Testing for criticality in ecosystem dynamics: the case of Amazonian rainforest and savanna fire

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Abstract

We test for two critical phenomena in Amazonian ecosystems: self-organized criticality (SOC) and critical transitions. SOC is often presented in the complex systems literature as a general explanation for scale invariance in nature. In particular, this mechanism is claimed to underlie the macroscopic structure and dynamics of terrestrial ecosystems. These would be inextricably linked to the action of fire, which is conceived as an endogenous ecological process. We show that Amazonian savanna fires display the scale-invariant features characteristic of SOC but do not display SOC. The same is true in Amazonian rainforests subject to moderate drought. These findings prove that there are other causes of scale invariance in ecosystems. In contrast, we do find evidence of a critical transition to a megafire regime under extreme drought in rainforests; this phenomenon is likely to determine the time scale of a possible loss of Amazonian rainforest caused by climate change.

Keywords

Abrupt shift, fractal, global warming, macroecology, percolation, power law distribution, self-organized criticality, tropical rainforest, tropical savanna, wildfire.

INTRODUCTION

Ecosystems display regularities, without which there would be little room for ecological theory. Many of these regularities involve scale invariance (Brown *et al.* 2002; Halley *et al.* 2004; Solé & Bascompte 2006). It is no exaggeration to say that we cannot understand the nature of ecosystems without understanding the ultimate roots of scale invariance, but these roots are largely unknown. Here we use empirical data to explore this deep theoretical issue in a specific context: fire in tropical ecosystems. Furthermore, we connect it to another major theme of ecological theory: abrupt shifts. In addition to their academic interest, our findings have practical implications because they improve our understanding of the interaction between ecosystems and climate change.

The concept of "scale invariance" is closely associated with the concepts of "self-similarity" and "fractal". By "scale invariance" we mean that patterns with some given features appear again and again over a broad range of spatial or temporal scales. This is particularly apparent in the physical environment; e.g. in a mountain we can distinguish smaller mountains, and in each smaller mountain we can distinguish even smaller mountains. Scale invariance has also been claimed for various kinds of ecosystem features, either in space, in time or in abstract representation spaces (Brown *et al.* 2002; Halley *et al.* 2004; Solé & Bascompte 2006).

In the complex systems literature, scale invariance is often attributed to a mechanism known as "self-organized criticality", or SOC (Bak 1996; Jensen 1998, Christensen & Moloney 2005). This mechanism could be important for understanding many aspects of ecosystem structure and function (Solé *et al.* 1999; Levin 2005; Pascual & Guichard 2005). In ecology, SOC has been suggested for bird population dynamics (Keitt & Stanley 1998), epidemics (Rhodes & Anderson 1996), forest gap formation (Solé & Manrubia 1995), carbon exchanges (Cronise *et al.* 1996), species abundance distribution (Alonso & Solé 2000), species number (Keitt & Marquet 1996), macroevolution and extinction dynamics (Plotnik 1993; Solé *et al.* 1999) and, in relation to the last of these, for food or interaction webs. Special attention has been paid to the case of fire dynamics (Drossel & Schwabl 1992; Malamud *et al.* 1998, 2005; Pueyo 2007; Zinck & Grimm 2009). In these models fire is an ecological process rather than an external disturbance, because it is tightly controlled by the ecosystem.

Often, models displaying SOC in certain conditions display abrupt shifts known as "critical transitions" in other conditions. For example, some fire models display abrupt shifts from small fires to "percolating" fires, which can spread indefinitely (MacKay & Jan 1984; Binney *et al.* 1992; Pueyo 2007). This paper investigates both SOC and critical transitions.

The model

We depart from the model in Pueyo (2007), which is essentially equivalent to the original "forest fire" model by Drossel & Schwabl (1992), except that it contemplates environmental forcings. These models are very simple but the resulting fire dynamics often remain unaltered when adding more details (Zinck & Grimm 2009), a property known in physics as "universality" (Binney *et al.* 1992; Solé *et al.* 1999).

In the model the spatially-extended terrestrial ecosystem is represented as a square lattice. Certain information is assigned to each cell: whether or not it is currently burning and the time passed since the last fire. There is also a weather index, which is the same for all cells but fluctuates in time. Fire events start from cells that are ignited at random. Cells only burn during one time step. If one of the four closest neighbors of cell (i,j) is burning at time t, this cell has a probability p_{ij} of burning at time $t+1$ [if there are more neighbors burning there are more chances for cell (i,j) to burn]. The probability p_{ij} is a function of weather and time since last fire in (i,j). After burning, cells become refractory to fire ($p_{ij} = 0$). Then the susceptibility to fire increases gradually up to a limit, in a process of "fuel succession". The time scale of fire succession is sufficiently long that the duration of fire events can be ignored. We call $\overline{p}$ the mean of p_{ij} in all cells (i,j) at a given time. Simulations start with all cells at the final stage of fuel succession; since, by assumption, weather is also the same in all cells, they all begin with the same $p_{ij} = \overline{p}$.

The model supports two different modes of behavior, corresponding to two physical phenomena. Initially fires display a "percolation" dynamic (mode 1). If fire scars accumulate and interfere significantly with the propagation of new fires, the model develops SOC (mode 2). Such influences of previous fires are named "ecological memory" by Peterson (2002) and Zinck & Grimm (2009). Table 1 lists three features of the two modes, which we test with empirical data. The most obvious difference between them is that ecological memory is essential for mode 2 but irrelevant for mode 1.

Less obvious is the response to changes in $\overline{p}$ driven by external factors such as weather. In mode 1, the mean fire size $\overline{s}$ displays a critical transition at a threshold p_c. For $\overline{p} \le p_c$, $\overline{s} = a\left|p_c - \overline{p}\right|^{-1/\delta}$, where $\delta \approx 0.44$ (Pueyo 2007). Close to the threshold, a tiny increase in $\overline{p}$ is enough to cause a change from a negligible $\overline{s}$ to arbitrarily large fires. If and only if $\overline{p} \ge p_c$ can fires percolate (i.e. propagate from end to end of the lattice) independently of lattice size (MacKay & Jan 1984; Binney *et al.* 1992). If the weather conditions that initially caused $\overline{p}$ to exceed p_c are maintained or repeated frequently, the system switches to mode 2 (SOC) due to the proliferation of fire scars. Thereafter, the response to further weather changes is smoother, nearly exponential:

$$\bar{s} \approx \varphi e^{\alpha\bar{p}} \quad (1).$$

Furthermore, this response is partially dampened by the fuel feedback if these additional changes are also maintained.

The remaining row in Table 1 refers to scale invariance. Mode 1 displays scale invariance when $\bar{p}$ is fine-tuned to its critical value p_c. This is a widespread property of phase transitions (it is universal in so-called 2nd order phase transitions; Binney *et al.* 1992). However, it is not generally thought to explain scale invariance in natural complex systems because of the narrow environmental conditions in which $\bar{p} \approx p_c$ (e.g. Bak 1996). In contrast, when the system develops SOC (mode 2), scale invariance is observed for a broad range of environmental conditions, albeit over a limited range of scales (Pueyo 2007). Scale invariance is most apparent in the fire-size distribution, which roughly follows a power law:

$$f(s) = as^{-\beta}, \quad (2)$$

where f is probability density ("probability" sensu frequency), and a and β are constants.

The same two modes of behavior are found when modeling phenomena other than fire with the same basic ingredients: stochastic propagation of some kind of fluctuation, a refractory period and different time scales for fluctuation and recovery.

Power laws are often interpreted as evidence of SOC. This has been the case for wildland fire (Malamud *et al.* 1998, 2005). Other pieces of evidence are the response of fire to meteorological drivers (Pueyo 2007) and ecological memory, but the latter remains controversial (Goldammer 1999). Percolation has also been used to model wildland fire

(MacKay & Jan 1984; Sullivan 2009), but at single-fire level rather than landscape level like SOC.

Current evidence of SOC in wildland fire is suggestive but not definitive. Furthermore, similar to other areas of ecology, it is biased toward middle-to-high latitude ecosystems, in spite of the importance of tropical ecosystems in terms of area, biodiversity and interactions with climate.

The case of Amazonia

While tropical rainforest is the dominant vegetation in Amazonia, there are also some interspersed patches of savanna, the largest covering ~40,000 km^2 in the state of Roraima (Brazil). We used field and remote sensing data to study the three properties in Table 1, in this patch of savanna and in rainforest areas.

Savanna and rainforest are neighboring biomes with strikingly different fire regimes. Although there is little fire in Roraima's savanna during the rainy season, about one third of it burns in a normal dry season (with most fires taking place between December and March; Barbosa & Fearnside 2005). In contrast, the biogenic capacity of rainforests to maintain a humid microclimate is so large that they are virtually immune to fire (Uhl 1998; Cochrane 2003). However, during the extreme droughts caused by the El Niño event of 1997-98, which is the most intense on record, immense fires did affect rainforests in Roraima (Barbosa & Fearnside 1999), Borneo (Siegert *et al.* 2001) and elsewhere (Cochrane 2003). Roraima's fires burned 1.1-1.4 million ha of rainforest (Barbosa & Fearnside 1999). With 2.6 million ha burned in East Kalimantan (Borneo) alone, the Indonesian fires of 1997-98 have been described as the largest fire disaster ever observed (Siegert *et al.* 2001).

These general observations would suggest that rainforests are an instance of mode 1 behavior (percolation) and savannas are an instance of mode 2 behavior (SOC) in Table 1. In this paper we study the three properties in Table 1 to test if the dynamics of these two biomes can be identified with either of these two modes of behavior. We use a combination of field and remote-sensing data. With major droughts in Amazonia likely to become more frequent in the future (Cox *et al*. 2004, 2008), this research has not only theoretical but also practical interest.

MATERIALS AND METHODS

Study areas

We used data from two administrative areas: the Brazilian state of Roraima, in northern Amazonia, and the Bolivian department of Pando, in southwestern Amazonia. The first comprises large extensions of both rainforest and savanna; we studied both. The second is mainly covered by rainforest.

Remote-sensing data

We mapped the fire-scar sizes from remote-sensing images of Roraima's savanna in 2001 (Fig. 1a) and of Pando's rainforest in 2005 (Fig. 2b, c). The latter year corresponds to a severe drought in Pando and other parts of southern Amazonia (Cox *et al*. 2008). We obtained 9,687 savanna scars and 411 rainforest scars. We also used time series of hot-spot counts as a proxy for the annual cycles of burning in these areas. Hot spots are satellite-detected high temperature events, generally caused by active fires. Details are given in Appendix 1.

Analysis and simulation of scar-size distributions

The empirical probability density functions of scar sizes in savanna and in rainforest were plotted with the method used by Pueyo (2007). The range of values over which the distribution is scale invariant (i.e. in which the power law applies) can be identified because the data points corresponding to different bins appear aligned in the log-log plot. A Pearson regression was used to fit the exponent β of the power law (eqn 2) in this range.

In the case of Roraima's savanna this range is small, while the whole distribution resembles a truncated log-normal. The log-normal is often seen as a plausible distribution and is used as a null hypothesis in ecology and other disciplines because of its relation to the central limit theorem. We tested to determine if the truncated log-normal can explain a sequence of data points being so well aligned, using the method by Pueyo & Jovani (2006). A truncated log-normal is more difficult to reject than a standard log-normal, so by using the truncated distribution we make our test more conservative.

Conversely, we investigated if a power-law fire-size distribution with an abrupt cutoff (as is usually found in simulated and empirical fire sizes in other biomes; Malamud *et al.* 1998, 2005; Pueyo 2007) could give the log-normal-like scar size distribution observed in Roraima's savanna. There is no one-to-one correspondence between fires and scars, largely because some scars result from more than one fire. It is not difficult to find examples visually in the image, which is not surprising considering the large number of scars (9,687) and the large fraction of the area that was burned (13.6%). We explored the relation between fires and scars with a simple simulation. We generated N pseudorandom fire sizes sequentially, following a power law with an abrupt cutoff, and allowed them to join previously existing scars. Details are given in Appendix 1.

Microscopic dynamics in savanna

We performed field studies in Roraima's savanna that allowed us to quantify the strength of the local fuel-fire feedback. This feedback is an essential ingredient of SOC.

One of us (R.I.B.) traveled a 540.1-km triangular road transect representative of Roraima's savanna on 24 occasions over a period of three years (Barbosa & Fearnside 2005). At intervals of 100 m he registered whether there was evidence of recent fire on each side of the road. The observations spanned a year with much fire (1997-98), a year with little fire (1998-99) and a "normal" year (1999-2000). These data allowed us to estimate the probability of fire depending on whether a given site had or had not burned in the previous year.

In fact this conditional probability is not a direct expression of causality. There could be a heterogeneous probability of fire due to long-lasting features of the landscape such as geomorphology or proximity to ignition sources; this would cause a positive correlation between fire occurrence in different years. Observed conditional probabilities should be weighted against this background to investigate the causal role of previous fires. The presence of the road was useful to separate these two components. Landscape features are generally similar on both sides of the road. However, fire history is different because the road acts as a firebreak (Appendix 1). Therefore, the probability of fire at a given site conditional to fire occurrence in the previous year at the same site should be compared with the probability of fire at a given site conditioned to fire occurrence in the previous year on the opposite side of the road. The proper measure of error to assess the significance of the difference between these probabilities is not trivial because the same fire event can affect different sites, which causes large correlations over a broad range of spatial scales. Therefore, a nonparametric method was used. Details are given in Appendix 1.

Observations of the 1997-98 El Niño fires in Roraima's rainforest

The monitoring included overflights of active fires, ground transects, communication with multiple stakeholders and analysis of remote-sensing images (Barbosa & Fearnside 1999). This monitoring was not intended for the present study but rendered some qualitative observations that are highly relevant for our conclusions.

RESULTS

Scale invariance

With reference to the first row of Table 1, we conclude that both Roraima's savanna and Pando's rainforest display scale invariance in certain ranges of scales. In both cases the fire-scar size distributions follow power laws, which are apparent in the form of straight lines in Figs. 1b and 2c.

The power law is not so obvious in Roraima's savanna on first inspection. As apparent from Fig. 3a, the scar-size distribution is similar to a truncated log-normal in this case. However, the middle range (~1/3 to ~40 ha) is well fitted by a power law (exponent $\beta = 1.25$, $r^2 = 0.9997$). The data points in this range are much better aligned than a truncated log-normal could explain (Fig. 3b), which allowed us to reject this distribution in favor of the power law ($P < 10^{-5}$). Furthermore, with a simple simulation (Fig. 1c) we found that the gradual decay of probabilities for scar sizes larger than 40 ha (i.e. 7% of the scars, generating the log-normal-like shape) is compatible with a fire-size distribution consisting of a power law with an abrupt cutoff, considering that some scars result from the fusion of more than one fire.

The scar-size distribution of Pando's rainforest can be fitted with a power law (exponent $\beta = 1.60$, $r^2 = 0.993$) except in the lower range (Fig. 2c). However, the amount of data is much smaller than for Roraima's savanna.

Abrupt shifts

With reference to the second row in Table 1, neither Roraima's savanna nor Pando's rainforest give evidence of abrupt shifts, but Roraima's rainforest does.

Both for Roraima's savanna and for Pando's rainforest, the number of hot spots increases in a roughly exponential way during the dry season (Fig. 4). Due to the logarithmic scale of the ordinates, an exact exponential increase would appear as a straight line in Fig. 4. No abrupt shift in the number of hot spots can be seen in any part of the average cycle. Nor did we find evidence of abrupt shifts for the single-year counts, but the number of hot spots in a single year is usually too small to give any clear results.

However, the qualitative observations in Roraima's rainforest during the 1997-98 El Niño are consistent with the hypothesis of percolation. Widespread fires occurred in savannas and deforested areas neighboring rainforest beginning in August 1997, but only in early February 1998, after five months with almost no rain, did the fires penetrate into the forest. The rainforest began to burn from several foci, but the fire lines progressively coalesced. These lines persisted until the rains began at the end of March. Streams did not act as firebreaks because they had dried up and had become flammable before the forests themselves. As a result, a continuous or nearly continuous area of 1.1-1.4 million ha of rainforest was burned.

Ecological memory

With reference to the third row in Table 1, Roraima's savanna displays no memory from year to year (about memory in rainforests see Discussion).

The field study shows that the sites that burn in a given year have higher probabilities of burning again in the following year (Fig. 5). However, we can discard a memory effect because, when a site burns, the site on the opposite side of the road also has a higher probability of burning in the following year, and there is no significant difference between the two probabilities.

DISCUSSION

Critical phenomena in tropical fire ecology

Our results indicate that neither of the two modes of behavior in Table 1 gives a correct description of savanna fire dynamics and suggest that mode 1 gives a correct but partial description of rainforest fire dynamics. The importance of these findings lies in that, although we based our description of these modes of behavior on a particular model, they correspond to two fundamental physical concepts broadly used in complex systems theory, i.e. percolation and SOC.

Both Roraima's savanna (Fig. 1b) and Pando's rainforest (Fig. 2c) display a scale-invariant fire size distribution. This finding generalizes previous results (Malamud *et al.* 1998, 2005; Pueyo 2007) by extending them to two biomes that encompass a large fraction of Earth's biodiversity, biomass and fire. The power law is limited to a certain range of scales, as is always found in empirical and simulated data (Malamud *et al.* 1998, 2005; Pueyo 2007). This is mathematically unavoidable in a finite world (it is easy to prove that, for $1 \leq \beta \leq 2$ as usual, we cannot have a proper distribution and a finite mean unless there is a lower bound larger than zero and a finite upper bound). Furthermore, we would not expect any scale-invariant feature to be extrapolatable to the scale of individual plants or below. However, the empirical lower bounds in our study are primarily related to the resolution of our maps. In the case of Roraima's savanna, this bound corresponds to scars covering 1-3 pixels.

We expected tropical savanna to display SOC. This is often diagnosed from the sole observation of a scale-invariant power-law distribution (Table 1, 1st row) and our data agree with this expectation. However, this hypothesis is refuted because we found no memory (Table 1, 3rd row): our field studies indicate that there is a negligible causal connection between the previous year's fire history and current burning (Fig. 5). Since we did find an effect when the fire had taken place in the same fire season, we conclude that the mosaic of burned and unburned areas is erased every year as plants grow in the rainy season. SOC cannot develop if the mosaic is not conserved from year to year. In principle this would move us to the first column in Table 1 (percolation mode). As the system is reinitialized each rainy season, we would expect a percolation event causing an abrupt increase in burning rate at some point in the dry season (Table 1, 2nd row). However, no abrupt shift is observed in the annual cycle of hot spots. Their number increases in an approximately exponential way through the dry season (Fig. 4a), as we would expect from SOC (eqn 1) assuming that the relation between water deficit and local fire susceptibility *p* is not far from linear (water deficit can be assumed to increase linearly in the absence of rain; Malhi *et al*. 2009). We would not expect this result from percolation. Neither of the modes in Table 1 is compatible with our observations in Roraima's savanna.

In the case of rainforests we did not investigate their ecological memory (Table 1, 3rd row) directly, but we can exclude SOC because, in general, fire has been introduced recently and there has been no time for a historical process of self-organization relying on this memory. Furthermore, field observations indicate that fuel feedbacks are positive in rainforests (Cochrane *et al.* 1999), rather than negative as would be needed for SOC. However, in Pando's rainforest we found a power-law fire-size distribution and an approximately exponential increase in hot spots through the dry season, as we did in Roraima's savanna. In both cases, the first two criteria in Table 1 would suggest SOC while the third would suggest percolation.

The sequence of events in Roraima's rainforest in 1997-98 agrees with the hypothesis of percolation. During the first 9 months of severe drought the rainforest remained immune to fire. When it began to burn this occurred more-or-less simultaneously at several points, and the fire fronts coalesced and did not stop burning until the rains arrived almost two months later.

Role of spatial heterogeneity

Our results are better understood considering previous knowledge about the spatial structure of tropical ecosystems. In rainforest, patches degraded by logging and other anthropogenic disturbances lose their immunity to fire (Holdsworth & Uhl 1997; Nepstad *et al*. 1999). In areas at the frontier of deforestation, fires are frequent but have been predicted (Uhl & Kauffman 1990) and found (Alencar *et al.* 2004) to be confined to degraded patches. Also, a small fraction of rainforest consists of igapó (seasonally-flooded rainforest surrounding black-water rivers and streams), which is naturally less resistant to fire than upland forest (Nelson 2007). In agreement with this previous knowledge, Pando's 2005 fires affected igapós (Fig. 2c) and disturbed forests (Fig. 2b) exclusively or to a large extent (the initial level of degradation is not known in some parts of the department). The fire size distribution was necessarily affected by the size distribution of these susceptible areas. In the case of savanna we also found some areas to burn systematically more than others (Fig. 5; but this could also be influenced by ignition frequency).

A singularity of the 1997-98 El Niño fires in Roraima's rainforest was the widespread burning of intact upland rainforest after a well-defined moment in time. This suggests a defined percolation threshold in this type of forest, which is compatible with the observation of fires below the threshold if they take place in localized areas of other, more-susceptible types of forest. This reconciles the results from Roraima and Pando.

Notably, the fact that upland rainforest is more resistant to fire than igapós and some streams implies a geometry of fire resistance opposite to that in savannas and other biomes, where streams act primarily as firebreaks (this is e.g. apparent in Fig. 1a). While not necessarily the single or the most important one, this factor could help to explain why we find evidence of percolation only in rainforests.

Origin of scale invariance

SOC models could reproduce relevant aspects of fire dynamics in biomes other than tropical rainforest and savanna, but our findings show that SOC fire dynamics are not necessary for scale invariance. SOC turns initially homogeneous model ecosystems into scale-invariant systems, which translates into a scale-invariant fire-size distribution. However, this initial homogeneity is unrealistic. As discussed above, the preexisting spatiotemporal heterogeneity seems to be highly relevant for our results. A possible interpretation is that the ecosystem imports scale invariance from the environment but this results ultimately from SOC (for example, SOC in geomorphology, hydrology, meteorology, or human activity). However, there are fundamental reasons to expect scale invariance without need of SOC.

In an objective Bayesian framework (Jaynes 1968, Pueyo et al. 2007), a frequency distribution can be decomposed as follows:

$$f(s) = \pi(s) L(s; \mathbf{v}).$$

The function L introduces the relevant constraints, expressed as the vector $\mathbf{v}$. The function π is the prior distribution representing randomness and is the point of departure before introducing constraints. It follows from Jaynes (1968) that scale parameters or variables, like object size, have the prior distribution

$$\pi(s) \propto s^{-1}.$$

Therefore,

$$f(s) \propto s^{-1} L(s; \mathbf{v}).$$

Most mathematical models are strictly constrained by a small set of rules. Then the prior distribution plays no role, and it becomes difficult to find rules leading to power laws, such as the rules of SOC. Ecological phenomena resulting from the interplay of many heterogeneous factors have laxer constraints. Based on this fact alone, the frequency distribution f should bear some similarity to the prior distribution π (Pueyo et al. 2007; see also Storch et al. 2008), as it does in the fire distributions that we observed.

SOC remains suggestive as a tentative explanation for many phenomena. However, this or other model-based explanations for scale invariance (Reed & Hughes 2002; Pascual

& Guichard 2005) are only needed if we assume that the dynamics of fire (or any other phenomenon) obey a simple set of rules, which is not necessarily true. In no case should the sole observation of a power law be considered a strong proof of SOC, as is often assumed in the literature (but see Solow 2005). The precedent set by our results is a reason to revise many claims of SOC in many fields.

Implications for climate change

Due to the absence of ecological memory in tropical savannas (at least in the region that we studied), the response of fire to climatic changes is more likely to resemble the response to weather in this than in other biomes. Our results suggest that this response is roughly exponential (eqn 1), as in SOC. In the case of rainforests, the possibility of critical transitions at certain thresholds is especially relevant.

Our 1997-98 and 2005 case studies concern early instances of two types of climatic events expected to become frequent in the warmer and drier Amazonia that some models forecast (Cox et al. 2004, 2008; see also Salazar et al. 2007). Most of the rainforest will be lost according to these models, but this is not necessarily true considering scientific uncertainty and existing options for mitigation and adaptation (Fearnside 2008; Cochrane & Barber 2009; Malhi *et al.* 2009). However, if the loss is to take place, it will be sped up by fire, which these models ignore. While the above-mentioned models predict a delay of decades to centuries between committed and actual forest loss (Jones *et al.* 2009), critical transitions of the kind that we suggest in this paper are likely to reduce this delay and cause a stepwise rather than a continuous loss.

Concluding remarks

Scale invariance can result from mixing heterogeneous processes. Mechanisms such as SOC are suggestive but are not needed to explain scale invariance unless we think that the system obeys simple rules. In the case of rainforest and savanna fires we found scale-invariant power laws without SOC. In themselves, power laws should no longer be considered evidence of SOC.

In rainforests we found evidence of a different type of critical phenomenon: critical transitions. If the Amazonian rainforest is to be lost to climate change as some models suggest, the process is likely to take the form of a series of critical transitions.

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APPENDIX 1

This appendix provides additional information on the methods used.

Fire scar mapping

We mapped Roraima's savanna fire scars from a Landsat ETM+ image (232/58, R3G4B5 color composition, 2001-01-22). The three first components from a principal component analysis (PCA) of the six optical bands were used as an input to a decision-tree classifier. A comparable image from a different date (2001-11-22) was used as a reference to discard permanent features that could be mistaken for scars. The results were edited based on expert knowledge of the area. The estimated kappa accuracy is 0.82. See an example in Fig. 1a.

We mapped Pando's rainforest fire scars visually from a series of CBERS-2 images obtained at the end of the 2005 fire season. We first sought the scars with the help of active fire information from the MODIS sensor (onboard Terra and Aqua). Then the scars were mapped from the CBERS images, using a classification system by visual interpretation from a false-color composition R3G4B2. See details in Cots & Cardona (2006) and Cots *et al.* (2007). We used only the data from the fires that had some visible effect on tree canopies, either directly or indirectly. See the examples in Fig. 2.

Annual cycles

We estimated the mean annual fire cycle in Roraima's savanna and Pando's rainforest area using hot-spot counts from NOAA-12 AVHR, handed over by INPE/CPTEC (BDQueimadas). We used the night-time passes (9 p.m. GMT). These time series cover the period from 1998-99 to 2006-07. They are useful for calculating approximate burning rates in savannas. In rainforests they are a poor indicator because many fires are hidden by the canopy. Therefore, fires in deforested and other open areas are comparatively over-represented in rainforest hot-spot counts.

We compared the estimated fire cycles with the rainfall cycles. In Roraima we used data from the Boa Vista Climatological Station for the same period covered by the hot spot time series. In Pando we used data from DEKLIM VASClimO (Beck *et al.* 2005) for the period available, from 1951 to 2000; they were averaged for the area 10^{o}S to 12^{o}S, 69.00^{o}W to 66.50^{o}W.

Simulation of the scar-size distribution

We generated *N* pseudorandom fire sizes *s* sequentially, following the distribution $f(s) \propto s^{-\beta}$ if $s \in [1, s_M]$, and $f(s) = 0$ otherwise. Each fire *i* had a probability $\lambda s_i^{\theta} s_j^{\theta}$ of joining each previously existing scar *j*, without excluding multiple junctions. We did not use any precise criterion to decide the parameter values because we only wanted to explore the question of whether fusions among scars had the potential to generate the type of shape that we had found for the size distribution. We used $\theta = 0.5$ based on simple geometric assumptions, $\beta = 1.25$ and $s_M = 500$ pixels based on the scar distribution, and $N = 20{,}000$ to have a large enough sample size. We then sought a value of λ that gives a distribution similar to the observed one, and selected $\lambda = 3.10^{-6}$. For the graphical display (Fig. 1c), we multiplied the simulated sizes by the area of a pixel in the image of Roraima.

Field data analysis

Here we add some technical details of the treatment of the data obtained from the ground transect in Roraima's savanna, described in *Materials and Methods*.

We developed a nonparametric measure of error that is robust despite the correlations in these data, which are large and extend to a broad range of scales. For one year in each pair, each site's datum was moved to a different position, while conserving the relative order of the data. Since the transect is a closed loop, this is the same as rotating one year's data in relation to the other. The conditional probabilities were recalculated for each possible lag. In this way we obtained a set of surrogate datasets. Our error bars indicate the standard deviations of the conditional probabilities obtained from these datasets.

In this experiment we assumed that the road acts as a firebreak. This is based on field observations (Barbosa & Fearnside 2005) and data analysis. The estimated probability for a given site burning in a given fire season is 0.346 ± 0.003. Fire propagation generates correlations; therefore the estimated probability of finding a burned point beside another burned point on the same side of the road in the same fire season is 0.892 ± 0.003. This probability drops to 0.466 ± 0.017 across the road (this error term was calculated with the method above, which cannot be applied in the other two cases; the other two error terms are standard errors and are thus less meaningful in this context).

FIGURE CAPTIONS

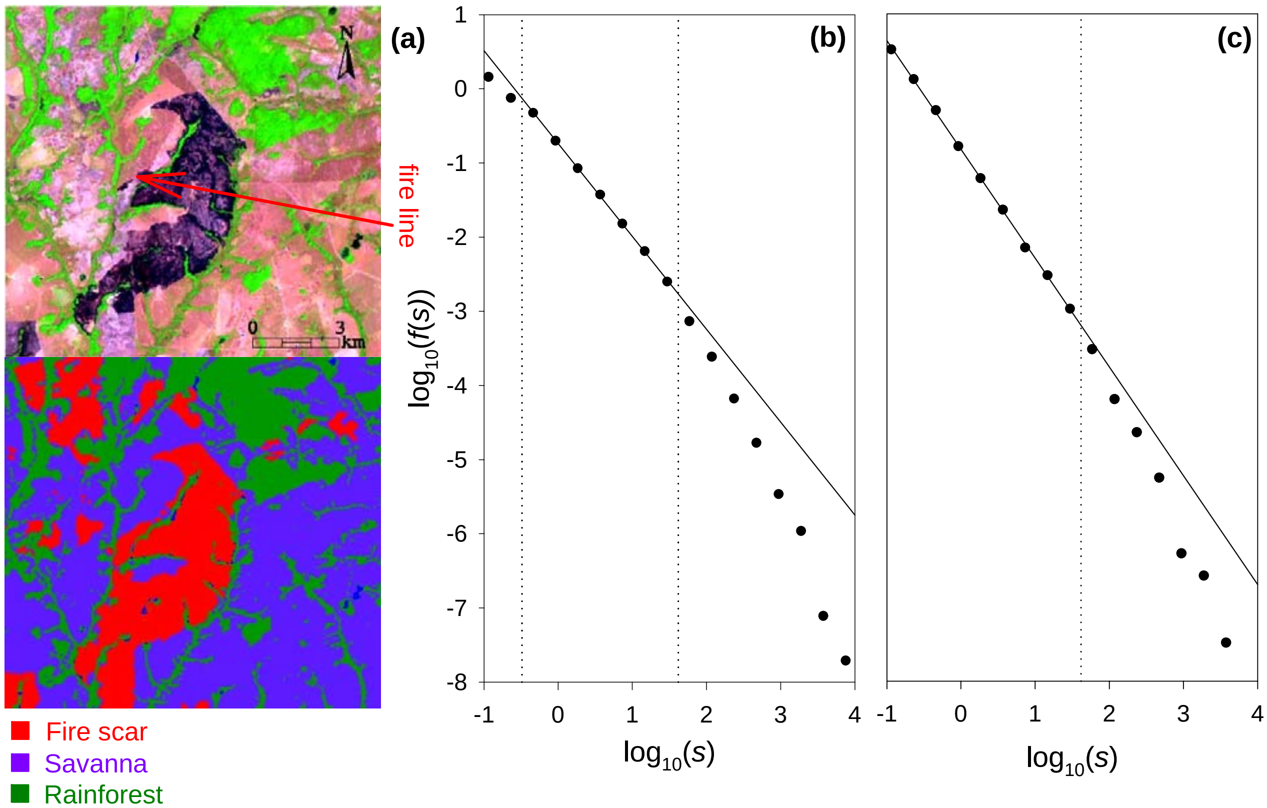
Figure 1 Savanna fire scars in Roraima (Brazilian Amazonia), mapped from a Landsat ETM+ image. (a) Example of scar identification. (b) Empirical probability density function *f* of scar size *s*. The small frequencies in the lower range, corresponding to 1-3 pixels, could be due to insufficient resolution. (c) Probability density function obtained from a simple simulation in which fire sizes follow a truncated power law and some of the scars result from more than one fire. In both cases, the part that has been fitted with the power law is limited by vertical lines.

Figure 2 Rainforest fire scars in Pando (Bolivian Amazonia), mapped from CBERS-2 images. (a) Scars around a road. (b) Scars in an area of igapó (forests seasonally flooded by black water). (c) Empirical probability density function *f* of scar size *s*. This function agrees with a power law except in the lower range (indicated by the vertical line), possibly because of insufficient resolution.

Figure 3 Comparison of Roraima's savanna fire scars to a truncated log-normal. Solid symbols: log-normal; empty symbols: empirical data. (a) Probability density function; *s* size in ha, *f* probability density. The empirical data display a power law in the middle range, from ~1/3 to ~40 ha, which has been delimited by vertical lines. (b) Residuals from a linear regression in the middle range of the previous plot.

Figure 4 Annual cycles of the mean number of hot spots. Mean cycles from 1998-99 to 2006-07, NOAA-12 AVHRR, night-time passes, with their standard errors. Since the scale is logarithmic, straight lines correspond to exponential variations. (a) Savanna in Roraima, Brazilian Amazonia (with mean 20th century rainfall). (b) Rainforest in Pando, Bolivian Amazonia (with mean rainfall 1951-2000).

Figure 5 Fire probability in a dry season conditioned to fire occurrence in the previous dry season, along a road transect in Roraima's savanna (Brazilian Amazonia). There is no significant difference depending on whether the previous fire took place at the same point or on the opposite side of the road, even though the road acts as a firebreak. This suggests that fire is not regulated by the ecosystem through a fuel feedback.



(a)
N
0
3
km
fire line
Fire scar
Savanna
Rainforest
(b)
(c)
log10(f(s))
log10(s)
log10(s)
1
0
-1
-2
-3
-4
-5
-6
-7
-8
-1
0
1
2
3
4

Figure 1

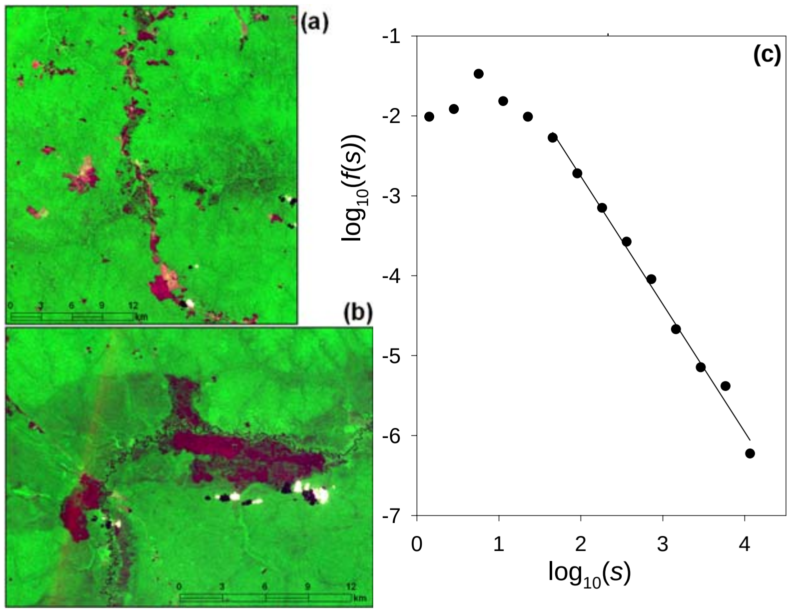


Figure 2

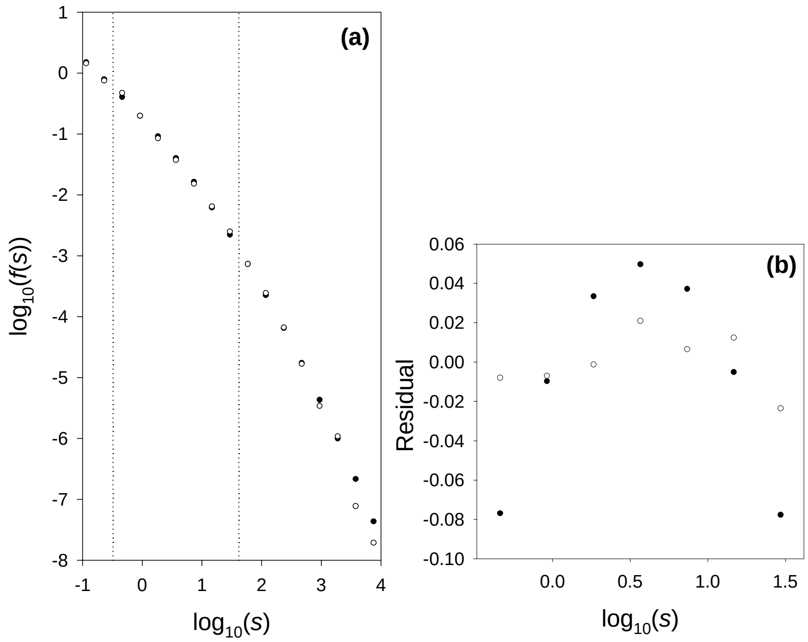

(a)
(b)
log10(f(s))
log10(s)
Residual
1
0
-1
-2
-3
-4
-5
-6
-7
-8
-1
0
1
2
3
4
0.06
0.04
0.02
0.00
-0.02
-0.04
-0.06
-0.08
-0.10
0.0
0.5
1.0
1.5

Figure 3

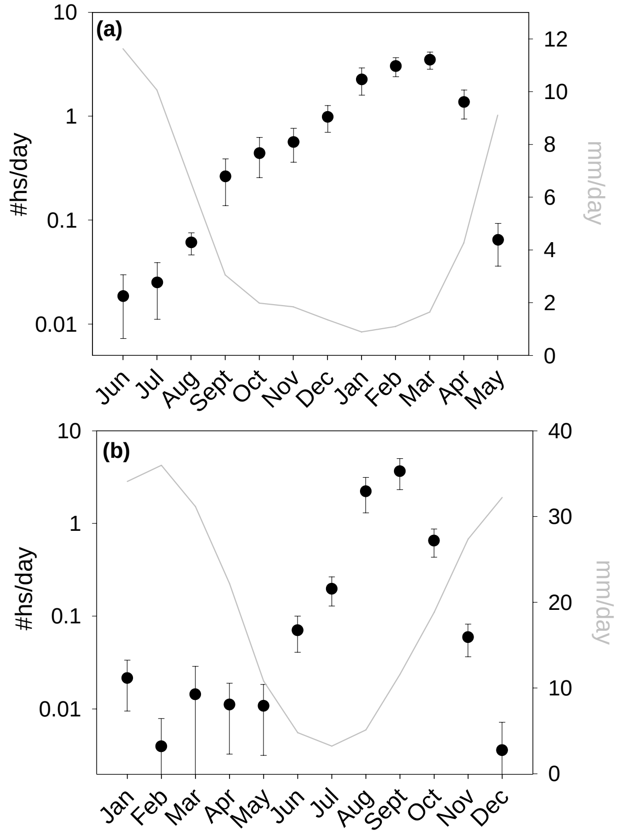
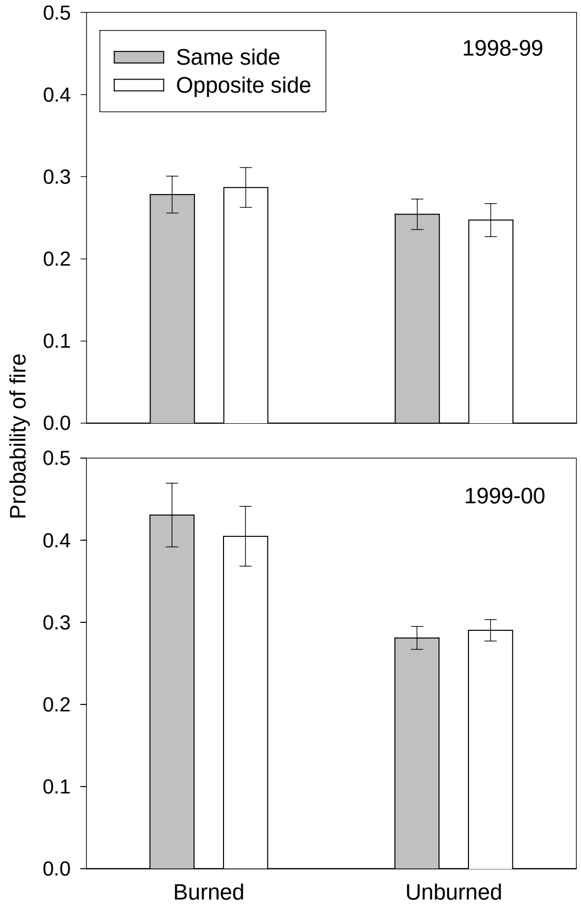

(a)
#hs/day
mm/day
10
1
0.1
0.01
12
10
8
6
4
2
0
Jun Jul Aug Sept Oct Nov Dec Jan Feb Mar Apr May
(b)
#hs/day
mm/day
10
1
0.1
0.01
40
30
20
10
0
Jan Feb Mar Apr May Jun Jul Aug Sept Oct Nov Dec

Figure 4



Probability of fire
0.0
0.1
0.2
0.3
0.4
0.5
Same side
Opposite side
1998-99
1999-00
Burned
Unburned

1

2

3 Figure 5

TABLES

Table 1 Comparison of the features of two different physical phenomena involving criticality. They arise as two different modes of behavior of our model but have a more general interest.

Property	Mode 1: Percolation	Mode 2: SOC
Scale invariance	Only after fine tuning the parameters	Yes, robust
Response to environmental forcings	Abrupt	More gradual
Memory	Irrelevant	Yes, needed