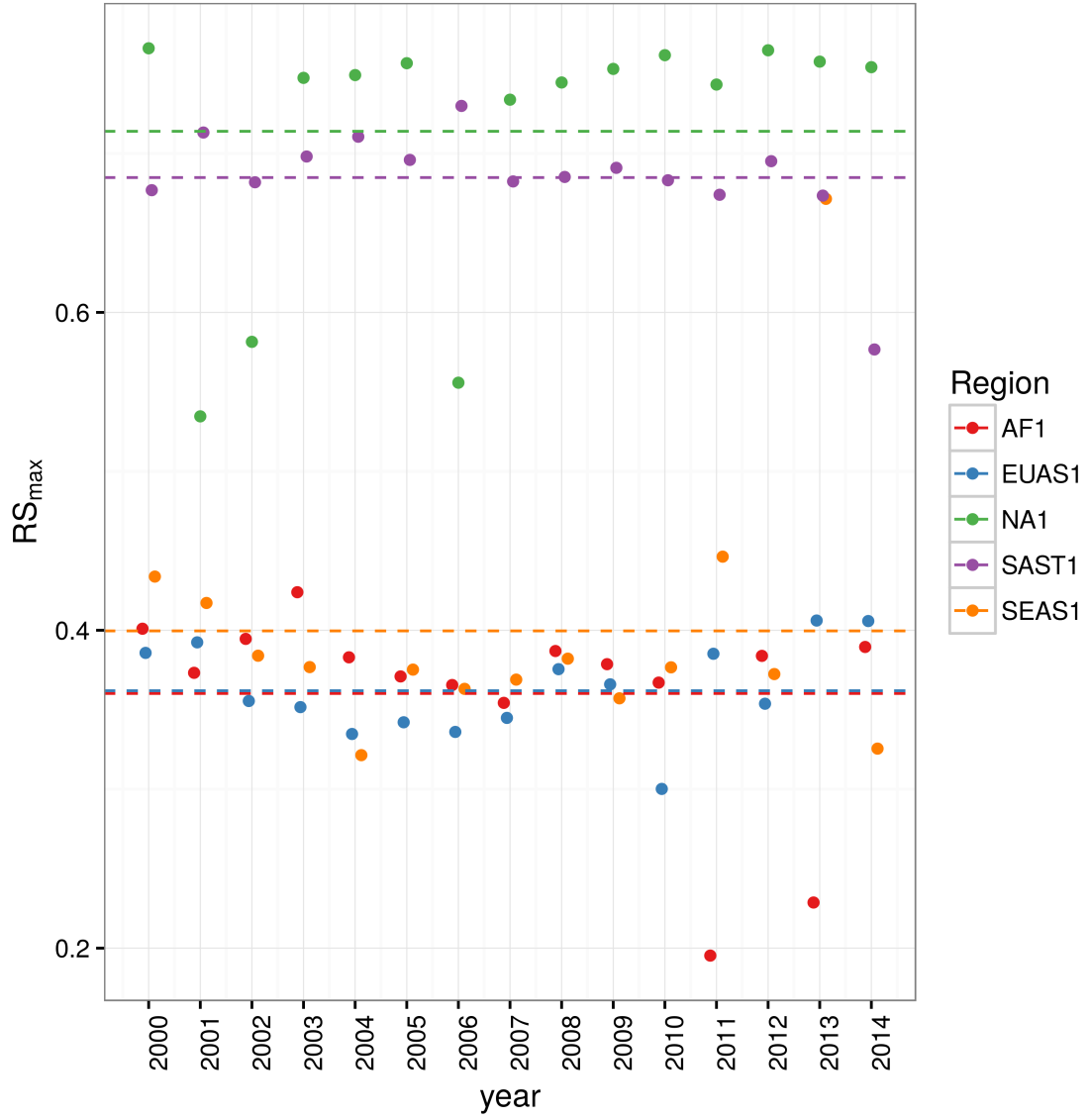
Figure 2: Largest patch proportion relative to total forest area RS_{max}, for regions with total forest area $> 10^7$ km^2. Dashed lines are averages across time. The regions are AF1: Africa mainland, EUAS1: Eurasia mainland, NA1: North America mainland, SAST1: South America tropical and subtropical, SEAS1: Southeast Asia mainland.

1 positive slope thus variance is decreasing. For Australia mainland all quantiles are significant, the slope of

2 the lower quantiles is greater than the upper ones thus variances is decreasing (Supplementary figure S10). A

3 summary of the results about variances and all the other indicators is shown in table 1.

4 Thus the conditions that indicate that a region is near a critical fragmentation threshold are that patch size

5 distributions follows a power law, temporal ΔRS_{max} fluctuations also follow a power law, variance of ΔRS_{max}

6 is increasing in time and skewness is negative, all these conditions are given only for: Africa mainland (AF1)

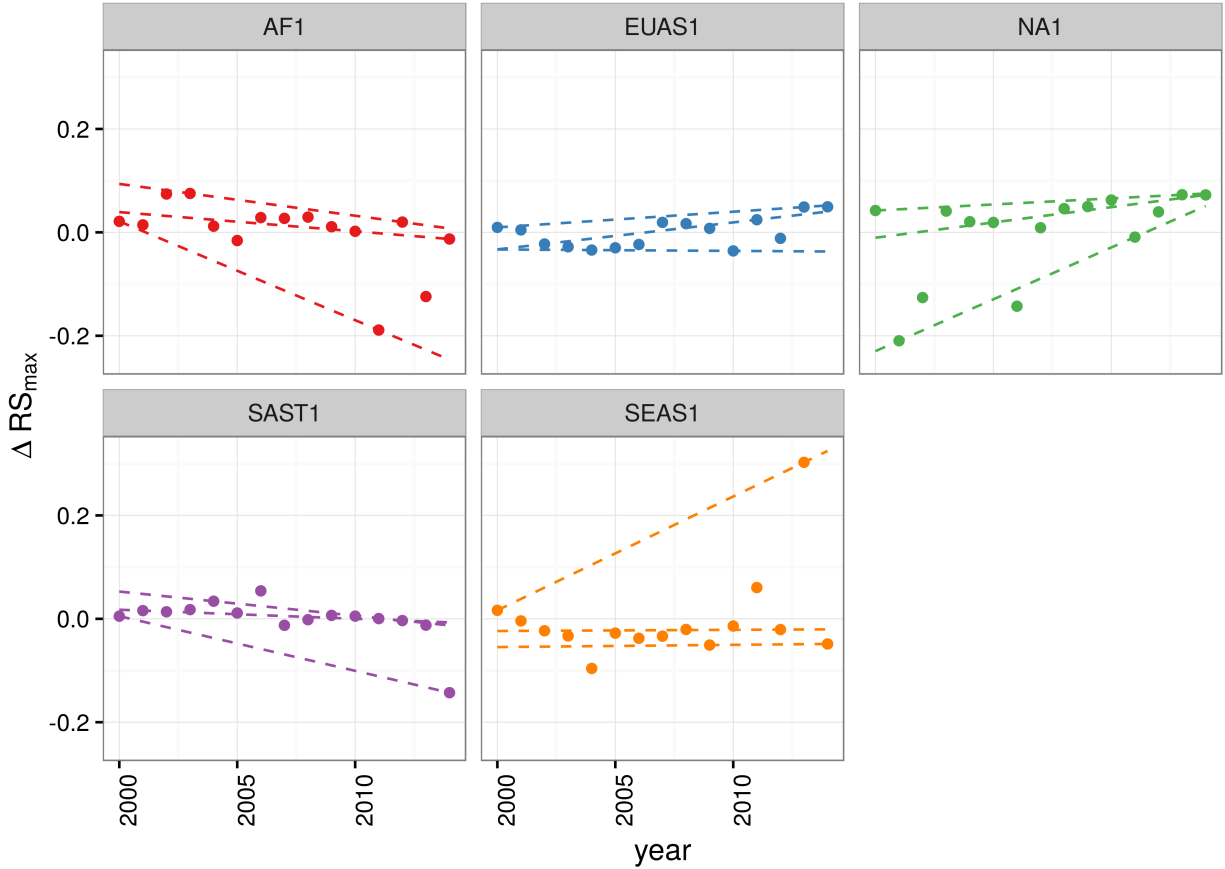7 and South America tropical & subtropical (SAST1).

Figure 3: Largest patch fluctuations for regions with total forest area $> 10^7 \mathrm{km}^2$. The patch sizes are relative to the total forest area of the same year. Dashed lines are 90%, 50% and 10% quantile regressions, to show if fluctuations were increasing. The regions are AF1: Africa mainland, EUAS1: Eurasia mainland, NA1: North America mainland, SAST1: South America tropical and subtropical, SEAS1: Southeast Asia mainland.

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Table 1: Regions, subregions and indicators of closeness to a critical fragmentation threshold. Where, RS_{max} is the largest patch divided by the total forest area, ΔRS_{max} are the fluctuations of RS_{max} around the mean, skewness was calculated for RS_{max} and the increase or decrease in the variance was estimated using quantile regressions.

Region		Description	Average RS_{max}	Patch Size Distrib	ΔRS_{max} Distrib.	Skewness	Variance
AF	1	Africa mainland	0.36	Power	Power	-1.8630	Increase
	2	Madagascar	0.65	Power	Power	-0.2478	NS
EUAS	1	Eurasia, Mainland	0.36	LogNormal	Exp	0.4016	Increase
	2	Japan	0.94	Power	Power	0.0255	NS
	3	United Kingdom	0.07	Power	Power	2.1330	NS
NA	1	North America	0.71	Power	Power	-1.5690	Decrease
	5	Newfoundland	0.87	Power	Power	-0.7411	NS
OC	1	Australia, Mainland	0.28	Power	Power	0.0685	Decrease
	2	New Guinea	0.97	Power	Exp	0.1321	Decrease
	3	Malaysia/Kalimantan	0.97	Power	Exp	-0.9633	NS
	4	Sumatra	0.92	Power	Power	1.3150	Increase
	5	Sulawesi	0.87	Power	Power	-0.3863	NS
	6	New Zealand south island	0.76	Power	Exp	-0.6683	NS
	7	Java	0.38	Power	Exp	-0.1948	NS

Region		Description	Average RS_{max}	Patch Size Distrib	ΔRS_{max} Distrib.	Skewness	Variance
	8	New Zealand north island	0.75	Power	Exp	0.2940	NS
SAST	1	South America, Tropical and subtropical forest up to Mexico	0.68	Power	Power	-2.7760	Increase
	2	Cuba	0.21	Power	Power	0.2751	NS
SAT	1	South America, Temperate forest	0.60	Power	Power	-1.5070	Decrease
SEAS	1	Southeast Asia, Mainland	0.40	Power	Power	3.0030	NS
	2	Philippines	0.54	Power	Power	0.3113	Increase

1 Discussion

2 We found that the forest patch distribution of most regions of the world followed power laws spanning seven

3 orders of magnitude. These include tropical rainforest, boreal and temperate forest. Power laws have been

4 found for several kinds vegetation, but never at global scales as we found in this study. Several mechanisms

5 have been proposed for this: the first was related self organized criticality (SOC), in this case the system is

6 driven by its internal dynamics to the critical state, this was suggested mainly for fire-driven forests [20,63].

7 Real ecosystems do not seem to meet the requirements of SOC dynamics: their dynamics is influenced

8 by external forces, interactions are non-homogeneous–they might vary from place to place [64]. Moreover,

9 SOC for forest-fire dynamics requires the memory effect: fire scars in a site should accumulate and interfere

10 with the propagation of a new fire. Pueyo et.al [34] do not found that effect so they suggested that other

11 mechanisms produce the power laws patterns.

12 The mechanism suggested by Pueyo et.al [34] is isotropic percolation, when a system is near the critical point

13 power law structures arise. This is equivalent to the random forest model that we mentioned previously, and

14 requires the tunning of an external environmental condition to carry the system to this point. We did not

15 expect that forest growth is a random process but it could be that combinations of factors cancel out and at

this large scales the forest dynamics would seems random. If this is the case the power law exponent should be $\alpha = 2.05495$ and this value is outside the confidence interval we found for α (1.898–1.920).

We observed power laws in a wide array of conditions thus mechanisms need the tunning of a parameter are not favoured. The mechanism of facilitation has been suggested as an explanation of pervasive power laws in patch size distribution [40], thus we hypothesize that models that include this process should explain this patterns. Scanlon et al. [36] represent the dynamics of savanna trees using a model including a global constraint (mean rainfall), a local facilitation mechanism and two states: tree/ non-tree. This model produced the observed power laws across a rainfall gradient without the need of tunning an external parameter as with isotropic percolation. A model with three states (tree/non-tree/degraded) including local facilitation and grazing was also used to obtain power laws patch distributions without tunning, and also representing the deviations of power laws at high grazing pressures [35]. At the scales of this study grazing does not seem to be important as we did not observe exponential cut-offs, but the combination of three states, local facilitation, and global constraints seems to be the most general way of modeling forest at global scales. This was in fact our assumption to estimate the early warning signals in this study. In this case the power law structures are present in all the range external conditions and two critical transitions are present: the first was the fragmentation transition the second is the extinction transition.

Eurasia does not follow a power law, but it is a geographically extended region, that probably consist of different domains. The union of two independent power law distribution gives a lognormal [65], thus using another criteria to split this region might convert them to power laws. We did not consider geographical features like big rivers and mountains to define regions and that could merge areas that behave independently from each other.

We found that the tropical forest of Africa and the southeast Asia seems to be near a critical fragmentation threshold, this means that the combined influence of human pressures and climate forcings can trigger all the undesired effects of fragmentation in these extended areas. An small but continuous increase in forest loss could produce a biodiversity collapse [28]. When habitat is reduced species population will decline proportionally [66]. This happens while the habitat fragments retain connectivity but as habitat reduction continues, the critical threshold is approached and as happens with the largest patch, connectivity will have large fluctuations. This could trigger several effects that act synergically: will enhance populations fluctuations and the possibility of extinctions will raise, this in turn will increase patch isolation that decrease connectivity [66]. This positive feedback mechanism will be enhanced when the fragmentation threshold is reached with the result of the loss of most habitat specialist species at a landscape scale [67]. Some authors argue that as species have heterogeneous responses to habitat loss and fragmentation and that as biotic

dispersal is limited, the importance of thresholds is limited to local scales or even its existence is defied [66]. Fragmentation is by definition a local process that at some point produces an emergent phenomena that spreads over the entire landscape and this could happen even if the area considered is infinite [68]. Thus limited dispersal is no a barrier to a fragmentation threshold that extends its influence to the continental areas considered in this study. To know if these thresholds will sum up and produce a cascading effect to reach a planetary tipping point [4], we should extend the effects of these changes to know how it will feedback on global land-atmosphere that affect climate change.

Why exponential cut-off are not observed?

The patch size distribution for Eurasia is log-normal and has smaller fluctuations than the other regions of comparable size (Figure 3). Exponential fluctuations are compatible with a combination of independent Poisson or Gaussian processes [65]. The other regions with exponential fluctuations have all power law patch size distributions. From these, the ones that have RS_{max} greater than 60% (Table 1) are above the fragmentation threshold thus the largest patch have a more compact structure and small losses do not affect its size so much. There is only one region (OC7, Java) that has RS_{max} below 40%, this is probably in a fragmented state

End discussing why fragmentation thresholds matters for the application of management efforts.

The delimitation of areas should be improved using orography and hydrography, this will improve the detection of early warnings because in this way only the internal dynamics are considered.

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