Growing aridity and seasonality can drive catastrophic changes in the Amazon forest

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The consolidation of a non-analogous climate shortly will likely affect the structure and functioning of Amazon, the most biodiverse terrestrial ecosystem on the planet. However, the ecological mechanisms underlying these potential events are still poorly understood. Here, we investigate the mechanism responsible for controlling the forest-savanna transition regime through an objective measure of resilience, based on the multidimensional climatic niche of ecosystems. Our results suggest that there is an alternating dominance, where forest and savanna have their respective basins of attraction. However, we note that the two stable states can coexist only in a narrow ecotonal zone of bistability. In this particular region, there is an equivalence between forest and savanna in quantitative terms and its presence indicates, in addition to a low hysteresis, a propensity for a catastrophic transition regime between forest and savanna. In this sense, we determine the critical levels of resilience that intermediate the dynamics of transition between forest and savanna through such bistable ecotonal zone. Also, we found that bistable region is strongly associated with critical climatic thresholds, mainly on the axis of the moisture availability and climatic seasonality, but with the lower effect of the average annual temperature. Thus, we can expect that if such climatic thresholds are reached, due to ongoing climate change, and forest resilience limits are exceeded; largescale catastrophic events will suddenly be triggered. The expected effects are the erosion of Amazonian biodiversity, with the massive extinction of species, culminating in the consolidation of a stable state with simplified ecosystems, with a lower density of tree cover.

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27 Abstract

The consolidation of a non-analogous climate shortly will likely affect the structure and 28 functioning of Amazon, the most biodiverse terrestrial ecosystem on the planet. However, the 29 ecological mechanisms underlying these potential events are still poorly understood. Here, we 30 investigate the mechanism responsible for controlling the forest-savanna transition regime through 31 an objective measure of resilience, based on the multidimensional climatic niche of ecosystems. 32 Our results suggest that there is an alternating dominance, where forest and savanna have their 33 respective basins of attraction. However, we note that the two stable states can coexist only in a 34 35 narrow ecotonal zone of bistability. In this particular region, there is an equivalence between forest and savanna in quantitative terms and its presence indicates, in addition to a low hysteresis, a 36 propensity for a catastrophic transition regime between forest and savanna. In this sense, we 37 determine the critical levels of resilience that intermediate the dynamics of transition between 38 forest and savanna through such bistable ecotonal zone. Also, we found that bistable region is 39 strongly associated with critical climatic thresholds, mainly on the axis of the moisture availability 40 and climatic seasonality, but with the lower effect of the average annual temperature. Thus, we 41 can expect that if such climatic thresholds are reached, due to ongoing climate change, and forest 42 resilience limits are exceeded; large-scale catastrophic events will suddenly be triggered. The 43 expected effects are the erosion of Amazonian biodiversity, with the massive extinction of species, 44 45 culminating in the consolidation of a stable state with simplified ecosystems, with a lower density 46 of tree cover.

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48 Keywords: Tipping point, Resilience, Bistability, Forest-savanna transitions.

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50 Introduction

Observational data indicate that the 2016 year was the warmest and driest in the Amazon 51 basin since the beginning of observations (Jiménez-Muñoz et al., 2016). In this context, El Niño 52 (ENSO) plays an essential role as a determining factor of extreme interannual climatic events in 53 the Amazon. This climate pattern, with higher temperatures and longer dry season duration, seems 54 55 to compose a trend for the biome, especially in its eastern to southwestern borders (Li et al., 2008b; Fu et al., 2013; Jiménez-Muñoz et al., 2013). For the foreseeable future, this scenario is expected 56 to accentuate. Climate simulations predict that by the end of the 21st century the Amazon basin 57 will suffer from non-analogous conditions with little overlap with the current climate (Williams et 58 al., 2007; Malhi et al., 2009; Garcia et al., 2014). 59

Terrestrial ecosystems are known to depend on energy and moisture availability to 60 maintain their structure and functioning (Murphy & Bowman, 2012; Donoghue & Edwards, 2014; 61 Oliveras & Malhi, 2016)(Murphy & Bowman, 2012; Donoghue & Edwards, 2014; Oliveras & 62 Malhi, 2016). However, forests are not only a passive recipient of abiotic conditions (Zemp et al., 63 2017)(Zemp et al., 2017). Amazon forest, with its immense biological richness (Mittermeier et al., 64 2003), plays a vital role in the global climate system, integrating an intricate network of material 65 66 and energy feedbacks at large scales (Aragão et al., 2014; Nobre et al., 2016). Therefore, it is expected that ongoing climate change, promoted mainly by the increasing rate of greenhouse gas 67 68 emissions to the atmosphere (IPCC, 2014), will affect the integrity and functioning of the Amazon 69 forest (Davidson et al., 2012). Such climate state will entail the commitment of a vast set of goods and services provided to humans (Cardinale et al., 2012; Pecl et al., 2017). 70

However, there are still many uncertainties about how the forest will respond if there is a
consolidation of such changes in the climate. In this regard, in large part, is due to the non-inclusion

of biological mechanisms in the construction of predictive models (Urban et al., 2016). According 73 to the ecological stability theory (Scheffer et al., 2001), along with an environmental gradient, a 74 catastrophic transition regime can be triggered suddenly between stable states if a given resilience 75 threshold is reached. In this way, it is possible to identify the effects of bistability (Hirota et al., 76 2011; Staver, Archibald & Levin, 2011). A central concept in ecological stability theory is that of 77 78 resilience. Resilience, in the context of complex ecological systems, can be interpreted as the ability of an ecosystem to recover after suffering a disturbance (Holling, 1973; Pimm, 1984; 79 Scheffer et al., 2001; Folke et al., 2004). 80

81 In this study, to understand the potential responses of the Amazon forest to changes in climate, we propose to investigate the ecological mechanism that controls forest-savanna transition 82 regimes and the implications for the forest ecosystem. To achieve this goal, we measured and 83 mapped the resilience of forest and savanna by modeling the multidimensional climatic niche of 84 ecosystems using high spatial resolution remote sensing data. This new approach, which integrates 85 different theoretical and methodological bodies, represents a significant advance for the 86 conservation of Amazonian biodiversity in order to will improve our predictive capacity in 87 anticipating catastrophic transitional events. 88

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90 Material & Methods

91 Modeling the multidimensional climate niche of forest and savanna

The presence-absence data of the stable ecosystem states, used as input in ecological niche modeling, were defined from a trimodal frequency histogram of the tree cover variable (0-100%) from the MODIS (Moderate Resolution Imaging Spectroradiometer Satellite) (Townshend et al., 2011). The spatial resolution of the raster is 6 km inside and covers all of South America. The

96 stable savanna state presents tree cover values between 5 and 60%, while forest presents values 97 over 60% (Hirota et al., 2011). Within this range, the steady state in question assumes the presence 98 value (1), and out is considered as absent (0). After correction of classification inaccuracies due to 99 the historical land use bias, based on a consensual basis of high-resolution vegetation classes 100 (Tuanmu & Jetz, 2014), the raster was converted to the point vector format, where each observation 101 received its geographical coordinate of longitude and latitude.

As bioclimatic predictors for ecological niche modeling, we used the climatic dataset CHPclim 102 (v.1.0) produced by the Climate Hazards Group's Precipitation Climatology with a spatial 103 resolution of 0.05 ° (~6 km) to describe the precipitation patterns of South America (Funk et al., 104 2015). The temperature patterns along the continent were represented with the WorldClim 105 database (Hijmans et al., 2005) with a spatial resolution of 0.041° (~ 5 km). We have selected four 106 bioclimatic predictors related to energy availability (temperature) and humidity (precipitation), 107 which are recognized as essential factors from the ecophysiological point of view of ecosystems 108 (Lehmann et al., 2014; Oliveras & Malhi, 2016): annual cumulative precipitation (ACP); (2) 109 precipitation seasonality coefficient (PSC); (3) annual average of temperature (AAT) and (4) 110 annual range of temperature (ART). 111

To model the ecological niche of ecosystems as stable states, we used the biomod2 package implemented in the R software (Thuiller et al., 2009). Niche models were calibrated using presence-absence data from each ecosystem combined with the four bioclimatic predictors described above. We have adopted the ensemble strategy, which emphasizes the most consensual predictions among different modeling methods (Araújo & New, 2007; Franklin, 2010), thus minimizing the effect of uncertainties on model prediction (Diniz-Filho et al., 2009)(Diniz-Filho et al., 2009). We utilized ten different methods for build the models: Bioclim (SRE), Classification

Tree Analysis (CTA) (Scull, Franklin & Chadwick, 2005); Maxent (Phillips et al., 2006, 2016); 119 Random Forest (RF) (Breiman, 2001); Generalized Linear Models (GLM) (Guisan, Edwards & 120 Hastie, 2002); Generalized Aditive Models (GAM) (Hastie & Tibshirani, 1986); Function 121 Discriminant Analysis (FDA) (Manel, Dias & Ormerod, 1999); Artificial Neural Networks (ANN) 122 (Manel, Dias & Ormerod, 1999); Multiple Aditive Regression Splines (MARS) (Friedman, 1991). 123 124 For each method, we ran ten replicates with 75, and 25% partition for training and test, respectively. We evaluated the quality of the models produced by the different methods with the 125 True Skill Statistics (TSS) and Receiver Operating Characteristic (ROC) metrics. The best models 126 to compose the ensemble were selected using the TSS metric that measures quality combining 127 sensitivity and specificity (Allouche, Tsoar & Kadmon, 2006). For threshold effect, only the 128 models with $TSS \ge 0.6$ were considered to compose the ensemble. The model of consensual 129 distribution was then obtained through the arithmetic mean among the best models of the different 130 methods (Diniz-Filho et al., 2010). 131

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133 Spatial resilience boundary for forest and savanna

This study emphasizes the natural transition mechanisms between the Amazonian forest and adjacent savanna ecosystems (e.g., cerrado) from a resilience gradient based on the multidimensional climatic niche of steady states. Therefore, the study area comprises the entire Amazon basin and the adjacent regions bordering the biome, located between latitudes 10 °N and 20 °S and longitudes 40 ° W and 80 °W. The spatial resolution of the raster is 0.05 ° (~ 6 km) containing 432,042 pixels.

Here, climate suitability models derived from ecological niche modeling are used alternatively asa direct and objective measure of ecosystem resilience. To identify the geographical limits of

resilience between the Amazon forest and adjacent savannas, we calculated the amplitude between the resilience gradients of the two stable states over all the pixels in the study area to identify the dominance zones and those where there is bistability in spatially explicit ways. Regions with high amplitude values indicate that forest or savanna, depending on the area, dominate regarding resilience, while low amplitude values (close to zero) suggest that there is a counterbalance of the resilience between the two ecosystems, ecosystems would be equivalent to having bistability.

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149 Predicting resilience thresholds in transition regimes

To identify critical resilience thresholds before forest-savanna transition regimes, we calculated 150 the observed proportion of each stable state (forest or savanna) along each measured unit of forest 151 resilience to the study area. We counted a total of 446 independent and non-autocorrelated samples, 152 where the forest and savanna ratio were calculated, ranging from 0 (zero) to 1 (one) along the 153 resilience gradient. The observed proportions, such as response variable, were then plotted as a 154 function of the forest resilience gradient. Then, we fitted a non-linear local regression statistical 155 model (LOESS) to the observed data to estimate the critical cut points under the resilience gradient 156 at the moment the curves assumed independent behavior and diverged each other. 157

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159 Calculating the trend towards a transition regime and its associated climatic thresholds

We measured the propensity for transitions regimes from the spatial anomaly of resilience calculation between the rasters of the two stable states. The values of the output of the operation vary between [+1000] (positive), which are related to the increase of the forest resilience, and [-1000] (negative) indicating an increase of the resilience of savanna. Using this gradient, we counted the number of forest and savanna observations under each unit of the measured anomaly

to calculate the observed proportion of forest and savanna along the gradient of the anomaly. After this procedure, which generated a set of 1,805 observations with statistical independence and without spatial autocorrelation, we plot the observations under a two-dimensional scatterplot, where the respective bioclimatic predictors are the axes.

We separate the factors under the two-dimensional climate space in (a) energy availability and humidity and (b) climatic seasonality. After this, we then fit a linear model, which the orientation of the line will indicate the type of statistical relationship between the predictors and the tendency to transformations between the ecosystems. By assigning a color gradient, related to the trend variable to a transition regime, it was also possible to identify the climatic thresholds critical to the transition between stable states from abrupt color changes.

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176 **Results**

We map the distribution of ecosystem resilience of stable forest and savanna states based on the 177 occupation of their respective multidimensional climatic niches (Figure 1A and B). The models 178 presented high sensitivity in predicting the alternating dominance of stable states over space with 179 synchronized geographic substitution between ecosystems. Such pattern of alternating dominance 180 between the two stable states is further evident in Figure 1C, where high resilience amplitude 181 values dominate almost the entire study area. However, we have detected only a narrow boundary 182 of bistability between the two ecosystems, where low values of resilience amplitude (close to zero) 183 184 prevail, highlighted by the black rectangles in Figure 1C. Such a bistable ecotonal zone should be responsible for the mediation of transition events between the two stable states, being described in 185 the theoretical field as Maxwell's point. Its presence indicates, in addition to bistability among the 186 187 ecosystems, a low hysteresis, in case the return to the original stable state occurs.

Figure 1. Ecosystem resilience gradient and Maxwell point detection. Estimated climate resilience for the forest (A) and savanna (B). In (C), the amplitude of resilience between forest and savanna gradients. The rectangles in (C) under the lowest values indicate the boundary between the two ecosystems, where a bistability pattern and low hysteresis prevail.

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193 In Figure 2, we observed empirically, under the forest resilience gradient, that, from a given boundary, towards the highest values, there is a predominance of the stable state of forest (green 194 balls), reflected in the highest proportion of observations when compared to savannas (purple 195 balls). Below an absolute limit of resilience, toward the lower values, the pattern reverses, since 196 there is proportionately more savanna than forest. However, between the two extremes of the 197 gradient, we identified an ecotonal resilience zone (green-moss rectangle), where the observed 198 values between forest and savanna are proportionally similar (~ 0.5). Such pattern indicates the 199 presence of mosaics of habitats in the landscape, where there is a dominance of either of the two 200 stable states (Figure 2). With the aid of a non-linear local regression model fitted to the data, we 201 observed that critical resilience values before catastrophic transition events between forest and 202 savanna are between 704 to 448 under the forest resilience gradient. 203

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Figure 2. Critical resilience thresholds and the bistable ecotonal zone. Under high resilience values (>= 704) dominance of forests (green balls), while in low values (<= 448) savannas stand out (purple balls). Under an intermediate zone of the resilience gradient (green-moss polygon), there is a balance of the observed proportions of forest and savanna, indicating an area of bistability. This transition zone should play a vital role in the mediation of stable state change events between forest and savanna.

In Figure 3, we present a trend metric for catastrophic transition regimes under the two-211 dimensional climate space of the study area. In the graph of energy availability and humidity for 212 ecosystems (Figure 3A), we observed that there is a strong tendency towards catastrophic 213 transformations between forest and savanna associated with a critical threshold of moisture 214 availability. At precipitation levels below the threshold of 1500 mm/year (ACP), there is a sudden 215 change with an evident increase in the chance to savanna, independent of the observed mean annual 216 temperature (AAT) values. On the other hand, in the climatic seasonality graph (Figure 3B), the 217 results indicate that the increase in climatic seasonality, both regarding temperature (ART) and 218 precipitation (PSC), are positively correlated with the tendency to more open environments in the 219 area of study. Such pattern may lead to events of sudden transitions from forest to savanna. 220

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Figure 3. The propensity for catastrophic transition regimes under bidimensional climate space. In (A) on the X-axis is the average annual temperature gradient (AAT) and on the Y-axis the annual cumulative precipitation (ACP). In (B) on the X-axis is the annual range of temperature (ART) and on the Y-axis is the seasonal precipitation coefficient (PSC). In all, we used n=1805observations.

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228 Discussion

The evidence presented here, such as Maxwell's point detection in a spatially explicit way, reinforces that a possible transition regime between forest and savanna would occur suddenly and in catastrophic proportions, if the critical resilience threshold is reached (Staal et al., 2016). The erosion of biodiversity, with the massive extinction of forest species through a phenomenon described as die-back forest (Cox et al., 2004), would result in the systematic loss of resilience

induced by anthropogenic environmental changes. This process of degradation, in theory, would
culminate in the consolidation of another level of ecological stability on the Amazon basin, with a
lower density of tree cover (e.g., savannas) (Zemp et al., 2017). This result is possible because
forests are more vulnerable to climate change shortly than other terrestrial ecosystems (Perez,
Stroud & Feeley, 2016).

239 It appears that the transition process over the Amazon basin has already begun (Malhi et al., 2008; Davidson et al., 2012). Observed empirical evidence, with data from different sources, has shown 240 that the forest is losing its natural self-regeneration capacity. In general, slower recovery of these 241 ecosystems has been observed in structural and functional terms after disturbances, mainly under 242 the southeastern and eastern edges of the biome, near the ecotonal zone with the cerrado. For 243 example, the ability of forests to retain carbon in biomass in this region has been compromised as 244 a function of the observed moisture deficit (Phillips et al., 2009; Brienen et al., 2015; Feldpausch 245 et al., 2016; Baccini et al., 2017). Amazonian floodplain forests have also shown a slower recovery 246 rate after fire events and prolonged dry periods (Flores et al., 2017). In the same sense, severe 247 drought events are also associated with high tree mortality rates (Allen et al., 2010; Greenwood et 248 al., 2017), with effects aggravated by forest fires (Barlow & Peres, 2008; Brando et al., 2014). 249

In this sense, the explicit determination of critical thresholds of resilience at large scales means a particularly significant advance for Amazonian conservation, since we would have a better predictive capacity to anticipate the effects of climate changes on the forest. Such information will guarantee a more precise action towards ecosystem conservation plans (Scheffer et al., 2015). Some authors have already explored this hypothesis previously based on coupled models of climate and vegetation dynamics (Oyama & Nobre, 2003; Nobre & Borma, 2009; Salazar &

Nobre, 2010), but without explicitly exploring the ecological mechanism underlying transitionregimes.

The bistable ecotonal zone (Maxwell point) is associated with catastrophic transition regimes and also indicates the presence of an environmentally well-defined threshold (Wuyts, Champneys & House, 2017). In this sense, the correlation of the observed trends to a transition regime under the two-dimensional climate space allowed the design of a useful climatic metric, which indicates the thresholds for the monitoring of catastrophic events. Also, with such a procedure it was possible to measure the importance of bioclimatic predictors in determining potential devastating transition regimes.

Our findings indicate that changes in mean temperature would have little influence on the transition regime between forest and savanna. In other words, with a higher concentration of greenhouse and increasing global temperatures, will not be the primary factor that will determine catastrophic transition events between forest and savanna. Although the relevance of the effect of CO2 fertilization on forest productivity is recognized (Lloyd & Farquhar, 2008; Cox et al., 2013; Huntingford et al., 2013).

Our results indicate that the most important factor when analyzing the energy and humidity 271 272 availability axis is the annual cumulative volume of precipitation. According to our findings, in order not to trigger catastrophic transition events between forest and savanna, it would have to rain 273 at least 1500 mm/year in a particular region. Some authors corroborate this critical climatic 274 275 threshold with other methodological approaches (Malhi et al., 2009; Wuyts, Champneys & House, 2017). In a recent study, the author indicates a breakpoint of approximately 2000 mm/year 276 277 (Ahlström et al., 2017) as a critical value for the maintenance of high values of gross primary 278 productivity. Although, the conclusion was not based on an objective measure of ecosystem

resilience. However, all the data observed and simulated indicate a tendency to increase aridity 279 over the Amazon basin (Li et al., 2008a; Malhi et al., 2009; Fu et al., 2013; Boisier et al., 2015; 280 Erfanian, Wang & Fomenko, 2017), specially on the southwest and east edges of the biome. 281 Under the climatic seasonality, our results indicate that the increase in seasonality of precipitation 282 and temperature has a direct association with a higher propensity for catastrophic transition 283 284 regimes between forest and savanna. These data suggest that rainfall is more frequent in the Amazon basin due to the prolongation of the dry season, mainly on the eastern edges of the 285 southwest (Li et al., 2008a; Fu et al., 2013; Boisier et al., 2015). Another negative factor, which 286 has further accentuated the increasing seasonality of precipitation, is the increase in the frequency 287 of extreme drought events, mainly caused by more severe El-Niño (Jiménez-Muñoz et al., 2016). 288 Our results indicate that, as a function of the alternating dominance pattern through the resilience 289 gradient, the Amazonian forest and adjacent savanna ecosystems represent two independent stable 290 states, where each one has its basin of attraction, previous corroborating studies (Hirota et al., 291 2011; Staver, Archibald & Levin, 2011). However, our findings suggest that coexistence between 292 savanna and forest is restricted to a narrow ecotonal zone of best ability, known as Maxwell's 293 point, contrary to the hypothesis that forests and savannas have extensive areas of bimodality 294 295 (Staver, Archibald & Levin, 2011). Such pattern can be explained by the fact that our models were based on the multidimensional climatic niche of stable states, which means a higher sensitivity due 296 297 to better ecological resolution when compared to previous, generally two-dimensional, studies. 298 Wuyts et al. (2017) found a similar result to this study, also indicating that human activities, such as changes in soil use, have promoted the increase of bistability in the tropical region of South 299 America. 300

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302 Conclusions

The loss of resilience due to climate change can lead to sudden catastrophic transition events between forest and savanna in the tropical region. Reducing the availability of moisture and increasing climatic seasonality appear as the main risk factors. If such critical climatic thresholds

are reached, there will probably be the massive extinction of biodiversity in the Amazon rainforest.

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308 Acknowledgments

309 We are grateful to Ima Celia Guimaraes Vieira, Aline Meiguins de Lima, Roberta Macedo

310 Cerqueira and Edson Jose Paulino da Rocha for their valuable contributions and suggestions

throughout the development of this work.

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Figure 1

Ecosystem resilience gradient and Maxwell point detection.

Estimated climate resilience for the forest (A) and savanna (B). In (C), the amplitude of resilience between forest and savanna gradients. The rectangles in (C) under the lowest values indicate the boundary between the two ecosystems, where a bistability pattern and low hysteresis prevail.



Figure 2

Critical resilience thresholds and the bistable ecotonal zone.

Under high resilience values (>= 704) dominance of forests (green balls), while in low values (<= 448) savannas stand out (purple balls). Under an intermediate zone of the resilience gradient (green-moss polygon), there is a balance of the observed proportions of forest and savanna, indicating an area of bistability. This transition zone should play a vital role in the mediation of stable state change events between forest and savanna.



Figure 3

The propensity for catastrophic transition regimes under bidimensional climate space.

In (A) on the X-axis is the average annual temperature gradient (AAT) and on the Y-axis the annual cumulative precipitation (ACP). In (B) on the X-axis is the annual range of temperature (ART) and on the Y-axis is the seasonal precipitation coefficient (PSC). In all, we used n=1805 observations.

