



São José dos Campos, 25/09/2018

Dear Editor,

On behalf of my co-authors, I am pleased to resubmit the original manuscript after minor revisions for publication in the Biogeosciences journal: "Life cycle of bamboo in southwestern Amazon and its relation to fire events".

We have addressed the few minor corrections suggested by the reviewer, including fixing all the copy editing problems we were able to find (e.g. revising the text, and checking typos, missing references, hyphens, quotes, dashes, units and spaces) by following the journal manuscript preparation guidelines. Specifically to the last two minor notes from the reviewer, we agree and have (i) adjusted the Figure 5, reporting r with three significance figures, and (ii) adjusted the sentence on potential Landsat satellite data starting in 1972, as suggested by the reviewer.

Please find the original reviewer comments and our responses and the latest version of the manuscript with track-changes.

I hereby confirm that this work has not been published or accepted for publication, and is not under consideration for publication in another journal. Submission for publication has been approved by all co-authors and all persons entitled to authorship have been so named.

Sincerely yours,

A handwritten signature in black ink that reads "Ricardo Dal'Agnol da Silva".

Ricardo Dal'Agnol da Silva

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Reviewer #1

Interactive comment on “Life cycle of bamboo in southwestern Amazon and its relation to fire events” by Ricardo Dalagnol et al.

Ricardo Dalagnol et al.

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General comment: This manuscript uses Landsat and MODIS imagery over the MODIS time period (2001 to 2017) to map bamboo patches (living and dead) in the SW Amazon. The authors then estimate patch age based on change over time and test the 'bamboo-fire hypothesis' by comparing presence of dead bamboo to active fire maps from MODIS. Overall I think that this is an interesting and well researched exploration of an important and understudied part of tropical forests - the presence of large patches of bamboo. My main criticism, however, is in the overall clarity of the description of analyses and results - as I note specifically below, there are many places where it is not clear, at least to me, whether the analysis is at the single pixel, pixel over time, or patch scale, what certain terms mean, and how the analyses support or do not support the

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conclusions. One other general comment is on the use of active fire detection to conclude that 'most bamboo cohorts did not burn after die-off' (abstract). While this may be the case, this conclusion is based on the assumption that the MODIS Aqua satellite detects 100% of pixels on fire, while in reality it's likely that fire in some pixels was blocked by clouds, was too small to be detected by MODIS, or wasn't burning as the satellite passed overhead. I'm not sure if/how these uncertainties were incorporated into the INPE database, but this source of uncertainty should at least be acknowledged.

Response: We thank the reviewer for the fruitful comments and suggestions. We improved the text clarity regarding the units (pixel, patch) and terms, and the description of analysis as specifically pointed out. We have also included some new statistics regarding the omission errors of the presented bamboo die-off detection method as a result of a comment from the reviewer. We agree that the fire dataset (the one we used, but also all MODIS-derived in general) underestimate the total fire occurrence because of its coarse spatial resolution and high cloud cover in Amazon, and, thus, we properly acknowledged that in the discussion. We should miss only 5% of the fire occurrence for fires bigger than 0.09 km², or approximately 10% of MODIS spatial resolution. The MODIS-INPE fire dataset that we used does not have a source of uncertainty product, but it has been validated in a previous paper (cited in the specific comment below) and showed similar results to a product by NASA-EOS also based on MODIS observations. It also presented fairly good results when compared to a finer scale active fire retrievals from ASTER (30 x 30 m spatial resolution) – detailed in the specific comment below. Nevertheless, we don't believe that the underestimate of total fire frequency has affected the conclusions, because, as pointed out by the reviewer, and acknowledged by us, only a small fraction of bamboo-dominated forests burned during the 16 analyzed years, and dead bamboo did not burn more than live bamboo, so the "bamboo-fire" hypothesis was clearly not supported.

Specific comments:

1- p. 1 lines 1-5: I don't think it's necessary to describe this other study in the abstract.

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I would just cut the sentences "In southwest Amazon...quantities of necromass."

Response: We agree with the reviewer. We have shortened the first few sentences to: "Bamboo-dominated forests comprise 1% of the world's forests and 3% of the Amazon forests. The *Guadua* spp. bamboo that dominate the southwest Amazon are semelparous, so flowering and fruiting occur once in a lifetime before death. These events occur in massive spatially organized patches every 28 years and produce huge quantities of necromass."

2- p. 1 line 8: "the fire hypothesis" -> "the bamboo-fire hypothesis"

Response: Corrected.

3- p. 1 line 9: "the MODIS thermal anomalies product"

Response: Corrected.

4- p. 2 line 7: I'm not an expert in Amazon landforms, but I think this should be 'terra firme' throughout (not 'terra fime') - if 'terra firme' is right it probably deserves a short definition since this appears to be an uncommon land type.

Response: Yes, you are correct, it was a typing error, we corrected it to "terra firme" in both p. 2 line 7 and p.4 line 7.

5- p. 2 line 20: "In the region" which region is being described here?

Response: It is the southwest Amazon. To improve clarity, we adjusted the sentence to "A total of 74 different bamboo populations, that is, patches having individuals of the same internal age, have been so far identified in the southwest Amazon, with a mean patch area of 330 km², and up to 2,570 km² for the largest patch (Carvalho et al., 2013).

6- p. 2 line 22: "in" -> "as"

Response: Corrected.

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7- p. 2 line 28: "forming a small" -> "forming small"

Response: Corrected.

8- p. 2 line 30: "maximize once in a lifetime chance..." - I read the Carvalho paper but I still don't totally understand how a temporal offset would maximize the chance of cross pollination.

Response: We re-read the papers that discuss the mast-flowering patches (Franklin, 2004) and realized that this sentence was not making sense with the paragraph idea, which was to give background on flowering waves, dead biomass production, and a brief explanation on why they happen. Thus, we decided to remove the sentence. Franklin, 2004. <https://doi.org/10.1111/j.1365-2699.2003.01057.x>

9- p. 4 line 21: it's helpful to refer to the actual MODIS codes, like MC19A1 (v006, I assume) for consistency

Response: Agreed. The text was adjusted to: "Daily surface reflectance data were obtained from the MODIS product MCD19A1-C6, acquired from Terra and Aqua satellites, from 2000 to 2017 (Lyapustin and Wang, 2018), corrected for atmospheric effects by the MAIAC algorithm (Lyapustin et al., 2012)." Lyapustin, A., Wang, Y. (2018). MCD19A1 MODIS/Terra+Aqua Land Surface BRF Daily L2G Global 500m, 1km and 5km SIN Grid V006 [Data set]. NASA EOSDIS Land Processes DAAC. doi: 10.5067/MODIS/MCD19A1.006

10- p. 4 line 22: Do you actually use all of these bands in the analysis?

Response: Yes, they were used on empirical bamboo-age reflectance curves analysis (Figure 6) to explore the spectral variation according to bamboo age and demonstrate that NIR band is the most useful to detect die-off.

11- p. 4 line 28: How did you handle the daily vs 8 day product mismatch?

Response: We don't think there is a possible correction to be done here, as we applied

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the BRDF correction as it is described in Lyasputin et al. (2012) paper. During the 8-day window, the MAIAC algorithm integrates daily observations with different view angles and retrieve the parameters for BRDF correction of daily observations. The paper report that robust and consistent retrievals are obtained with at least 4 observations. It also tests and corrects the parameters for potential land surface change within the window (Lyasputin et al., 2012). Besides that, variations in sun illumination geometry during the 8-day window are insignificant. We adjusted the sentence in the text to better describe this to the reader: "Parameters of the RTLS model and BRDF kernel weights are part of the MAIAC product suite with a temporal resolution of 8 days – a period which daily observations of different view angles were integrated and used for BRDF parameters retrieval". Lyasputin et al., 2012. <https://doi.org/10.1016/j.rse.2012.09.002>

12- p. 5 line 4: Awesome that this was done in R! Is the code available?

Response: The MAIAC atmospheric corrections and creation of BRDF parameters were performed and made available by NASA, led by Dr. Alexei Lyasputin. However, the rest of processing (BRDF normalization, composite, mosaic) for the whole South America during 2000-2017 was coded by me, and yes, in R. It was quite a challenge and took some months. The code is available here https://github.com/ricds/maiac_processing. The code is not clean as my specialization is not on programming, but whoever would have the interest to use it to process MAIAC data into composites by himself can contact me and I can help.

13- section 2.2.2: More detail would be great in this section - did you use 1 image per year?

Response: Yes, it was one image per year. In this section, we described the Landsat data that was used in the section 2.3.4 to visual interpret die-off events and validate the prediction model. We adjusted the sentence to make it clearer that we used one image per year: "A time series of Thematic Mapper (TM)/Landsat-5 data was obtained from 1985 to 2000 (one image per year) in order to visually detect die-off events that oc-

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curred in the last life cycle of bamboo and validate age predictions – further described in the die-off prediction section.". By the end of the paragraph, we added the information on which scenes (path/row) were analyzed: "The path-row (World Reference System 2) of the time series were: 006-065, 003-066, 002-067, 003-067, 005-067, and 003-068."

14- p. 6 line 22: What is a 'percentile' in this context? I've tried pretty hard to figure it out, but I really don't get it, and it's pretty critical to the rest of the manuscript. Is it based on the distribution of values in a pixel? in a patch? This term is also not used in the Carvalho paper.

Response: We analyzed the 1st, 50th and 99th percentile of tree cover product (Hansen et al., 2013) considering all pixels inside the bamboo map delineated by Carvalho et al. (2013). We reworked the paragraph to improve clarity: "In order to analyze the tree cover variability in forests with and without bamboo, we used the bamboo map from Carvalho et al. (2013) as a mask to analyze the tree cover product (Hansen et al., 2013) considering all pixels inside the bamboo map. This map was obtained in the previous study by visual interpretation of live-adult bamboo using two Landsat mosaics 10 years apart from each other (1990 and 2000), supported by the known locations and dates of five bamboo dominated areas. Considering only the pixels inside the bamboo-dominated map, we calculated the 1st, 50th and 99th percentiles of the tree cover product and generated a map of areas below the 1st, between the 1st and 99th, and above the 99th percentiles of tree cover."

15- p. 6 lines 26 - 29: What are these distributions telling us? Again, in a given pixel across time? or...?

Response: They are telling us about the average, standard deviation and skewness of NIR signal overtime for all pixels in each tree cover percentile class in order to compare the NIR signal between forests with and without bamboo. For normal distribution, the average and standard deviations were calculated. When different than normal,

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we applied a more appropriate method to estimate average, standard deviation and skewness parameter (Fernandez and Steel, 1998). As we discussed in the results, for example, if the distribution has a higher NIR average value and is right-skewed, the pixels are likely belonging to bamboo-dominated forests, because of higher NIR values from adult bamboo. We adjusted the text to improve clarity: “In order to compare the NIR signal between forests with and without bamboo, we analyzed the MODIS NIR-1 reflectance for all pixels overtime in the tree cover classes: below 1st, between 1st and 99th, and above the 99th percentile. We tested the distribution of NIR values for normality using a two-sided Kolmogorov-Smirnov test at a 1% significance level. For normal distribution, the average and standard deviation of distributions were computed. For skewed distribution, a more appropriate method was applied to estimate the average, standard deviation and skewness parameter (ξ) (Fernandez and Steel, 1998).”

16- section 2.2.4: as mentioned above, can uncertainty be quantified in the fire data?

Response: Unfortunately, the MODIS-INPE active fire dataset we used does not have an uncertainty parameter. However, Morisette et al. (2005) conducted a validation of MODIS active fire retrievals from both (1) NASA EOS and (2) INPE, comparing their results to active fire retrievals from ASTER satellite (finer resolution, 30 x 30 m) and concluded that they were both fairly good. The MODIS-INPE dataset presented high accuracy (95%) for active fires bigger than 0.09 km², which correspond to 9% of the MODIS spatial resolution. Even though, as the reviewer pointed out in the review introduction, Morisette et al. (2005) highlighted that MODIS active fire detections should be treated as a lower bound of total fire occurrence, as it underestimates small fire occurrences due to the coarse spatial resolution, high cloud cover, and when having high viewing angles (> 15 °). We added this limitation to the discussion in section 4.6, p. 22, line 23: “The MODIS active fire detections should be treated as a lower bound of fire occurrence, as it underestimates fire occurrences, mainly the small ones with less than 0.09 km², due to the coarse spatial resolution, high cloud cover, and when

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having high viewing angles (> 15 °) (Morisette et al., 2005). Morisette et al., 2005. <https://journals.ametsoc.org/doi/abs/10.1175/E1141.1>

17- p. 7 line 13: not sure what $Y=x$ means here.

Response: It was a failed attempt to describe the linear equation between bamboo age and NIR signal, but we agree that it was confusing and not helpful, so decided to remove it. We reworked the sentence to improve clarity of the bilinear model: “A linearly increasing NIR reflectance vector (1 to 28%) with bamboo age (1 to 28 years), followed by an abrupt NIR decrease to 0% at 29 years of bamboo age.”

18- p. 7 line 23: are 'geolocations' the patches of 5 pixels? if there are 390 here, why are there fewer in Fig 4c and d? (I think these should be the same?)

Response: Good question. For each patch (of several pixels), 5 pixels' geolocations were acquired. So, 78 patches equal to 390 pixels/geolocations for validation. Now, there are two explanations: First, if you mean the number of circles in Fig 4c and 4d, it is because we aggregated the samples when they hit the same observed and estimate die-off year. We did this as a way to improve visualization of the agreement, or otherwise, samples would just overlap. To improve clarity, we changed “Samples” to “Pixels”, and added this sentence to the caption of Fig 4 (and also Fig 8, which is the prediction): “Size of circles is related to the number of pixels that hit the same observed/estimate die-off year”. Second, in order to map the die-off (Fig 4a and 4b), we selected only the pixels with significant relationship with the bilinear model ($p < 0.001$). When we compared our validation dataset (390 pixels) with the resulting maps, for NIR-1 (Fig 4c) and NIR-2 (Fig 4d) there were actually only 334 and 362 pixels available ($p < 0.001$), respectively. Thus, a total of 56 and 28 pixels were not classified as die-off, so they were not included in the accuracy assessment. However, now that you pointed this out, we decided to include this information in the results to represent the omission errors of $56/390 = 14.4\%$ and $28/390 = 7.2\%$ for NIR-1 and NIR-2, respectively. When the two maps are merged, the omission error was reduced to 4.1%, while accuracy

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was maintained (80%). Thus, we added this sentence after p.11 line 5: "From the 390 pixels in the validation dataset, 334 and 362 pixels were detected as bamboo die-off by the bilinear model ($p < 0.001$) using the NIR-1 and NIR-2, respectively. The missing 56 (14.4%) and 28 (7.2%) pixels were considered as omission errors for NIR-1 and NIR-2. When we merged the two maps into a single die-off detection map, a total of 374 pixels from the validation dataset were successfully detected, resulting in only 16 (4.1%) missing pixels not detected as bamboo die-off, while accuracy and RMSE were 80% and 0.51 yr, respectively."

19- p. 7 line 30: "it" = "a bamboo dominated pixel" (I think?)

Response: Yes, it is. We rephrased to improve clarity: "We used two assumptions to map the live bamboo. Over the 18 years' period, a live bamboo dominated pixel should present: (i) mean NIR reflectance equal to or greater than the median signal of bamboo-free forests; and (ii) an increasing NIR reflectance over time."

20- p. 8 line 24: 'geolocations' = 'patches'? pixels? random samples?

Response: The multiple terms were indeed confusing. Geolocation and pixels meant the same thing, so we decided to change the term geolocation for pixel in all paper, so it is easier to understand. A total of 2 occurrences were found and adjusted.

21- p. 9 line 27: 'followed a normal distribution ($p=0.33$)' -> this is a K-S test, right? if yes, 'did not significantly differ from normal' would be more clear, I think.

Response: Yes, corrected.

22- Figure 3 caption: "(hatched)" -> "(hatched in Figure 1)"

Response: Corrected to "(hatched in Figure 2)" as the bamboo area in Figure 1 is not hatched.

23- section 3.2.3: I'm having a hard time grasping exactly how this cohort age analysis using NIR reflectance fits with everything else, especially given that the results differ

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when different bands are used...

Response: We believe the cohort analysis was important to improve the understand of remote sensing signal variability with bamboo growth overtime, that is, when the signal changes and why, in order to validate our simple bilinear model that we applied to detect the die-off events. The empirical curves showed the "true" remote sensing signal variation with bamboo age, not only for NIR, but in diverse wavelengths. We extracted the ages using the NIR bands, but we were able to reconstruct the time series of the other bands, which, we believe, is a unique and very interesting result. We discussed the implications of such variations, for example, in the Red band, which is related to chlorophyll content. The first paragraph from section 2.3.3, p.8, l.10, was adjusted to improve the clarity of the analysis: "In order to validate the simple bilinear model that was applied to detect the die-off events and improve the understand of remote sensing signal variability with bamboo growth overtime, that is, when the signal changes and why, we used the die-off map to analyze the remote sensing signal variability. Data from all MODIS bands were extracted using the estimated die-off year with very significant correlation ($p < 0.001$) as a starting point. Bamboo cohort age was then calculated backwards and forwards in time during the 2000-2017 period. Reflectance percentiles (1st, 50th and 99th) per age were calculated obtaining, what we called, empirical bamboo-age reflectance curves."

24- (Figure 7) and the accuracy seems low (p 13 line 10)? Is this meaningful? If patches of dead bamboo are being mapped visually, is this fitting necessary to estimate future dieoff?

Response: In our understanding, the reviewer is commenting on Figure 8, instead of Figure 7, which present the map and accuracy of die-off predictions. We agree with the reviewer that the accuracy on predicting the exact die-off year is fairly low. However, we think that the importance here is that the correlation of predicted and reference die-off is actually moderately strong and statistical significant ($r = 0.41$ and $p < 0.01$ for NIR-1), with RMSE less than 3 years, which, we think, is meaningful. Regarding

C10

the last part of the question, we tested the prediction of future die-off to increase our sampling of die-off areas to test the fire hypothesis. Since MODIS data only span the 2000-2017 period, a big portion of bamboo patches did not undergo die-off during that period and, thus, does not present the decrease in NIR with die-off. Mapping all the die-off patches manually would be time consuming and probably less precise, with bias toward identification of big patches.

25- Figure 5: These colors are really hard to see even for a non visually impaired person -> check out colorbrewer2.org for color schemes that are colorblind friendly.

Response: Agreed and corrected. You can check the adjusted figure in the updated manuscript.

26- p. 17 line 15: 'did show' what?

Response: We complemented with "statistical significance on area-normalized mean active fire detections".

27- p. 17 line 19: "...in dead and live bamboo" in non drought years?

Response: The comparison was between dead and live bamboo in drought years. The sentence was not written correctly, so we adjusted it to: "For severe drought years, the area-normalized active fire detections in 2005 (0.32 and 0.18 fires ha⁻¹), 2010 (0.22 and 0.12 fires ha⁻¹), 2015 (0.35 and 0.20 fires ha⁻¹) and 2016 (0.57 and 0.33 fires ha⁻¹) over dead and live bamboo, respectively, were not statistically different between the two bamboo life stages ($p = 0.127$)."

28- p. 18 line 3: 96.95 to 99.89% of what?

Response: Tree cover. We rephrased to improve clarity: "We found that the bamboo-dominated forests had a narrow range of tree cover values (96.95 to 99.89%)".

29- p. 18 line 6: "that" -> "where"

Response: Corrected.

C11

30- p. 18 line 9: "The presence of canopy trees could explain why the tree cover is so high." I'm not sure what this is saying that isn't obvious?

Response: Agreed and removed.

31- p. 21 line 29: it seems like there also might be some interesting carbon cycle implications to this work?

Response: We partly agree, but we are not sure if we should add something to the paper. The bamboo-dominated forests have lower aboveground biomass (AGB) (212 Mg/ha) than dense forests (272 Mg/ha) (e.g. Saatchi, et al., 2007). However, it has more AGB than open forests (200 Mg/ha), probably due to bamboo AGB contributing to that stock. It is interesting that, in this paper, the AGB map shows even lower AGB (100-150 Mg/ha) in bamboo-dominated forests of southwest Amazon. Bamboo may limit aboveground biomass stocks through resources competition and increases in tree mortality (Castro et al., 2013), because of the physical harm it causes on trees (Griscom and Ashton, 2003), while the die-off dynamics may trigger something similar to gap dynamics - because of the suddenly more open canopy and increased sun illumination input. However, we don't expect these dynamics to have implications for carbon cycle in long-term, because the die-off events occur every bamboo cohort life cycle, and, thus, that ecosystem should be already adapted to this. It is expected, though, short-term responses such as pulses of net CO² emissions after die-off, followed by a period of net C uptake as trees and bamboo grow back. Saatchi, et al. 2007. <https://doi.org/10.1111/j.1365-2486.2007.01323.x>

32- p. 21 line 32: I don't know if Keeley and Bond would insist on ALL patches burning to confirm the bamboo-fire hypothesis

Response: We haven't considered that before, but we agree. The need for all patches burning is not commented in the Keeley and Bond (1999) paper. What we observed in the results was that the total fire frequency was so low that it wouldn't be feasible that fire should be a driver of bamboo dominance in the study area. We adjusted the

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first two sentences in discussion in order to highlight the small magnitude of burning areas compared to the total bamboo area: "Fire occurred only in a small fraction of bamboo-dominated areas during the 16 years of fire analysis (Fig. 5), equivalent to 2371 km² of burnt area or 0.0955% of the total bamboo area (155,159 km²) burning each year. Besides that, the statistical tests comparing dead and live bamboo fire frequency showed that dead bamboo did not burn more than live bamboo (Fig. 11). Thus, we cannot support the 'bamboo-fire hypothesis' from Keeley and Bond (1999)."

33- p. 22 line 35: "nearby" -> "near"

Response: Corrected.

34- p. 23 line 11: "not fully supported"? not at all supported, right? I think the uncertainty in the fire observations is an important caveat here, but these results really refute the bamboo-fire hypothesis at least in this setting.

Response: Yes, we agree with the reviewer. We adjusted the text to: "The 'bamboo-fire hypothesis' was not supported by our results, because only a small fraction of bamboo areas burned during the analysis timescale, and, in general, bamboo did not show higher fire probability after the reproductive event and die-off." The uncertainties were discussed specifically in the fire section. We believe that even though we have an underestimate of the "true" fire frequency, the observed fire frequency was so small that it shouldn't affect the conclusions.

Please also note the supplement to this comment:

<https://www.biogeosciences-discuss.net/bg-2018-207/bg-2018-207-AC1-supplement.pdf>

Interactive comment on Biogeosciences Discuss., <https://doi.org/10.5194/bg-2018-207>, 2018.

Reviewer #2

Interactive comment on “Life cycle of bamboo in southwestern Amazon and its relation to fire events” by Ricardo Dalagnol et al.

Ricardo Dalagnol et al.

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Received and published: 24 July 2018

General comments: This paper proposes methods to address a very challenging problem in remote sensing - distinguishing between two spectrally similar types of land cover (bamboo forest and bamboo-free forest) using moderate spatial and spectral resolution imagery (MODIS and Landsat). The aim is to map a little-studied, yet spatially expansive, ecosystem in the southwest Amazon - and to establish evidence (or lack thereof) for one hypothesis of bamboo forest establishment and expansion. The study focuses on a fascinating ecosystem, and remote sensing provides the most realistic means of collecting data over such a vast spatial extent in a very remote region. However, I have a number of concerns about the style, methods, and conclusions of the current manuscript, as follows:

C1

1. The methods and results sections include overwhelming detail without clearly outlining goals - both in terms of holistically linking the steps in the methods, and in terms of how the methods relate to broader scientific questions. I am left wondering how the conclusions inform our understanding of the origin and/or biogeochemical processes that maintain/promote expansion of the bamboo forest.

Response: We thank the reviewer 2 for the comments that led to the improvement of the paper, mainly on increasing the clarity of methods section and discussing important aspects on the validation datasets. Specifically to this comment, we agree with the reviewer 2 that the methods section had too much details, and the goal of each analysis was in general not well described. Therefore, we corrected the methods text to address this problem, providing information on how each analysis is linked to the goals, and why the proposed method was chosen for each analyses. The reviewer 2 can check the changes in the updated manuscript, although some of them were shown in the subsequent comments.

About the conclusions, we tested and rejected the bamboo-fire hypothesis which argues that fire is the driver of bamboo domination in the forest. As pointed out by the reviewer 1 comments in a previous revision, and later acknowledged by us, the evidence we presented in the paper did not support the bamboo-fire hypothesis at all even with the underestimate of fire dataset. This was first stated in p.23 l.30: “We cannot support the ‘bamboo-fire hypothesis’ from Keeley and Bond (1999) because fire occurred only in a small fraction of bamboo-dominated areas during the 16 years of fire analysis (Fig. 6), equivalent to 2371 km² of burnt area or 0.0955% of the total bamboo area (155,159 km²) burning each year, and the statistical tests comparing dead and live bamboo fire frequency showed that dead bamboo did not burn more than live bamboo (Fig. 11). Hence, we believe that there should be other explanations for bamboo maintenance in the forest, such as bamboo itself being responsible for its maintenance in the forest due to the damage it causes in the trees while increasing tree mortality (Griscom and Ashton, 2003).”.

C2

Then, aspects of the detection were further discussed in p.24 l.11: “The fire occurrence beyond 2 km inside the forest was probably underestimated because the forest canopy can obscure fires that occur only on the understorey, and, thus, are not detected by the MODIS/Aqua satellite (Roy et al., 2008). In addition, the MODIS active fire detections should be treated as a lower bound of fire occurrence, as it underestimates fire occurrences in the order of 5% for small fires with less than 0.09 km², or 10% of MODIS spatial resolution, due to the coarse spatial resolution, high cloud cover, and when having high viewing angles (> 15 °) (Morissette et al., 2005). Nevertheless, we do not believe this might have an impact on rejecting the ‘bamboo-fire hypothesis’ due to the minimal fraction of fire occurrences occurring over the large bamboo-dominated forests.”.

Besides that, the bamboo die-off maps that were produced in the paper can help future studies addressing the bamboo dynamics processes.

2. The great amount of detail included in the methods swamps any discussion of why specific methods were chosen. As a result, there are many places in the manuscript where the reader may be left feeling that they must take things on faith, or, that the steps presented are the result of a circular logic.

Response: We agree. We have included a flowchart in the manuscript (Figure 1) to give a broad view of the analyses and how the sections interact before going into detail. Also, we have adjusted each paragraph in the methods section by first introducing why the analysis was done, stating the method to perform it and why this method was chosen.

Two examples: (1) In p.7 l.4: “The tree cover product was analyzed considering a pre-existent bamboo-dominated forests map from Carvalho et al. (2013) in order to explore the variability of tree cover in forests with and without bamboo which might help mapping the bamboo-dominated forests. We expect that bamboo-dominated forests present lower tree cover values than bamboo-free forest due to its fast dynamics and

C3

higher mortality (Castro et al., 2013; Medeiros et al., 2013). This map was obtained by visual interpretation of live-adult bamboo using two Landsat mosaics 10 years apart from each other (1990 and 2000), supported by the known locations and dates of five bamboo dominated areas. Considering only the pixels inside the bamboo-dominated map, we calculated the 1st, 50th and 99th percentiles of the tree cover product and generated a map showing the areas below the 1st, between the 1st and 99th, and above the 99th percentiles of tree cover. The map was qualitatively analyzed exploring the areas which each percentile covered.”;

(2) In p.7 l.28: “To automatically detect the bamboo die-off from 2001 to 2017 we compared each pixel of MODIS (MAIAC) NIR reflectance time series to a bilinear model using Pearson’s correlation and an iterative shift approach. The model consisted in a linear increase in reflectance from 1 to 28% between 1 and 28 years of bamboo age followed by an abrupt decrease to 0% when the die-off occur. The model conception was based on Carvalho et al. (2013) findings which showed that forests with adult bamboo have higher NIR reflectance than forests with juvenile and dead bamboo, or without bamboo, and that bamboo present a life cycle approximate to 28 years. Thus, since not much is known about the spectral behavior of bamboo growth with age, we chose a bilinear model to characterize the bamboo signal change overtime because it was the simplest way to represent the change between life stages. We also assumed the signal coming from the trees as constant over time. Therefore, inter-annual reflectance variations were attributed to structural changes in the canopy related to bamboos. The Pearson’s correlation coefficient (r) between the NIR reflectance time series and the bilinear model for a given pixel was iteratively tested by shifting the position of the NIR time series inside the bilinear model vector. The position showing the highest r corresponded to the estimated age of that pixel from which the die-off year was retrieved. Only pixels with very significant correlations ($p < 0.001$) were selected. The model was tested with both MODIS (MAIAC) NIR bands: NIR-1 band 2 (841-876 nm) and NIR-2 band 5 (1230-1250 nm). Both bands are sensitive to canopy structure scattering, but NIR-2 is also partially sensitive to leaf/canopy water scattering

C4

(Gao, 1996), so that could lead to a different detection between bands.”

3. Several of the steps in the methods depend on thresholds which are determined from sample means, completely ignoring the impact of spectral (and/or spatial) variability. This topic is briefly addressed in the discussion section, but should be treated more rigorously throughout the methods and analysis sections. In fact, I am left feeling that the authors have failed to demonstrate the practical significance of some of their conclusions because the within group variability seems to overwhelm the between group differences.

Response: We agree that the impact of spectral variability was not properly discussed in the paper. We have showed in the empirical bamboo-age spectral curves (Figure 7) that there is a lot of variability in the data. We believe the variability comes mainly from variations in forest structure and bamboo density. However, even though such variability exists, it did not affect the die-off detection, because our method was not based on absolute reflectance values, but on the correlation between the data and a reference, such as the simple bilinear model or the empirical curve. Besides that, even with such huge spectral variability, the method was able to detect the bamboo die-off with great performance (80% accuracy) and, although the predictions for 2017-2028 did not have high accuracy on estimating the exact die-off year, it had acceptable levels of error (around 3 years). We have added this sentence to the discussion in p.23 l.4 to complement the discussion on the large spectral variability: “Nevertheless, because our detection and prediction methods were not based on absolute reflectance values, but on the correlation between the time series and a reference, such as the bilinear model or the empirical curve, we do not believe that the large spectral variability should have a major impact on the detection/prediction.”

4. In a similar vein, because many of the steps in the methods depend on sampling statistics, it is problematic that the sampling unit (point, pixel, polygon?) and

C5

sampling protocol (sampling strategy, sample size) remain unspecified in most sections of the paper.

Response: We agree. The reviewer 1 has also pointed the terms (pixel, patch, geolocation, polygon) were confusing. Thus, we have improved the clarity on sampling protocols and terms on methods section. For the first validation dataset (MODIS) for die-off detection during 2001-2017, the new sentence in p.8 l.11 is: “For validation purposes, we compared the detected die-off events with recently dead bamboo areas visually detected in MODIS false color composites (bands 1, 2 and 6 in RGB). In this color composite (Fig. 2), adult bamboo patches show bright green color due to the comparatively higher NIR reflectance, while dead bamboo patches present dark blue/gray color. The visual inspection of bamboo die-off using MODIS and Landsat data was consistent with five bamboo mass flowering events observed in the field (Carvalho et al., 2013). In each of the dead bamboo patches visually detected, the geographic location and die-off year were registered for a sample of 5 random pixels. A total of 78 dead bamboo patches were identified in the 2001–2017 period, thus the validation dataset was composed of 390 pixels with corresponding year of bamboo death - the spatial and temporal distribution of the samples are shown in the supplementary material. For these pixels, the die-off year detected by our model was retrieved and compared to the validation dataset. To assess the detection, we calculated the accuracy (%) on detecting the exact die-off year, Pearson’s correlation and p-value, and the root mean square error (RMSE) between the automatically detected and visually interpreted die-off year.”

For the second validation dataset (Landsat) for die-off prediction during 2018-2028, the new sentence in p.9 l.20 is: “Since the validation for 2018-2028 predictions could not be conducted using MODIS data because its time series do not span that time period, we used yearly TM/Landsat-5 color composites (bands 2, 4 and 1 in RGB) during the 1985-2000 period to visually detect the bamboo die-off events that occurred in the last bamboo life cycle and validate the predictions. We assumed that the die-off events

C6

that happened in this period would happen again in the next life cycle of the bamboo, from 2018 to 2028. Therefore, we added 29 years to the visually detected die-off year in order to match the next life cycle. The sampling procedure for the validation dataset was similar to the detection, where 5 pixels were randomly collected for each recently dead bamboo patch visually identified in a given year. A total of 35 dead bamboo patches were identified and 175 pixels were collected with the corresponding years of death. The assessment was conducted by calculating the same metrics as in the die-off detection section. Additionally, in order to assess if the prediction error was randomly distributed, the residuals from predicted minus observed die-off year, where observed is the die-off from the Landsat validation dataset, was tested for normality using a two-sided Kolmogorov-Smirnov test at a 1% significance level.”

5. Finally, I find it difficult to follow how each step and/or product is validated - in terms of methods, reference datasets, and sampling units and protocols.

Response: We agree that it was not easy to understand in the way it was presented. There were two validation datasets for two different analyses. One dataset used MODIS data from 2000-2017 and the other used Landsat data from 1985-2000. In both of them, color composites were used to visually inspect die-off events and collect pixels to create validation datasets. The validation dataset from 2000-2017 (MODIS) was used to assess the bamboo-die off detection by the bilinear model running on MODIS time series during 2001-2017. The validation dataset from 1985-2000 (Landsat) was used to assess the predictions of bamboo die-off during 2018-2028 by the model running on MODIS time series and the NIR empirical bamboo-age reflectance curve. This was possible because the die-off events that occurred in the previous life cycle of bamboo (1985-2000) were expected to occur again 28 years later (2018-2028). As we have shown in the last comment, we have improved the description on sampling pixels from bamboo die-off patches for validation datasets. We also believe that the flowchart that we have included (Figure 1) will help the reader

C7

to better understand how each validation dataset was used.

Specific examples:

1. The level of detail presented in the methods often seems like a list of what was done, versus a careful retelling of the salient details. For example, the detailed comparisons of NIR1 to NIR2 get confusing and are perhaps unnecessary – an alternative would be to simply state that the two bands were each tested as input data and compared based on some criteria. The NIR 1 was determined to be more useful based on specified criteria. Then the discussion and figures that follow could focus on the results for NIR1 only. But, also see question below. Perhaps more importantly, additional discussion is needed to link specific results to broader scientific questions.

Response: We agree. We have showed the results for both NIR bands because they mapped slightly different areas of bamboo die-off probably because of the different sensitivities to vegetation composition. This is specially highlighted in the Figure 7 where the NIR-2 remains at its lowest during 0-2 years. Thus, we have included a sentence informing on these differences in mapped areas between NIR-1 and NIR-2 in p.12 l.5: “When comparing the areas detected solely by one of the two bands, NIR-1 detected more pixels towards the end of the time period, i.e. die-off areas from 2017 in the north-east between 8-9°S and 69-70°W, while NIR-2 detected additional pixels in the beginning of the time period, i.e. die-off areas from 2001 in the central region between 9-10°S and 70-71°W.”, and adjusted the discussion on why they provided different maps in discussion in p.20 l.21: “When comparing the NIR-1 and NIR-2 bands, the leaf/canopy water sensitivity from NIR-2 might have contributed for a slightly better performance on bamboo die-off detection and the detection of different areas between the bands, which contributed for a larger coverage of the bamboo-dominated forests. This different sensitivity to vegetation structure is specially highlighted in the Figure 7 where the NIR-2 remains at its lowest during 0-2 years, explaining why NIR-2 band maps different areas than NIR-1.”.

C8

When we combined both maps, we were able to obtain a map covering a larger area of bamboo die-off with similar accuracy (80%), but lower omission errors (4.1%) than the NIR-1 (14.4%) and NIR-2 (7.2%) maps. We decided to include the combined die-off map to the supplementary material (attached Figure 1 - Bamboo die-off during 2001-2017 from the combined detections using MODIS (MAIAC) NIR-1 and NIR-2 and the bilinear model). Regarding the scientific questions, our evidences clearly do not support the bamboo-fire hypothesis, and, in relation to the die-off patches, we believe that knowing where and when the bamboo dies is an important information for future studies of the bamboo-dominated forests ecosystems. Thus, we added this sentence to discussion in p.23 l.25: "It could also be used to explore broader scientific questions on the ecology of bamboo-dominated forests such as studies on maintenance/expand of bamboo patches, flowering waves, cross-pollination between patches, fauna habitat dynamics, impacts on short and long-term carbon dynamics.". However, the pursuit of such analyses was out of the scope of this paper. In order to highlight the best prediction map (NIR-1) we have adjusted the Figure 9 to only include results from the NIR-1 prediction: the map, estimate vs. predicted, and residual error. Thus, the predictions from NIR-2 should be added to supplementary material as shown in attached Figure 4.

2. Steps described in the methods (and the results) often lack a presentation of the logic behind why specific methods were tested in the first place (and/or ultimately, selected). A few places where more justification is needed about proposed methods: 1- Why only test NIR bands (rather than combinations of other bands, standard vegetation indices, etc.)? 2- Why assume a linear model? 3- Why choose thresholds vs. probabilities? 4- How confident are you in Carvalho's estimates? 5- What percent of pixels are highly correlated?

Response: We agree that justifications were missing in the methods. As we stated in previous comments, we have improved the methods description to address

C9

each of the presented problems. Now answering the specific points, which also provide examples of the changes:

(1) We focused the die-off detection on the NIR bands because of two reasons: (i) a previous work from Carvalho et al. (2013) showed that NIR band presented the best separability between bamboo life stages, where higher NIR was observed for adult bamboo than juvenile and dead bamboo; and (ii) we actually did some testing with other bands before the manuscript was written and they provided poor detections; the empirical curves (Fig. 7) corroborate that the other bands does not have a clear change with die-off. When adjusting the methods section, we added this sentence to clarify why we used the NIR band in p.7 l.31: "The model conception was based on (Carvalho et al., 2013) findings which showed that forests with adult bamboo have higher NIR reflectance than forests with juvenile and recently dead bamboo, or without bamboo, and that bamboo present a life cycle approximate to 28 years.". By retrieving the empirical bamboo-age spectral curves, we were able to demonstrate that the remaining spectral bands do not show an abrupt change in reflectance in the die-off year. We did not explore additional attributes such as combinations of bands and spectral indices because our simple model with only the NIR band already presented high accuracy (80%) and very low RMSE error (0.5 RMSE). Even though, we think that should be interesting to use different attributes to potentially improve detection. We added this sentence to conclusions in p.25 l.28: "The mapping approach can be applied with other remote sensing data, such as Landsat data with better spatial resolution and longer time series, and tested with different spectral bands and attributes to further improve the detection."

(2) We used the bilinear model because it was the simplest way to represent the spectral variation changes with bamboo growth overtime as there was no current knowledge on the spectral responses of these bamboos over time. Once we have detected the die-off with this method and reconstructed the empirical spectral variation, we further demonstrated that the relation is not really a linear increase with age, but, in general, more like an abrupt increase when bamboo reach the canopy after 12

C10

years of age, and then an abrupt decrease with die-off (Fig. 7). To improve clarity, we have added this sentence to methods p.8 l.1: “Thus, since not much is known about the spectral behavior of bamboo growth with age, we chose a bilinear model to characterize the bamboo signal change overtime because it was the simplest way to represent the change between life stages.”

(3) Regarding the thresholds, in some parts of the paper where we used thresholds, based on statistics that represent our data with high confidence, such as percentiles that capture 99% of the data or that have very low p-value. For example, in the die-off detection we filtered our map based on p-value statistics from the correlation, so only pixels with very high confidence ($p < 0.001$) would be mapped as a die-off. Also, when we extracted the bamboo-free median NIR signal, in order to get the signal from forests without bamboo, we applied the threshold of 99.88% tree cover that excluded at least 99% of the previously known bamboo-dominated areas.

(4) We are confident that the results from Carvalho et al. (2013) are accurate because their validation was made with field campaigns, aerial flights, and independent field data from previous field studies. Hence, it supports that the visual interpretation of bamboo die-off using color composites is indeed associated with the field processes, and, thus is adequate for our validation purposes.

(5) In the second paragraph of section 3.2.1 we have briefly stated that “The correlation coefficients found in the mapped pixels with significant relationship with our bilinear model ($p < 0.001$) were very strong ($r > 0.7$).”. That meant that all pixels presented $r > 0.7$. Since more information could be added to it, we extracted additional statistics and adjusted the text in p.13 l.3 to: “The correlation coefficients found in all the mapped pixels with significant relationship with our bilinear model ($p < 0.001$) were strong ($r > 0.7$). More than 50% presented even stronger correlations ($r > 0.8$), and 15% of pixels presented very strong correlation ($r > 0.9$).”

3. The first two conclusions of this study - first, that bamboo-dominated forests have lower tree cover values than bamboo-free forests, and second, that the MODIS

C11

NIR values have different distributions over the two forest types - are not supported by convincing evidence. In each case, the differences reported are so small ($< 0.1\%$ tree cover and $< 0.1\%$ reflectance) that I would predict other sources of variability and/or error (e.g., radiometric calibration, sensor signal-to-noise ratio, atmospheric correction uncertainties) might overwhelm these differences.

Response: We don't agree with Reviewer 2. The tree cover is lower in bamboo-dominated forests than bamboo-free forests as shown for example in the attached Figure 5 (Tree cover over the whole study area and a tree cover percentiles of bamboo forests in a small subset). The differences in the NIR distribution, more thoroughly discussed below, also supports that these differences distinguish the forest types to a certain degree and were useful to help us detect the live bamboo. However, we did not intend that the tree cover would map the bamboo forests, but rather help us to do it with the NIR signal.

Most bamboo-free forests (north east of study area) presented near 100% tree cover, while the bamboo-dominated forests presented values between 96.95 and 99.88%, and only 1% of bamboo-dominated forests showed tree cover of 100%. Even with this small difference in tree cover percentage, it was possible to observe a coincidence between the tree cover percentile map and a previous mapped bamboo-dominated forests in a few areas of the attached Figure 5, which highlight the difference of tree cover in the borders of the bamboo forests. The percentiles were extracted as a way to select the most probable bamboo-free forests and separate from potential bamboo-dominated forests with high confidence. Hence, later on, we used the bamboo-free median signal as part of the live bamboo detection.

Since it was not easy to visualize the difference in the NIR distributions between the tree cover classes in the Figure 4, we have adjusted it in the updated manuscript by separating the three histograms. The mean difference between NIR reflectance in bamboo-dominated forests (mean = 28.7%) and bamboo-free forest (27.3%) is 1.4% and the distributions largely overlap each other. However, the important message

C12

is that the bamboo-dominated forests NIR signal is skewed to the right, because of the adult bamboo have higher NIR values than juvenile bamboo or forests without bamboo, as shown in Fig. 4. Hence, the first rule used to map the live bamboo was “(i) mean NIR reflectance equal to or greater than the median signal of bamboo-free forests”. When we added the second rule “(ii) an increasing NIR reflectance over time”, the light green pixels in the bamboo spatial distribution (Figure 6) were mapped, which mostly coincided with the remaining non-dead bamboo areas inside the map from Carvalho et al. (2013). This difference in NIR distributions between the three classes supports that differences in tree cover should occur.

4. In many cases, the methods lack a description of the sampling procedure employed to inform classification strategies. In all cases where data are sampled for “training” statistics, the authors should provide a concise description of the sampling unit, sampling protocol, and datasets sampled. For example, Section 2.3.1 mentions five pixels, 78 patches, and 380 geolocation points - but I am not sure how these numbers are related, nor what datasets are being compared. Section 2.3.4 mentions different numbers of pixels, patches, and geolocation points, and perhaps uses a different reference dataset? Additionally, no information is provided to place the samples within the larger context of the entire study area - i.e., what percent of pixels (or percent area) of the entire study area is sampled, and how might this impact confidence in the resulting predictions. That is, the predictive model is developed based on a very small sample of the entire study area, but little information is provided to assess what impact this has on the “predictive accuracy” for unknown pixels?

Response: Agreed. We have improved the description of the sampling as pointed out by reviewer 2, and also reviewer 1 comments. The two paragraphs were previously cited in the general comment 4. In order to show the spatial and temporal distribution of the validation datasets, we intend to add to the supplementary material two figures

C13

which are attached in this document: (i) Figure 2 - Spatial distribution of validation samples obtained from MODIS (2001-2017) imagery in red and Landsat (1985-2000) imagery in blue. The image at background is a false-color composite from MODIS (MAIAC) images of bands 1 (Red), 2 (NIR) and 6 (shortwave infrared), in RGB, respectively, in August 2015; (i) Figure 3 - Temporal distribution of validation samples for bamboo die-off detection (2001-2017) from MODIS imagery and for bamboo die-off prediction (2018-2018) from Landsat imagery.

We agree that a discussion on the representativeness of the validation datasets was missing. We sampled a total of 390 pixels in 78 bamboo patches to validate detections between 2001-2017, and 175 pixels in 35 patches to validate predictions between 2018-2028. We believe that the sampling was at acceptable levels given that we found a total of 802 patches between 2001-2017 and 778 patches during 2018-2028, which equals to around 10% and 4.5% of the total patches, respectively. It is noted, however, that our visual analysis sampled mostly big patches that died-off, because those were the ones that we could be sure that were attributable as bamboo die-off. This information was added to the discussion in p.21 l.3: “Our validation dataset was composed of 390 pixels visually detected in 78 bamboo patches during 2001-2017. Therefore, we can be confident that the sampling was representative to our study area given that we found 802 patches in the same time period, that is, the sample consisted in around 10% patches. It is noted, however, that our visual analysis mostly sampled big patches that died-off, because those were the ones that we could be sure that were bamboo die-off.”, and p.23 l.17: “The validation dataset for the predictions (2017-2028) corresponded to 175 pixels in 35 bamboo patches and represented 4.5% of the 778 bamboo patches predicted for the 2018-2028 time period.”.

Our models did not require any training pixels, because they were based on the correlation of the MODIS NIR time series and a reference – such as the bilinear model and the empirical bamboo-age reflectance curves. Therefore, the validation datasets were used as independent sources of validation, providing robust accuracy metrics for the whole map.

C14

5. Building on the previous point, each validation dataset should be clearly (and concisely) described (perhaps summarized in a table) - and discussions of predictive uncertainty should be included in the results section (not just the discussion section).

Response: We agree. We have adjusted the description of each validation dataset (cited in the general comment 4) and added a brief discussion on its representativeness as pointed out in the previous comment (specific comment 4). Nevertheless, we believe that the report of results is appropriate in the results sections, and its interpretations in the discussion section. We have included two figures in supplementary materials (attached Fig 2 and 3) where one can see the spatial and temporal distribution of samples instead of a table, because we believe that would be more useful for the reader.

Technical corrections/suggestions:

1- Consider refining methods to state the goal of each step first, as well as to identify how each of the steps in the methods sections are related. Currently, the steps are presented in isolation from each other, and in some cases, the almost overwhelming detail makes it difficult to follow how the individual steps are related. Start in the abstract by clearly stating research questions and goals.

Response: We agree. We have added a flowchart (Fig 1) to help the reader get a quick grasp of the whole paper before going into detail. Regarding the abstract, we have added a sentence specifying the main goals of the paper, and then described more specifically what was done. The sentences in p.1 l.5: "In this study, our aim is to map the bamboo-dominated forests and test the 'bamboo-fire hypothesis' using satellite imagery. Specifically, we developed and validated a method to map the bamboo die-off and its spatial distribution using satellite-derived reflectance time series from MODIS (MAIAC) and explored the 'bamboo-fire hypothesis' by evaluating

C15

the relationship between bamboo die-off and fires detected by the MODIS thermal anomalies product in the southwest Amazon."

2- Clearly cite previous work and clearly identify which steps were followed in the current study.

Response: We have improved the description of steps performed in the paper as commented in the previous responses. We believe we have cited all the previous works published in peer-reviewed journals that mapped the bamboo forests in the southwest Amazon, the most important being Nelson et al. (2004) and Carvalho et al. (2013).

3- Consider including a table to present the imagery used in the analysis, including Landsat WRS-2 and MODIS tile coordinates and image dates.

Response: We have prepared a table containing the Landsat images used for validation of bamboo die-off predictions to be included as supplementary material (attached Table 1).

4- Check the use of the term "cross-validation."

Response: Ok, it was incorrectly used in the paper. We have changed the terms "cross-validation" to only "validation".

5- Limitations of the MODIS active fire detection product are mentioned at the very end of the discussion section - what implications does this have for ecological process? Could it be that the bamboo fire hypothesis is still an open question because we are not measuring understorey fires?

C16

Table 1. Dates of TM/Landsat-5 images used for validation of bamboo die-off predictions. The date of each image (YYYY-MM-DD) is presented for each path-row (World Reference System 2) in the columns.

006-065	003-066	002-067	003-067	005-067	003-068
1985-06-28	1985-07-09	1985-09-04	1985-08-26	1985-07-23	1985-07-09
1986-08-02	1986-07-28	1986-08-06	1986-09-30	1986-07-26	1986-10-16
1987-08-05	1987-08-16	1987-08-25	1987-08-16	1987-08-14	1987-08-16
1988-08-07	1988-07-17	1988-08-11	1988-08-18	1988-07-15	1988-06-15
1989-08-26	1989-07-20	1989-08-14	1989-09-22	1989-09-04	1989-08-21
1990-04-23	1990-07-07	1990-09-18	1990-07-23	1990-06-19	1990-08-24
1991-06-13	1991-07-26	1991-07-27	1991-07-26	1991-07-08	1991-07-10
1992-10-05	1992-08-13	1992-07-21	1992-07-28	1992-08-27	1992-07-28
1993-08-05	1993-09-01	1993-08-25	1993-06-13	1993-08-14	1993-06-13
1994-07-23	1994-07-18	1994-07-27	1994-07-18	1994-06-30	1994-07-18
1995-08-27	1995-08-22	1995-07-30	1995-08-22	1995-06-17	1995-07-05
1996-07-12	1996-07-23	1996-08-01	1996-07-23	1996-07-05	1996-07-23
1997-09-01	1997-07-10	1997-07-19	1997-07-10	1997-07-24	1997-08-27
1998-07-18	1998-07-13	1998-09-24	1998-08-30	1998-09-13	1998-07-13
1999-08-06	1999-08-01	1999-08-10	1999-08-17	1999-07-30	1999-08-17
2000-10-11	2000-07-18	2000-07-27	2000-07-18	2000-09-02	2000-09-04

C17

Response: We adjusted the fire discussion as a response to Reviewer 1 comments which reinforced that we should fully reject the 'bamboo-fire hypothesis'. The adjusted sentences in p.23 l.30: "We cannot support the 'bamboo-fire hypothesis' from Keeley and Bond (1999) because fire occurred only in a small fraction of bamboo-dominated areas during the 16 years of fire analysis (Fig. 6), equivalent to 2371 km² of burnt area or 0.0955% of the total bamboo area (155,159 km²) burning each year, and the statistical tests comparing dead and live bamboo fire frequency showed that dead bamboo did not burn more than live bamboo (Fig. 11). Hence, we believe that there should be other explanations for bamboo maintenance in the forest, such as bamboo itself being responsible for its maintenance in the forest due to the damage it causes in the trees while increasing tree mortality (Griscom and Ashton, 2003)". In the updated manuscript, we acknowledged that the fire datasets underestimate the total fire occurrence but it should not affect the conclusions in p.24 l.11: "The fire occurrence beyond 2 km inside the forest was probably underestimated because the forest canopy can obscure fires that occur only on the understory, and, thus, are not detected by the MODIS/Aqua satellite (Roy et al., 2008). In addition, the MODIS active fire detections should be treated as a lower bound of fire occurrence, as it underestimates fire occurrences in the order of 5% for small fires with less than 0.09 km², or 10% of MODIS spatial resolution, due to the coarse spatial resolution, high cloud cover, and when having high viewing angles (> 15 °) (Morissette et al., 2005). Nevertheless, we do not believe this might have an impact on rejecting the 'bamboo-fire hypothesis' due to the minimal fraction of fire occurrences occurring over the large bamboo-dominated forests."

Please also note the supplement to this comment:
<https://www.biogeosciences-discuss.net/bg-2018-207/bg-2018-207-AC2-supplement.pdf>

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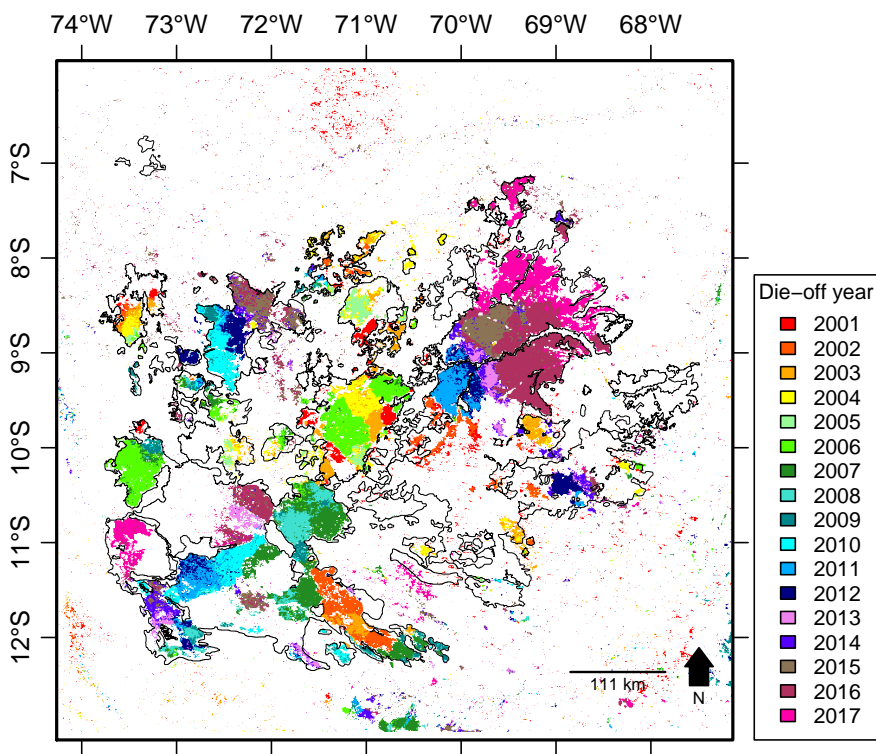


Fig. 1. Bamboo die-off during 2001-2017 from the combined detections using MODIS (MAIAC) NIR-1 and NIR-2 and the bilinear model.

C20

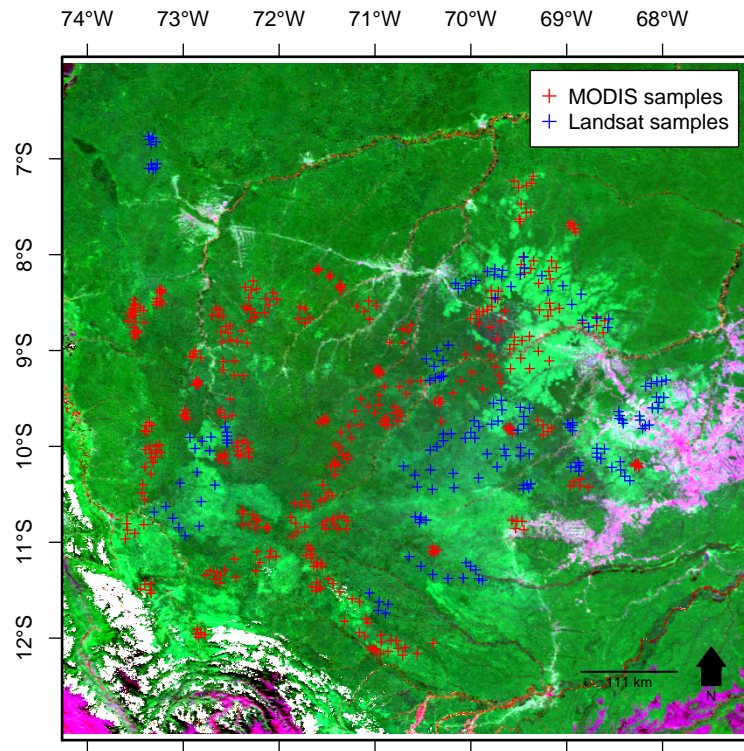


Fig. 2. Spatial distribution of validation samples obtained from MODIS (2001-2017) imagery in red and Landsat (1985-2000) imagery in blue. The image at background is a false-color composite from MODIS [...]

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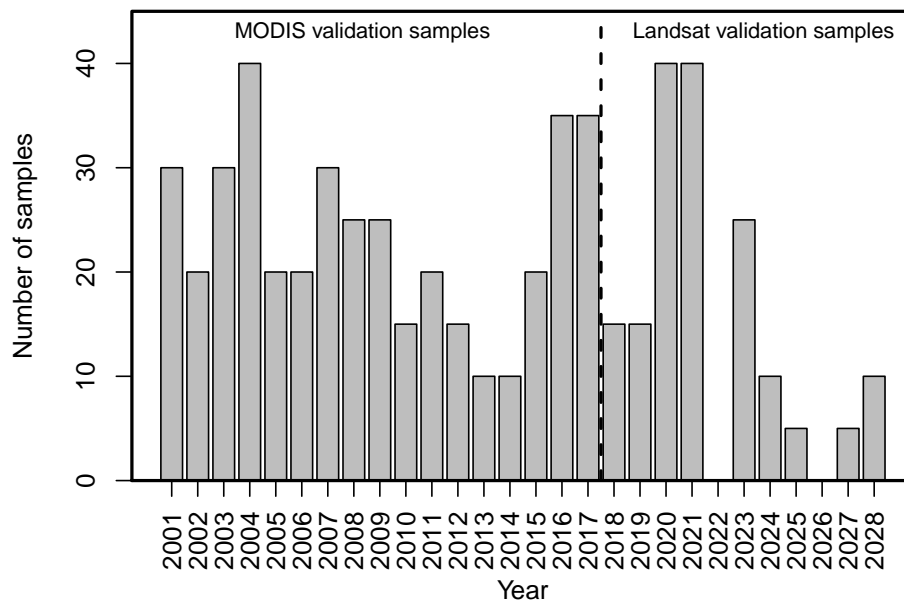


Fig. 3. Temporal distribution of validation samples for bamboo die-off detection (2001-2017) from MODIS imagery and for bamboo die-off prediction (2018-2018) from Landsat imagery.

C22

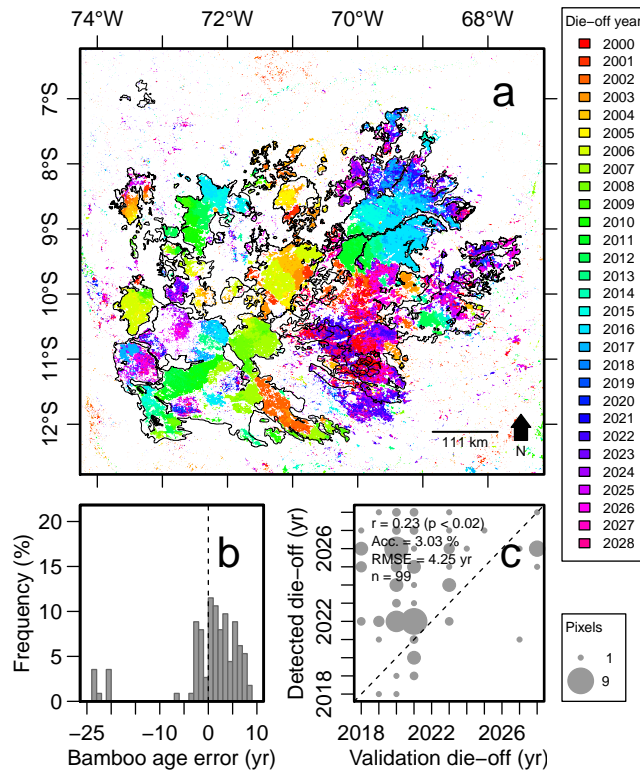


Fig. 4. MODIS bamboo die-off prediction map from 2000 to 2028 using the empirical curves of the near infrared 1 (NIR-2) reflectance as a function of bamboo cohort age (a). Validation between predicted [...]

C23

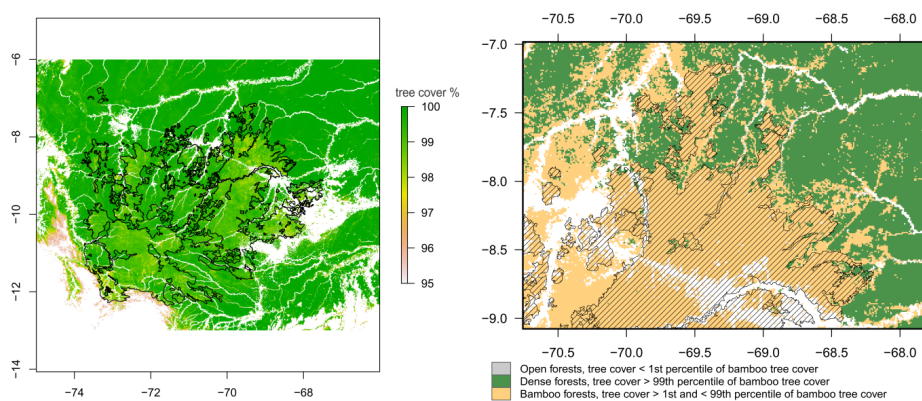


Fig. 5. Tree cover over the whole study area and a tree cover percentiles of bamboo forests in a small subset.

C24

Life cycle of bamboo in southwestern Amazon and its relation to fire events

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Abstract. Bamboo-dominated forests comprise 1 % of the world's forests and 3 % of the Amazon forests. The *Guadua spp.* bamboo bamboos that dominate the southwest Amazon are semelparous, so thus flowering and fruiting occur once in a lifetime before death. These events occur in massive spatially organized patches every 28 years and produce huge quantities of necromass. The 'bamboo-fire hypothesis' bamboo-fire hypothesis argues that increased dry fuel after die-off enhances fire probability, creating opportunities that favor bamboo growth. In this study, our aim is to map the bamboo-dominated forests and test the 'bamboo-fire hypothesis' bamboo-fire hypothesis using satellite imagery. Specifically, we developed and validated a method to map the bamboo die-off and its spatial distribution using satellite-derived reflectance time series from MODIS (MAIAC the Moderate Resolution Imaging Spectroradiometer (MODIS)) and explored the 'bamboo-fire hypothesis' bamboo-fire hypothesis by evaluating the relationship between bamboo die-off and fires detected by the MODIS thermal anomalies product in the southwest Amazon. Our findings show that the NIR near-infrared (NIR) is the most sensitive spectral interval to characterize bamboo growth and cohort age. Automatic detection of historical bamboo die-off achieved an accuracy above 79 %. We mapped and estimated 15.5 million ha of bamboo-dominated forests in the region. The 'bamboo-fire hypothesis' bamboo-fire hypothesis was not supported, because only a small fraction of bamboo areas burned during the analysis timescale, and, in general, bamboo did not show higher fire probability after the die-off. Nonetheless, fire occurrence was 45 % higher in dead than live bamboo in drought years, associated with ignition sources from land use, suggesting a bamboo-human-fire association. Although our findings show that the observed fire was not sufficient to drive bamboo dominance, the increased fire occurrence in dead bamboo in drought years may contribute to the maintenance of bamboo and potential expansion into adjacent bamboo-free forests, or. Fire can even bring deadly consequences to these adjacent forests under climate change effects.

20 1 Introduction

Bamboo-dominated forests represent 1 % of global forests. They occur in tropical, subtropical and mild temperate zones and are found mainly in Asia (24 million ha), South America (10 million ha) and Africa (2.8 million ha) (Lobovikov et al., 2007).

Their spatial distribution is likely underestimated in South America as a recent study showed that these forests cover at least 16.15 million ha of Amazonian forests over Brazil, Peru and Bolivia (Carvalho et al., 2013).

Bamboo is a major forest product that plays an important economic and cultural role in the Amazon. It has been used for over a millennium by indigenous people for shelter, food, fuel, hunting, fishing, and musical instruments (Lobovikov et al., 2007; Rockwell et al., 2014). The first studies on the distribution of these forests in the Amazon region postulated that they occurred as a consequence of human disturbance or were deliberately planted (Sombroek, 1966; Balée, 1989). However, recent phytolith analysis revealed that ~~bamboo-dominated~~ bamboo dominated these forests before human occupation in South America (Olivier et al., 2009; Watling et al., 2017).

In the southwest Amazon, the predominant forest type is non-flooded open-canopy rain forest on ~~terra firme~~ terra firme, often dominated by *Guadua* bamboos and mostly (93 %) preserved (IBGE, 2006; Trancoso et al., 2010). In bamboo-dominated areas, two species of semi-scandent woody bamboos predominate: *Guadua weberbaueri* Pilger and *Guadua sarcocarpa* Londoño & Peterson. Like many other woody bamboo species, these *Guadua* bamboos are semelparous, producing flowers and fruits once in a lifetime before dying (Janzen, 1976; Griscom and Ashton, 2003). Flowering, fruiting and death can be massive and highly synchronized in space and time. Their diameter at breast height (DBH) ranges from 4 to 24 cm (Castro et al., 2013). Height is up to 30 m but usually varies from 10 to 20 m (Londoño and Peterson, 1991). The juvenile bamboos usually reach the sunlit portion of canopy by 10 years of age, when they accelerate in growth (Smith and Nelson, 2011). They do not form continuous pure stands, being mixed among the trees, yet achieve remarkable high densities ($2,309 \pm 1,149 \text{ ind ha}^{-1}$) (~~Castro et al., 2013~~) and have significant ecological impacts (Castro et al., 2013). Thus, these forests support up to 40 % less tree species diversity than nearby bamboo-free forests and from 30 to 50 % less carbon stored as a consequence of the lower woody tree density (Silveira, 2001; Rockwell et al., 2014). Bamboo-dominated forests also have elevated tree mortality rates ($3.6 \pm 2.5 \text{ \% yr}^{-1}$) (Castro et al., 2013; Medeiros et al., 2013) when compared even to the typically fast-turnover forests in western Amazon (2.62 \% yr^{-1}) (Johnson et al., 2016). A total of 74 different bamboo populations, that is, patches having individuals of the same internal age, have been so far identified in the southwest Amazon, with a mean patch area of 330 km², and up to 2,570 km² for the largest patch (Carvalho et al., 2013). The mean lifetime of these bamboos was estimated as 28 years (Carvalho et al., 2013).

The locally synchronized death of semi-scandent bamboos produces large amounts of necromass in large patches over a short time. Decomposition of dead leaves and branches is rapid, but a layer of culms can remain intact on the forest floor for up to three years (Silveira, 2001). When neighboring populations (patches) of bamboo go through reproductive events one after another in successive years, this is known in the literature as a flowering wave. The current hypotheses to explain this phenomenon include climatic variations; severe environmental pressures such as floods and fire (Franklin et al., 2010; Smith and Nelson, 2011); and incipient allochronic speciation ~~—~~ stochastically forming small and rare temporally offset daughter patches at the margin of an expanding parent population.

Two main hypotheses, which are not competing but complementary, have been ~~advanced~~ proposed to explain the dominance of semi-scandent bamboos in Amazon forests. Firstly, they cause elevated physical damage to trees by loading and crushing, while also suppressing recruitment of late succession tree species (Griscom and Ashton, 2003). Secondly, they increase fire

probability via their mast seeding behavior followed by the synchronized death of the adult cohort, which produces large fuel loads. The fire would then eliminate canopy trees, form gaps and inhibit tree recruitment, while creating an optimal environment for the bamboo seedling cohort. This latter hypothesis is called the ~~'bamboo-fire hypothesis'~~ bamboo-fire hypothesis (Keeley and Bond, 1999). This hypothesis is attractive as it explains how bamboos can regain dominance of the forest after relinquishing
5 space to trees when the adults die. Analysis of charcoal in soils of three Amazon bamboo-dominated forests sites showed a long history of fire occurrence (McMichael et al., 2013). Smith and Nelson (2011) showed that fire disturbance favored the expansion of bamboos in the Amazon. Another study indicated that pre-Columbian people used fire and bamboo die-off patches to facilitate forest clearing and constructed geoglyphs, which, nowadays, can be found under the closed-canopy forest (McMichael et al., 2014). Although these studies do not support fire as the main driver of bamboo distribution (~~'bamboo-fire
10 hypothesis'~~ bamboo-fire hypothesis), they show associations between the bamboo die-off and increased fire occurrence, and potential human interactions on this processes.

Bamboo-dominated *terra firme* forests in the southwest Amazon can be detected ~~in~~ by the optical bands of orbital sensors at the adult stage ~~and~~, while the borders of each internally synchronized population can be detected after die-off events (Nelson, 1994). Carvalho et al. (2013) showed that the ~~near-infrared (NIR)~~ NIR band of the Thematic Mapper (TM)/Landsat-5 allowed
15 the best discrimination between bamboo-free forest, forest with adult bamboo and forest with recently dead bamboo. Forests with adult bamboos showed higher reflectance in the NIR than bamboo-free or with recently dead bamboo. Forests in which the newly sprouted cohort of seedlings is confined to the understory were not visually distinguishable from bamboo-free forest. The juvenile bamboo stays hidden in the understory up to 10 years of age, which is the moment they start reaching the canopy (Smith and Nelson, 2011; Carvalho et al., 2013). When analyzing Enhanced Vegetation Index (EVI) data from the Moderate
20 Resolution Imaging Spectroradiometer (MODIS), processed by the Multi-Angle Implementation of Atmospheric Correction (MAIAC) algorithm (Lyapustin et al., 2012), Wagner et al. (2017) detected some patches of adult bamboo during a climate driver study of Amazon forest greening. The bamboo patches presented two peaks of MODIS EVI per year (dry and wet seasons) compared to one peak observed in the wet season over bamboo-free forest.

Because the previous investigations used visual interpretation of satellite data and performed manual delineation of the
25 bamboo areas (Carvalho et al., 2013), they were limited to the identification of large areas and constrained by the analyst's visual acuity. Further studies are therefore necessary to understand the bamboo life cycle, its spectral characteristics, as well as, to establish automatic approaches for detecting die-off events in bamboo-dominated areas. These approaches can enable analyses of ecological processes associated with these events, such as the interactions between bamboo and fire (Keeley and Bond, 1999), bamboo flowering wave patterns (Franklin et al., 2010) and the distribution of 'bamboo-specialist' bird species
30 (Kratler, 1997).

In this study, our aim is to map the bamboo-dominated forests and test the ~~'bamboo-fire hypothesis'~~ bamboo-fire hypothesis. Specifically, we (i) described the tree cover and MODIS NIR reflectance variation in areas with and without bamboo, ~~;~~ (ii) assessed a method to map the die-off, spatial distribution and age structure of bamboo-dominated areas, ~~and~~; and (iii) investigated the relationship of bamboo with fire occurrence in the southwest Amazon. We also aimed to provide near-term,

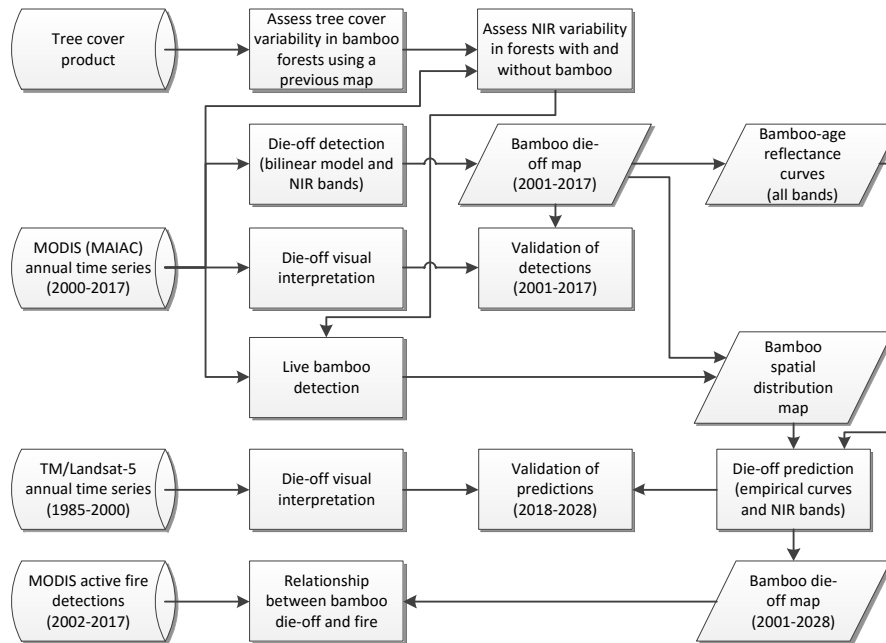


Figure 1. Flowchart of the analyses.

~~spatially-resolved~~ spatially resolved predictions of future bamboo behavior to allow our method to be further tested, validated, and improved over the coming years.

2 Material and Methods

An overview of the analyses conducted in the study ~~were presented in the~~ was presented in Fig. 1 and then described in detail
5 in the subsequent sections.

2.1 Study area

The study area is located in the southwest Amazon between the longitudes 74° W and 67° W and latitudes 13° S and 6° S, covering parts of Brazil, Peru and Bolivia (Fig. 2). The predominant forest type is non-flooding open-canopy rain forest on ~~terra firme~~ terra firme, often dominated by bamboos of *Guadua* genera and mostly (93 %) preserved from human disturbances
10 (IBGE, 2006; Trancoso et al., 2010).

The most important soil types are chromic alisol, red-yellow argisol, haplic cambisol, ferrocyclic podsol, haplic gleysol, red-yellow latosol, chromic luvisol, and haplic plinthosol (dos Santos et al., 2011). In bamboo-dominated areas, the soils have a tendency to be more fertile, richer in exchangeable cations, more easily eroded, more poorly drained, and more clay-rich than the soils where bamboo is excluded (Carvalho et al., 2013). Naturally high erosion leads to a gently rolling hilly landscape
15 (McMichael et al., 2014) with muddy streams and rivers. Based on a 19-year time-series of the Tropical Rainfall Measuring

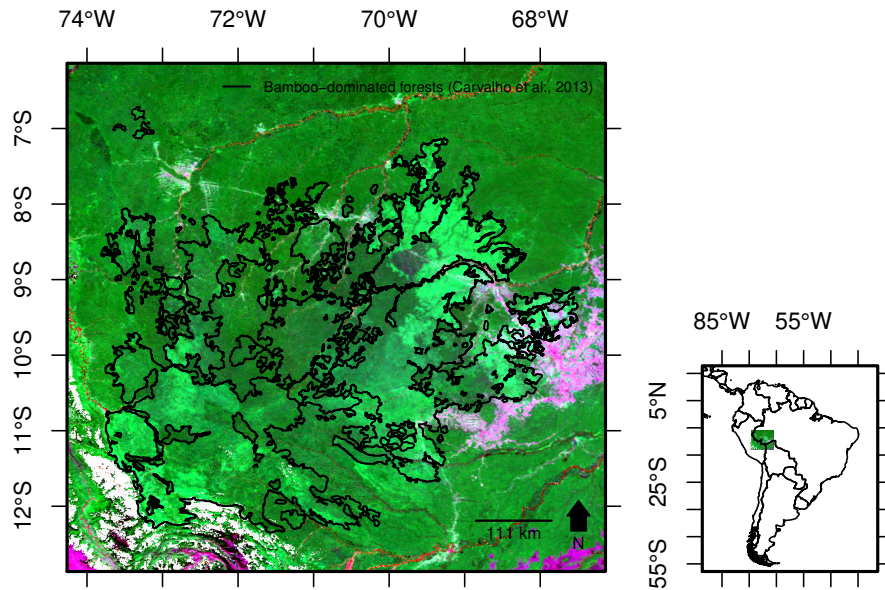


Figure 2. Bamboo-dominated forests in southwestern Amazon. The image at background is a false-color composite from MODIS (MAIAC) images of bands 1 (Red), 2 (NIR) and 6 (shortwave infrared), in RGB, respectively, in August 2015. The black lines indicate the perimeter of the bamboo-dominated areas delineated in a previous study (Carvalho et al., 2013).

Mission (TRMM) satellite, annual rainfall ranges from 1800 mm to 3400 mm, with zero to five dry months (i.e., less than 100 mm mo^{-1}). The average temperature is 27 °C. Minimum rainfall and temperature are in July (Dalagnol et al., 2017).

2.2 Satellite data and products

2.2.1 MODIS (MAIAC) surface reflectance data

5 A time series of MODIS (MAIAC) data was pre-processed in order to map the bamboo ages and die-off - further described in the die-off detection section. Daily surface reflectance data were obtained from the MODIS product MCD19A1-C6, acquired from Terra and Aqua satellites, from 2000 to 2017 (Lyapustin and Wang, 2018), corrected for atmospheric effects by the MAIAC algorithm (Lyapustin et al., 2012). The data were obtained from the NASA Center for Climate Simulation (NCCS) repository (available at: <ftp://dataportal.nccs.nasa.gov/DataRelease/>). We used MAIAC surface reflectance and BRDF products

10 at spatial resolution of 1 km, daily temporal resolution, in eight spectral bands: Red, ~~620-670~~ 620-670 nm (B1); NIR-1, ~~841-876~~ 841-876 nm (B2); Blue-1, ~~459-479~~ 459-479 nm (B3); Green, ~~545-565~~ 545-565 nm (B4); NIR-2, ~~1230-1250~~ 1230-1250 nm (B5); Shortwave infrared-1 (SWIR-1), ~~1628-1652~~ 1628-1652 nm (B6); SWIR-2, ~~2105-2155~~ 2105-2155 nm (B7); and Blue-2, ~~405-420~~ 405-420 nm (B8).

In order to minimize the differences in sun-sensor geometry between the MODIS scenes, which could affect our time series

15 analysis, the daily surface reflectance was normalized to a fixed nadir-view and a 45° solar zenith angle using a Bidirectional

Reflectance Distribution Function (BRDF) and the Ross-Thick Li-Sparse (RTLS) model (Lucht and Lewis, 2000). Parameters of the RTLS model and BRDF kernel weights are part of the MAIAC product suite with temporal resolution of 8 days - a period ~~which~~ when daily observations of different view angles were integrated and used for BRDF parameters retrieval. Hence, the normalized surface reflectance, called Bidirectional Reflectance Factor (BRF_n) ~~(Eq-1)~~, was calculated using the Eq. (1) and

5 RTLS volumetric (f_{vol}) and geometric (f_{geo}) parameters, and BRDF isotropic (k_{iso}), volumetric (k_{vol}) and geometric-optical (k_{geo}) kernel weights (Lyapustin et al., 2012).

$$BRF_n = BRF \times \frac{k_{iso} - 0.04578 \times k_{vol} - 1.10003 \times k_{geo}}{k_{iso} + f_{vol} \times k_{vol} + f_{geo} \times k_{geo}} \quad (1)$$

The BRF_n data were aggregated into 16-day composite intervals by calculating the median on a per-pixel basis. The composites were then merged and converted to geographic projection (datum WGS-84). All these procedures were implemented in

10 R language (R Core Team, 2016).

Annual composites of MODIS NIR surface reflectance data were selected for the die-off detection. The images were selected between July and September to minimize cloud coverage. Furthermore, during these months, the bamboo patches at the adult stage present a well-defined phenological response (peak in MODIS EVI), which is not present in primary forests without bamboo dominance (Wagner et al., 2017). When useful data were not available in the time series due to cloud cover or ~~bad~~

15 ~~pixel-quality~~ low-quality pixel retrievals, an imputation method was applied to fill the gaps using the whole time series. As the bamboo-dominated forests present a seasonal spectral response, the imputation was conducted by the Seasonal and Trend decomposition using Loess (STL) method (Cleveland et al., 1990). This method decomposes the signal into trend, seasonal and irregular components, interpolates the missing values, and then reverts the time series. It is effective when dealing with missing values in seasonal signals when compared to other imputation methods (Steffen, 2015).

20 2.2.2 TM/Landsat-5 surface reflectance product

A time series of Thematic Mapper (TM)/Landsat-5 data was obtained from 1985 to 2000 (one image per year), in order to visually detect bamboo die-off events and create a validation dataset for die-off predictions using MODIS (MAIAC) between 2018 to 2028 - further described in the die-off prediction section. We selected atmospherically corrected surface reflectance images (Landsat collection 1 Level-1) (available at: <https://earthexplorer.usgs.gov/>) from the quarter July-August-September

25 to increase the chances of obtaining cloud-free data and reduce spectral variations associated with vegetation seasonality. The path-row (World Reference System 2) of the time series were: 006-065, 003-066, 002-067, 003-067, 005-067, and 003-068. The acquisition dates for each path-row are shown in the ~~supplementary~~-Table S1.

2.2.3 Tree cover product

In order to mask areas that were not covered by intact forests (deforested, degraded, and secondary forests, pastures and swidden fields) and to analyze the tree cover variability of the bamboo-dominated forests, we used the global forest cover loss

30 ~~2000-2016~~ 2000-2016 dataset (Available at: https://earthenginepartners.appspot.com/science-2013-global-forest/download_

v1.4.html). The dataset is based on Landsat time series data at 30 m spatial resolution (Hansen et al., 2013), and consists of tree cover percentage, gain, and loss during ~~2000-2016~~2000-2016, and a mask indicating permanent water bodies. It was re-sampled to 1 km spatial resolution using the average interpolation in order to match the resolution of the MODIS (MAIAC) data. A mask of intact forests was created using the tree cover data to select pixels: (i) without permanent water bodies, (ii) 5 without gain or loss of tree cover during the ~~2000-2016~~2000-2016 period; and (iii) above a threshold of 95 % tree cover to detect and filter out non-forested pixels.

The tree cover product was analyzed considering ~~a~~the pre-existent bamboo-dominated ~~forests~~forest map from Carvalho et al. (2013) in order to explore the variability of tree cover in forests with and without bamboo which might help mapping the bamboo-dominated forests. We expect that bamboo-dominated forests present lower tree cover values than bamboo-free 10 ~~forest~~forests due to its fast dynamics and higher mortality (Castro et al., 2013; Medeiros et al., 2013). ~~This map~~The map from ~~Carvalho et al. (2013)~~Carvalho et al. (2013) was obtained by visual interpretation of live-adult bamboo using two Landsat mosaics 10 years apart from each other (1990 and 2000), supported by the known locations and dates of five bamboo dominated areas. Considering only the pixels inside the bamboo-dominated map, we calculated the 1st, 50th and 99th percentiles of the tree cover product and generated a map showing the areas below the 1st, between the 1st and 99th, and above the 99th percentiles of tree cover. 15 The map was qualitatively analyzed exploring the areas covered by each of the percentile classes.

The tree cover ~~percentiles~~percentile map was also used to assess the variability of NIR reflectance in forests with and without bamboo in order to test if their NIR signals ~~are different and contribute~~were different and contributed to the bamboo-dominated forests mapping. We tested only ~~NIR because it is expected to show the best~~the NIR because of the expected great separability between areas with and without bamboo ~~because of the greater~~resultant from the higher NIR signal in bamboo-dominated 20 areas (Carvalho et al., 2013). We analyzed the MODIS NIR-1 reflectance considering all pixels ~~overtime~~over time in each tree cover classes: below 1st, between 1st and 99th, and above the 99th percentile. The NIR ~~values~~value distributions were tested for normality using a two-sided Kolmogorov-Smirnov test at a 1 % significance level. For normal distribution, the average and standard deviation were computed. For skewed distribution, a more appropriate method was applied to estimate the average, standard deviation and skewness parameter (xi) (Fernandez and Steel, 1998).

25 **2.2.4 MODIS active fire detections product**

~~In order to test the 'bamboo-fire hypothesis'~~To test the bamboo-fire hypothesis, a fire occurrence dataset was obtained from MODIS/Aqua satellite active fire data at 1 km spatial resolution from the Brazilian Institute of Space Research (INPE) Burn Database (Available at: <http://www.inpe.br/queimadas/bdqueimadas/>) for the period of ~~2002-2017~~2002-2017 over the study area. This dataset corresponds to geolocations of active burning areas in the moment of satellite overpass.

2.3 Bamboo life cycle spectral characteristics

2.3.1 Die-off detection and validation

To automatically detect the bamboo die-off from 2001 to 2017, we compared each pixel of's MODIS (MAIAC) NIR reflectance time series to a bilinear model using Pearson's correlation and an iterative shift approach. The model consisted in a linear increase in reflectance from 1 to 28 % between 1 and 28 years of bamboo age followed by an abrupt decrease to 0 % when the die-off occur. The model conception was based on Carvalho et al. (2013) findings which, who showed that forests with adult bamboo have had higher NIR reflectance than forests with juvenile and recently dead bamboo, or without bamboo, and that bamboo present. They also showed that bamboo presented a life cycle approximate to of approximately 28 years. Thus, since not much is was known about the spectral behavior of bamboo growth with age, we chose a bilinear model to characterize the bamboo signal change overtime over time because it was the simplest way to represent the change between life stages. We also assumed the signal coming from the trees as constant over time. Therefore, inter-annual reflectance variations were attributed to structural changes in the canopy related to bamboos. The Pearson's correlation coefficient (r) between the NIR reflectance time series and the bilinear model for a given pixel was iteratively tested by shifting the position of the NIR time series inside the bilinear model vector. The position showing the highest r corresponded to the estimated age of that pixel from which the die-off year was retrieved. Only pixels with very significant correlations ($p < 0.001$) were selected. The model was tested with both MODIS (MAIAC) NIR bands: NIR-1 band 2 (841-876 nm) and NIR-2 band 5 (1230-1250 nm). Both bands are sensitive to canopy structure scattering, but NIR-2 is also partially sensitive to leaf/canopy water scattering (Gao, 1996), so that could lead to a different detection between bands.

For validation purposes, we compared the detected die-off events with recently dead bamboo areas visually detected-identified in MODIS false color composites (bands 1, 2 and 6 in RGB). In this color composite (Fig. 2), adult bamboo patches show bright green color due to the comparatively higher NIR reflectance, while dead bamboo patches present dark blue/gray color. The visual inspection of bamboo die-off using MODIS and Landsat data was consistent with five bamboo mass flowering events observed in the field (Carvalho et al., 2013). In each of the dead bamboo patches visually detected, the geographic location and die-off year were registered for a sample of 5 random pixels. A total of 78 dead bamboo patches were identified in the 2001–2017 period, thus 2001–2017 period. Thus, the validation dataset was composed of 390 pixels with corresponding year of bamboo death - the spatial and temporal distribution of the samples are shown in the supplementary Figures S2 and S3 were shown in Fig. S1 and S2. For these pixels, the die-off year detected by our model was retrieved and compared to the validation dataset. To assess the detection, we calculated the accuracy (%) on detecting the exact die-off year, Pearson's correlation and p-value p-value, and the root mean square error (RMSE) between the automatically detected and visually interpreted die-off year.

2.3.2 Spatial distribution detection

In order to map the spatial distribution of bamboo-dominated forests for the whole area, we first detect-mapped the live bamboo and then combine this map-combined it with the die-off detection map (2001-2017 2001–2017). We used two as-

sumptions to map the live bamboo. Over the 18 years' period, a live bamboo-dominated pixel should present: (i) mean NIR reflectance equal to or greater than the median signal of bamboo-free forests; and (ii) an increasing NIR reflectance over time. The median bamboo-free forest signal was derived using the tree cover mask and a threshold that excluded all the potential bamboo-dominated pixels. The threshold was defined as the tree cover percentage above the 99th percentile from bamboo-dominated forests as delineated by Carvalho et al. (2013). We tested whether the mean NIR reflectance of each pixel was statistically lower than the forest median signal using the Student's t-test, and excluded those pixels. Furthermore, we obtained a linear regression model between the reflectance of each pixel in the time series and a linear increasing vector to identify reflectance increase over time in the bamboo areas. We selected only pixels that showed a very significant ($p < 0.001$) and positive regression slope, indicating the reflectance increase in the NIR. ~~In order to~~ To assess the overall consistency of the map, we compared it with the available bamboo-dominated forests distribution map from Carvalho et al. (2013).

2.3.3 Bamboo cohort age and spectral variability

We used the die-off map to retrieve spectral data corresponding to each bamboo age in order to assess the spectral variability during the bamboo life cycle, that is, when the signal changes and why, and to corroborate the assumptions made in the bilinear model. Data from all MODIS bands were extracted using the estimated die-off year with very significant correlation ($p < 0.001$) as a starting point. Bamboo cohort age was then calculated backwards and forwards in time during the ~~2000-2017~~ 2000-2017 period. Reflectance percentiles (1st, 50th and 99th) per age were calculated ~~obtaining, what we called,~~ to obtain the entitled empirical bamboo-age reflectance curves.

The spectral variability with cohort age was also analyzed in relation to the bamboo-free signal in order to assess the separability of forests with and without bamboo. Pearson's correlation between the median bamboo-free signal, as obtained in a previous section, and bamboo-dominated forest pixel's signal were calculated and assessed as a function of cohort age. The assessment was conducted using the NIR-1 and NIR-2 bands.

2.3.4 Die-off prediction

To assess the ~~age-structure~~ age structure of bamboo patches during the whole life cycle, we explored the prediction of die-off events for the bamboo that did not die-off during ~~2001-2017~~ 2001-2017. This was conducted using the NIR-1 and NIR-2 empirical bamboo-age empirical curves as a reference instead of the bilinear model. Since the NIR time series would not present the abrupt change associated with the die-off, the empirical curves should reflect the spectral changes ~~overtime~~ over time with bamboo growth. The prediction followed the same procedures of the detection on assessing the point of maximum correlation between the NIR reflectance time series, but, now, comparing to the empirical bamboo-age reflectance curves and predicting the die-off for a whole life cycle ~~from 2001-2028~~ during 2001-2028.

Since the validation for ~~2018-2028~~ 2018-2028 predictions could not be conducted using MODIS data because its time series do not span that time period, we used yearly TM/Landsat-5 color composites (bands 2, 4 and 1 in RGB) during the ~~1985-2000~~ 1985-2000 period to visually detect the bamboo die-off events that occurred in the last bamboo life cycle and validate the predictions. We assumed that the die-off events that happened in this period would happen again in the next life cycle of the

bamboo, from 2018 to 2028. Therefore, we added 29 years to the visually detected die-off year in order to match the next life cycle. The sampling procedure for the validation dataset was similar to the detection, where 5 pixels were randomly collected for each recently dead bamboo patch visually identified in a given year. A total of 35 dead bamboo patches were identified and 175 pixels were collected with the corresponding years of death. The assessment was conducted by calculating the same metrics as in the die-off detection section. Additionally, in order to assess if the prediction error was randomly distributed, the residuals from predicted minus observed die-off year, where observed is the die-off from the Landsat validation dataset, was tested for normality using a two-sided Kolmogorov-Smirnov test at a 1 % significance level.

Since not much ~~is was~~ known about the size of bamboo patches, we analyzed the patch size distribution from the prediction map considering grouped pixels with the same die-off year as patches. These grouped pixels with same die-off year were segmented into patches and the patch size distribution was assessed by quantifying the number, minimum, maximum, mean and median size of bamboo patches. In order to filter out noise in the predictions (i.e. loose pixels), the minimum patch size was set to 10 km².

2.4 Relationship between bamboo die-off events and MODIS active fire detections

Active fire detections from MODIS/Aqua during ~~2002-2017~~ 2002-2017 were filtered using yearly non-forest fraction masks ~~considering~~ a threshold of 0% non-forest pixels. This assured. This ensured that active fires occurring over deforested and degraded forests, pastures or swidden areas were removed, and only pixels over forested areas remained in each year. ~~The~~ To visualize where the fire occurred, the active fires were plotted over the bamboo spatial distribution map ~~in order to visualize where the fire occurred.~~ The number of fires occurring over live bamboo and dead bamboo (died-off during ~~2001-2017~~ 2001-2017) was calculated.

~~In order to~~ To test whether there ~~is was~~ a higher fire occurrence over recently dead bamboo than live bamboo, the active fire detections were analyzed as a function of dead (28, 0 and 1 years) and live bamboo (2 to 27 years) classes. For this purpose, each active fire detection was labeled accordingly to the bamboo age of the pixel where it occurred from the prediction map and then merged into the two classes. We controlled for three factors that ~~can could~~ affect fire probability: area of bamboo mortality, climate, and proximity to ignition sources. Since the total area of a specific age class could interfere with fire frequency, that is, more area would mean higher probability of fire occurrence, we normalized the fire frequency by the area (ha) of its respective age class within the buffer with most fire occurrences, in the year of fire occurrence. Severe droughts affected Amazonia in 2005, 2010 and 2015/2016, and especially the southwest in 2005 (Aragão et al., 2007; Phillips et al., 2009; Lewis et al., 2011; Aragão et al., 2018). As drought years can enhance fire occurrence in Amazonia (e.g., Brando et al., 2014; Aragão et al., 2018), we analyzed separately the fire frequency in regular and drought years. ~~In order to~~ To assess the influence of ignition sources on the fire occurrence, we filtered active fire detections using buffers of 1, 2 and 3 km around the non-forested areas using the yearly non-forest fraction mask and assessed the number of active fire detections considering each buffer.

The area-normalized fire frequency over dead and live bamboo was compared using a two-way Analysis of Variance (ANOVA) ~~in order~~ to test whether there were more fire in dead than live bamboo. We tested the effects of bamboo life stage (live or dead), year of fire occurrence and their interactions over active fire detections.

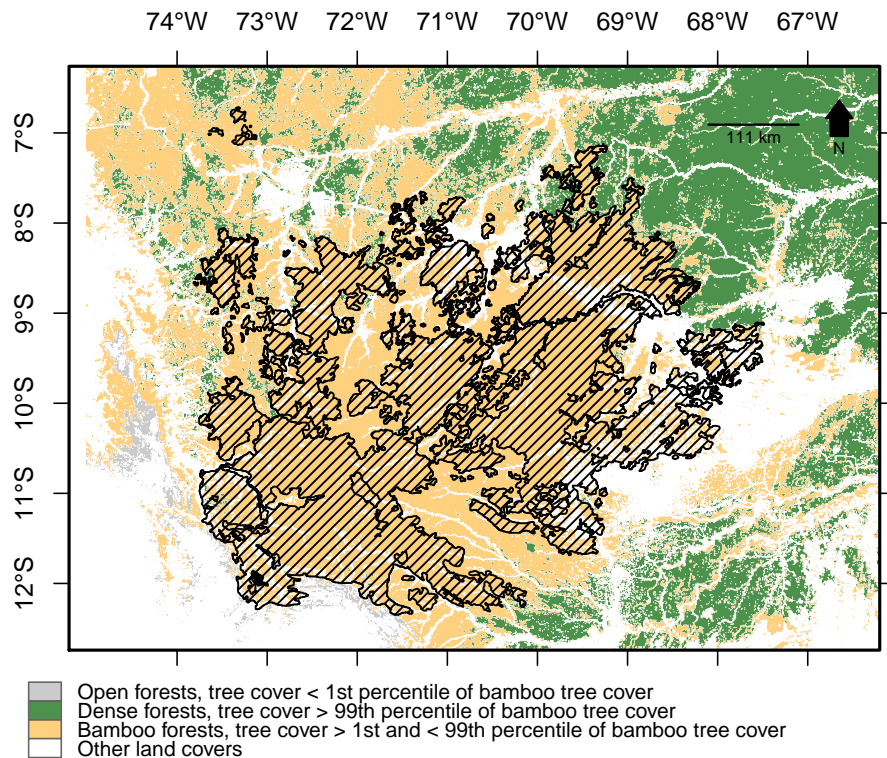


Figure 3. Spatial distribution of stable tree cover percentage percentiles (filtered for tree cover gain and loss, and for water bodies), indicating pixels below, above and within the 1st to 99th percentile range of tree cover found in bamboo-dominated forest (hatched), as delineated by Carvalho et al. (2013).

3 Results

3.1 Tree cover analysis

Bamboo-dominated forest, as mapped by Carvalho et al. (2013), spanned a very narrow range of values in the Landsat-derived percent of tree cover product. The 1st and 99th percentiles of tree cover in the bamboo areas were 96.95 % and 99.88 %, respectively, while the median was 99.18 % (Fig. 3). ~~The median was 99.18%.~~ Forests identified as bamboo-free by ~~the 2013 study~~ Carvalho et al. (2013) had tree cover above the 99th percentile at the northeast of the study area, but below the 1st percentile at the southwest of the study area. At the northwest, bamboo-free forests presented tree cover similar to that of bamboo-dominated, i.e., between the 1st and 99th percentile.

The MODIS NIR-1 reflectance values over the ~~2000-2017~~ 2000-2017 period in bamboo-free forests that had tree cover above the 99th percentile of bamboo-dominated areas (Fig. 4Bb) did not significantly differ from normal distribution ($p = 0.33$) ~~and~~. The bamboo-free forests showed the lowest standard deviation (mean = 27.3 % reflectance; SD = 0.9 %) when compared to the bamboo-dominated forests (Fig. 4Cc). Bamboo-free forests that had tree cover below the 1st percentile of

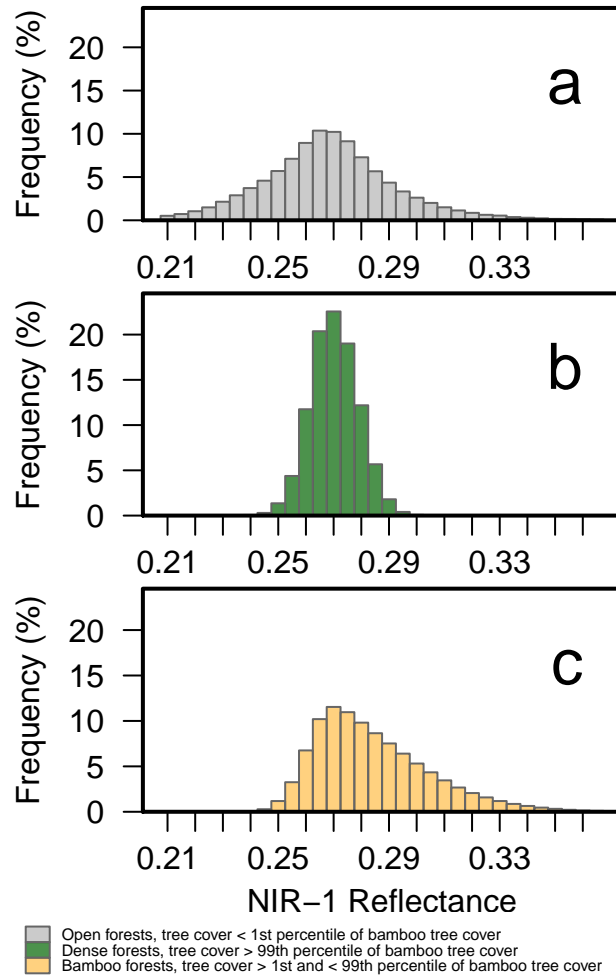


Figure 4. Relative frequency of MODIS NIR-1 reflectance (band 2) from pixels with tree cover percentage (a) below, (b) above and (c) within the 1st to 99th percentile range of tree cover found in bamboo-dominated forest (hatched in [Figure Fig. 3](#)), as delineated by Carvalho et al. (2013).

bamboo-dominated areas (Fig. 4Aa) presented a left-skewed distribution with similar reflectance to the 99th percentile but with higher SD (mean = 27.2 %, SD = 2.6 %, and xi = 1.2). Bamboo-dominated forests (Fig. 4Cc, pixels inside the hatched polygon in Fig. 3) presented a right-skewed distribution with higher NIR-1 reflectance (mean = 28.7 %, SD = 2.1 % and xi = 1.9) than the bamboo-free forests.

3.2 Bamboo life cycle spectral characteristics

3.2.1 Die-off detection

When we applied our automatic die-off approach over the canopy-scattering (NIR-1 band 2) and canopy-water (NIR-2 band 5) sensitive MODIS NIR bands, differences in detected bamboo areas were observed (81480 km² for NIR-1 and 86628 km² for NIR-2). Despite these differences, the resultant die-off year maps were consistent to each other (Figs. 5A and 5Ba and 5b) with 81 % of the detected die-off events located inside the bamboo-dominated area, as reported by Carvalho et al. (2013). The die-off patches that were detected over a ~~18-years~~ 18-year period inside the previous bamboo-dominated forest map represented 40.7 % and 42.7 % of the total bamboo area using MODIS NIR-1 and NIR-2, respectively. In ~~Figures 5A and 5B~~ Fig. 5a and 5b, 83.6 % of the dead bamboo pixels ~~generated from mapped using~~ the two NIR bands showed the same year of death between the maps. When comparing the areas detected solely by one of the two bands, NIR-1 detected more pixels ~~towards~~ toward the end of the time period, i.e. die-off areas from 2017 in the north-east between ~~8-9°S and 69-70°W~~ 8-9° S and 69-70° W, while NIR-2 detected additional pixels in the beginning of the time period, i.e. die-off areas from 2001 in the central region between ~~9-10°S and 70-71°W~~ 9-10° S and 70-71° W. Interestingly, some small patches between ~~8-9°S and 73-74°W~~ 8-9° S and 73-74° W presented a unidirectional wave of mortality from north to south with a delay of one year between adjacent patches.

The correlation coefficients found in all the mapped pixels with significant relationship with our bilinear model ($p < 0.001$) were strong ($r > 0.7$). More than 50 % presented even stronger correlations ($r > 0.8$), and 15 % of pixels presented very strong correlation ($r > 0.9$). When the automatic die-off estimates were validated with the visually inspected die-off from ~~2001-2017~~ 2001-2017, the accuracy from NIR-2 was slightly higher (82.6 %) than that from NIR-1 (79.3 %) (Figs. 5C and 5Dc and 5d). Both bands showed similarly strong Pearson's correlation ($r > 0.99$, $p < 0.01$), whilst NIR-1 showed slightly lower RMSE (0.48 years) than that from ~~NIR-1~~ NIR-2 (0.54 years). From the 390 pixels in the validation dataset, 334 and 362 pixels were detected as bamboo die-off by the bilinear model ($p < 0.001$) using the NIR-1 and NIR-2, respectively. The missing 56 (14.4 %) and 28 (7.2 %) pixels were considered as omission errors for NIR-1 and NIR-2. When we combined the two maps into a single die-off detection map (~~Supplementary Fig. S1~~ Fig. S3), a total of 374 pixels from the validation dataset were successfully detected, resulting in only 16 (4.1 %) missing pixels not detected as bamboo die-off, while accuracy and RMSE were 80 % and 0.51 yr, respectively.

3.2.2 Spatial distribution of bamboo-dominated forests

The bamboo-dominated forests were mapped by combining the die-off detection during ~~2001-2017~~ (~~Supplementary Fig. S1~~ 2001-2017 (Fig. S3)) with the live bamboo detection (Fig. 6). The die-off detection was based on both MODIS NIR-1 and NIR-2, which presented high accuracies ~~and mapped,~~ mapping slightly different bamboo patches in ~~Figure Fig. 5~~. The live bamboo detection was based only on NIR-1, which did not saturate with bamboo growth over time in ~~Figure Fig. 7~~. A total of 155,159 km² of bamboo-dominated forest was detected in the area. Of these, 112,570 km² or 72.5 % were located inside the bamboo forest mapped by Carvalho et al. (2013). A total of 68.8 % of the bamboo forest area from Carvalho et al. (2013) was

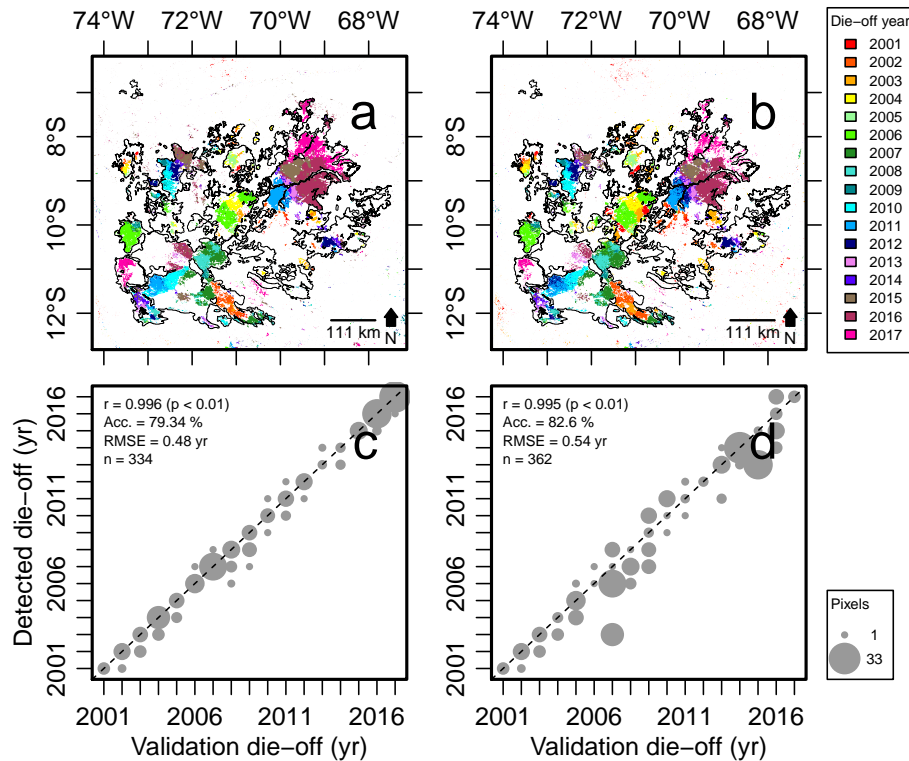


Figure 5. MODIS bamboo die-off detection map from 2001 to 2017 using the bilinear model of expected near-infrared-near-infrared (NIR) reflectance variations as a function of bamboo cohort age, for (a) NIR-1 and (b) NIR-2. Validation between detected die-off and visual interpreted die-off on MODIS false-color composites (2000-2017/2000-2017) for (c) NIR-1 and (d) NIR-2. The dashed line represents the 1:1 line. Size of circles is related to the number of pixels that hit the same observed/estimate die-off year.

covered by the detection. A few large patches were found outside of the previously mapped bamboo spatial distribution, such as in 11.5° S; 70° W, and 13° S; 71° W.

3.2.3 Bamboo cohort age and spectral variability

The reflectance of the MODIS NIR-2 and the two SWIR bands slowly increased with bamboo development up to about 12 years of age, and then increased very steeply from 12-14/12-14 years (Fig. 7). NIR-1 did not show the same reflectance increase up to 12 years as NIR-2, but also showed the steep increase in reflectance between 12-14 years. A pronounced but temporary dip in Red and Blue-2 reflectance occurred concurrently with this brief and rapid NIR and SWIR increase. Green reflectance increased up to about 17 years then leveled off. The response of two SWIR bands and the NIR-2 band all leveled off after 15 years. The NIR-1, however, showed increasing reflectance over the cohort remaining life span, until the age of synchronous die-off. The bamboo die-off was marked by a sharp decrease in MODIS NIR-1 and NIR-2 reflectance between 28 and 29

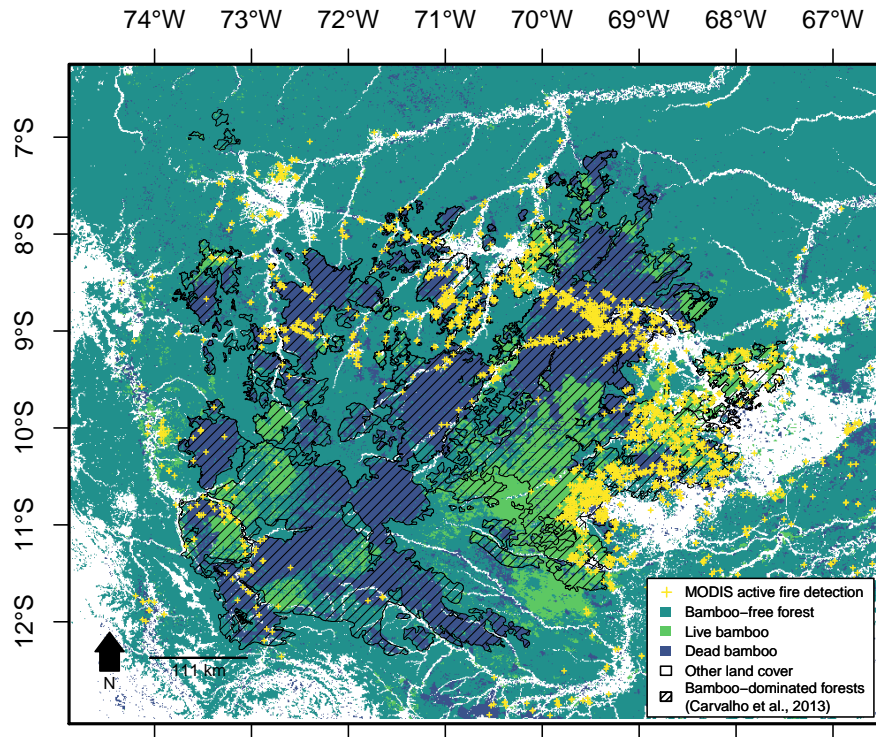


Figure 6. Bamboo-dominated ~~forests~~-forest map and MODIS active fire detections during ~~2002-2017~~ 2002-2017 (yellow crosses). Blue pixels are bamboo die-off patches detected during ~~2001-2017~~ 2001-2017 using the bilinear model. Light green pixels are bamboo that did not die-off, but showed increasing NIR signal during ~~2001-2017~~ 2001-2017, and presented greater NIR mean than forest. Dark green pixels are bamboo-free forests. White pixels are other land cover classes. The hatched polygon represents the bamboo-dominated forests delineated by Carvalho et al. (2013).

years of age (Fig. 7). A reflectance change with bamboo death was not well defined in the SWIR-1 and SWIR-2 bands. The reflectance of all bands presented high dispersion with coefficients of variation ranging from 5.9 to 20.3 %.

The mean Pearson's correlation between the median bamboo-free forest and bamboo-dominated forests NIR-1 reflectance decreased from 0.41 to -0.02 in the transition from juvenile (~~1-14~~ 1-14 years) to adult bamboo stage (~~15-28~~ 15-28 years) (Fig. 8, black boxes). The correlation in the partially water-sensitive NIR-2 did not follow the same pattern (Fig. 8, orange boxes). In NIR-2, the correlation was similar in juvenile ($r = 0.19$) and adult bamboo stages ($r = 0.2$). The correlation's standard deviation was 0.14 and 0.2 for juvenile and adult stages in both bands.

3.2.4 Die-off prediction

Based on the NIR-1 and NIR-2 reflectance from ~~0-28~~ 0-28 years of age, we predicted the die-off year from 2000 to 2028 for the whole bamboo spatial distribution (Fig. 9A and Supplementary Fig. S4Aa and Fig. S4a, respectively). The estimated die-

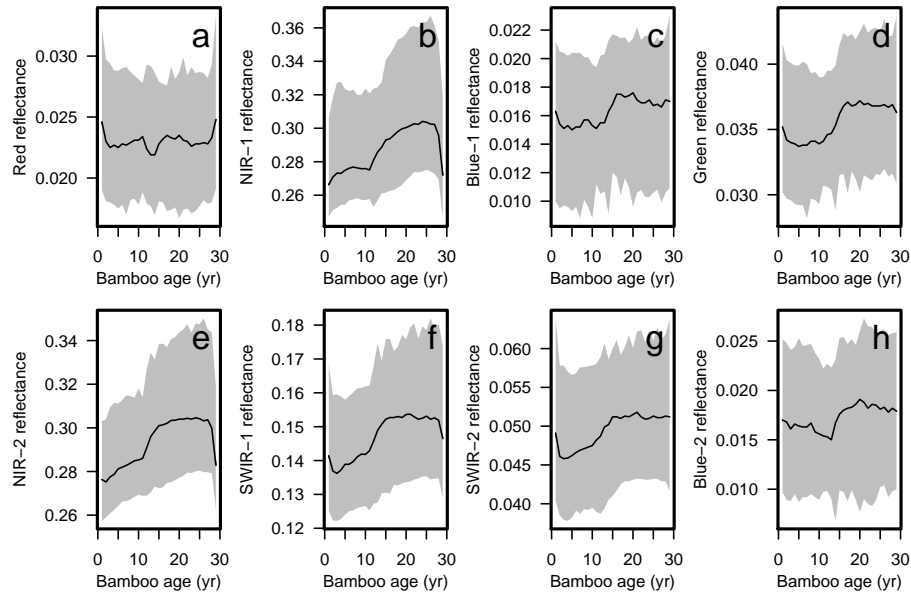


Figure 7. Empirical bamboo-age reflectance curves at ages 0-28 years from MODIS bands 1 to 8 (a)-(h). Black lines represent the median, while the shaded gray areas represent the 1st and 99th percentile.

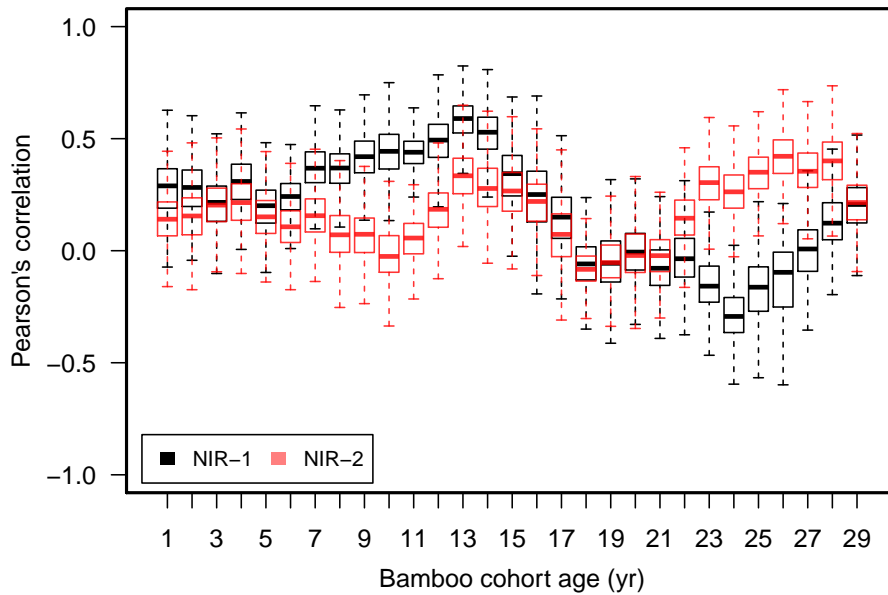


Figure 8. Pearson's correlation coefficients between the median reflectance of bamboo-free forest with the pixel spectral response of bamboo-dominated forests. The results are plotted as function of the bamboo cohort age for MODIS NIR-1 (in black) and NIR-2 (in orange).

off years using the empirical curves during ~~2001–2017~~2001–2017 were 85 % similar to the detection using the initial bilinear model (Fig. 5). The empirical curves achieved an accuracy of 75.45 % (RMSE = 1.11 years) and 69.23 % (RMSE = 1.08 years) for NIR-1 and NIR-2, respectively, on predicting the exact die-off year ~~from 2001–2017~~during 2001–2017, when compared to the visual inspection of MODIS color composites. Die-off prediction during ~~2018–2028~~2018–2028 using the empirical curves (Fig. 7) with NIR-1 and NIR-2 were inspected for consistency using the visual interpretation of TM/Landsat-5 time series (Fig. ~~9C and Supplementary Fig. S4C~~c and Fig. S4c, respectively). NIR-1 and NIR-2 presented low accuracy (20.5 and 3 %, respectively) to predict the exact die-off year with high RMSE (2.92 and 4.25 years, respectively) and significant weak to moderate correlations ($r = 0.41$ and $p < 0.01$; 0.23 and $p < 0.02$, respectively). The residuals distributions of both NIR-1 and NIR-2 prediction models (Fig. ~~9B and Supplementary Fig. S4B~~B and Fig. S4b, respectively) were not significantly different from normal ($p > 0.1$). The NIR-1 model had a mean age error closer to zero (-0.7 years) than that observed from NIR-2 (-1 years). This indicates an average underestimate of the true die-off year when using MODIS NIR-1 and NIR-2, respectively. The standard deviation of the residuals was smaller for NIR-1 (5 years) than for NIR-2 (9 years).

~~As~~Because the MODIS NIR-1 prediction model (Fig. 9) showed higher precision and less bias than the model based on NIR-2 (~~Supplementary Fig. S4~~), we extracted the predicted die-off years from the NIR-1 model to estimate the total area of bamboo die-off per year (Fig. 10) and bamboo population (patch) size distribution (Table 1). Total die-off per year was different from a uniform temporal distribution ($p < 0.01$). For an uniform distribution, the yearly die-off areas would be close to the average of 5350 km². Within the period ~~2000–2017~~2000–2017, the years 2006, 2007, 2011, 2015 and 2016 showed higher than average die-off area (Fig. 10). The largest die-off area was observed in 2016 (14099 km²). For the ~~2018–2028~~2018–2028 predicted period, the year of 2022 is expected to show the largest bamboo die-off area (16276 km²).

The detection for ~~2001–2008~~2001–2008, a period that matches the time interval analyzed visually by Carvalho et al. (2013), showed 372 die-off patches with mean size of 80 km² and maximum size of 2234 km² (Table 1). Carvalho et al. (2013) found 74 patches with mean size of 330 km² and maximum size of 2570 km² during the same period. The detection for ~~2001–2017~~2001–2017 showed 802 patches with mean size of 85 km² and maximum size of 6162 km² (Table 1). Some patch structures had long and linear perimeters, while others had rectangular shapes (for example near 69° 45' W, 8° 48' S, and 71° 13' W, 9° 47' S) or rounded borders (for example near 70° 45' W, 9° 39' S). We also detected a unidirectional flowering wave from north to south in the patch between ~~8–9° S and 73–74° W~~8–9° S and 73–74° W, which was also reported by Carvalho et al. (2013).

3.3 Relationship between bamboo die-off events and MODIS active fire detections

Active fire detections were not found in all bamboo patches that died (Fig. 6). We found a total of 2371 MODIS active fire detections inside bamboo-dominated forests between 2002 and 2017, from which 1424 detections (60 %) occurred in bamboo patches that died-off and 947 detections (40 %) occurred in live bamboo patches. Active fires were detected mostly near non-forested areas (Fig. 6 in gray). When we excluded the detections up to 1, 2 and 3 km around these areas, the total detections decreased to 1330 (56 %), 18 (0.76 %) and 3 (0.12 %), respectively.

In overall, there was a similar number of active fire detections per hectare in dead and live bamboo (0.18 fires ha⁻¹) (Fig. 11). The ANOVA did not show statistically significant differences in the area-normalized mean active fire detections for the

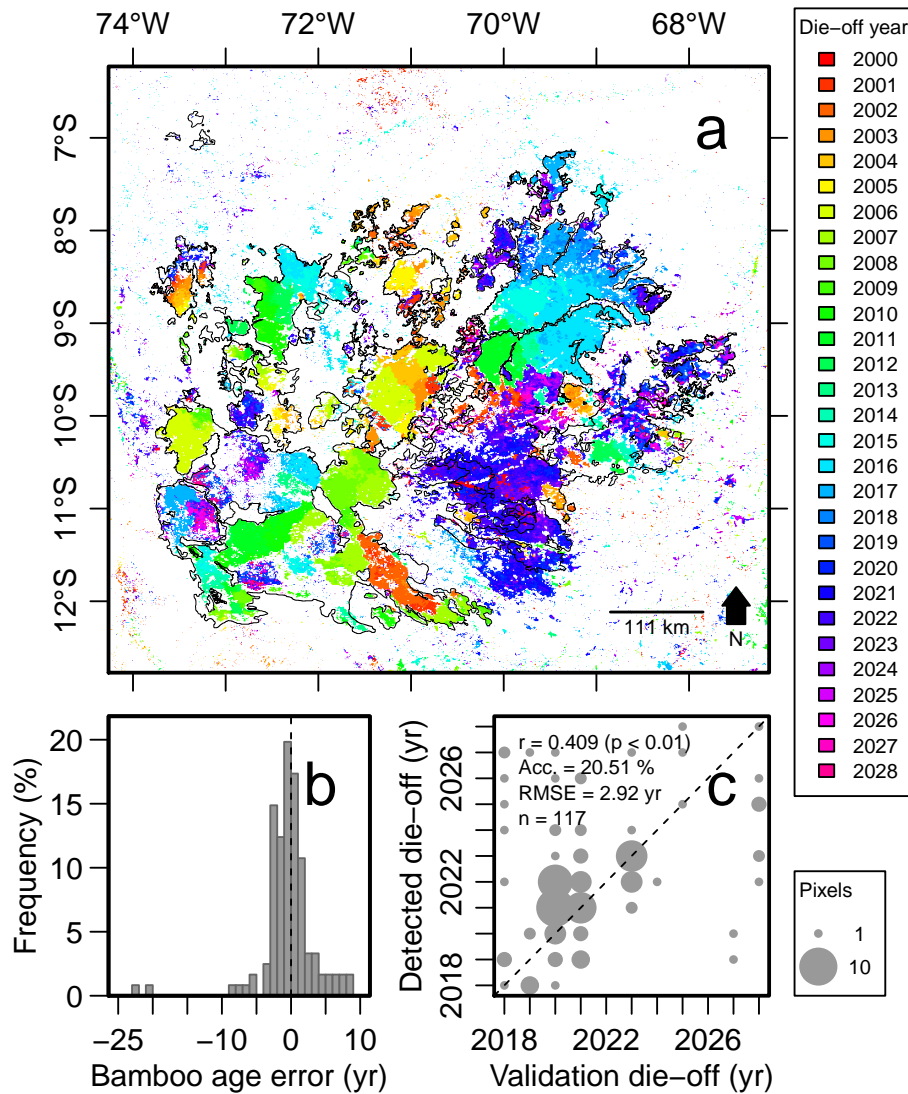


Figure 9. MODIS bamboo die-off prediction map from 2000 to 2028 using the empirical curves of the [near-infrared-near-infrared 1 \(NIR-1\)](#) reflectance as a function of bamboo cohort age (a). Validation between predicted die-off ([2017-2028](#)[2017-2028](#)) and visual interpreted die-off from previous life cycle in Landsat false-color composites ([1985-2000](#)[1985-2000](#)) (c) and residuals distribution (b). The dashed line represents the 1:1 line in (c) and age residual = 0 in (b). Size of circles is related to the number of pixels that hit the same observed/estimate die-off year.

interaction between bamboo stage (dead or live) and year of fire occurrence factors ($p = 0.67$). Individually, bamboo stage also did not show statistical significance on area-normalized mean active fire detections ($p = 0.986$). On the other hand, year of fire did show statistical significance on area-normalized mean active fire detections ($p < 0.01$). The years 2017 and 2016 presented

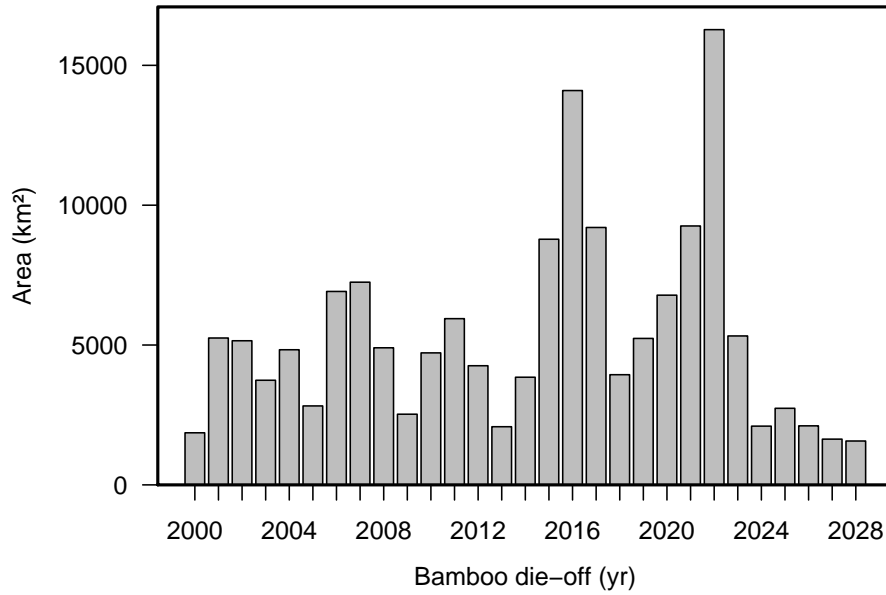


Figure 10. Distribution of predicted bamboo die-off area per year between 2000 and 2028 from MODIS NIR-1.

Table 1. Bamboo patch sizes obtained from die-off prediction using MODIS NIR-1 filtered by a minimum patch area of 10 km², and comparison of results with those from Carvalho et al. (2013).

Study	Period	n	Mean (SD km ²)	Range-SD (min, max km ²)	Median Min (km ²)	Max (km ²)	Median (km ²)
Carvalho et al. (2013)	2001–2008	74	330 (?)	?; ~	~	2570	?; ~
This study	2001–2008	372	79.56 €	242.89 †	10 †	2234	21
This study	2001–2017	802	84.57 €	310.39 †	10 †	6162	20
This study	2018–2028	778	33.84 €	72.38 †	10 †	1154	17
This study	2000–2028	1603	59.05 €	226.66 †	10 †	6162	18

significant higher area-normalized mean active fire detections (0.46 and 0.35 fires ha⁻¹, respectively) than the other years ($p < 0.01$).

For severe drought years, the area-normalized active fire detections in 2005 (0.32 and 0.18 fires ha⁻¹), 2010 (0.22 and 0.12 fires ha⁻¹), 2015 (0.35 and 0.20 fires ha⁻¹) and 2016 (0.57 and 0.33 fires ha⁻¹) over dead and live bamboo, respectively, were not statistically different between the two bamboo life stages ($p = 0.127$). Even though, drought years presented in average 45 % higher area-normalized mean active fire detections in dead (0.342 fires ha⁻¹) than live (0.236 fires ha⁻¹) bamboo.

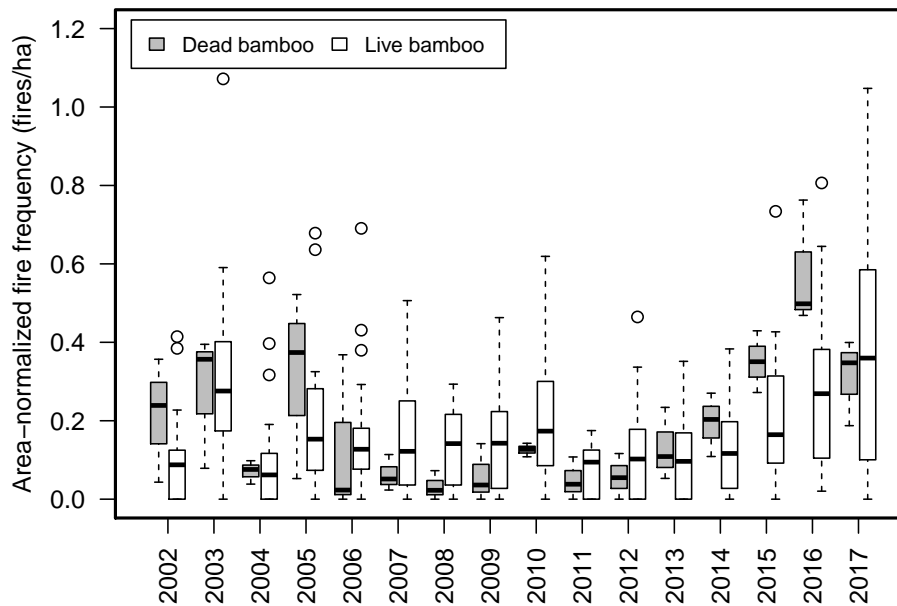


Figure 11. Area-normalized MODIS fire frequency during ~~2002–2017~~. 2002–2017. Gray boxes represent fire in dead bamboo (28, 0 and 1 years) and white boxes represent fire in live bamboo (2 to 27 years).

4 Discussion

4.1 Tree cover of bamboo-dominated and nearby forests

We found that the bamboo-dominated forests had a narrow range of tree cover values (96.95 to 99.89 %) and was below the tree cover values of the closed forests nearby (above 99.89 %). This suggests that these forests have a ~~largely-closed~~ largely closed canopy but are slightly more open than closed forests without bamboo. Evergreen trees are the dominant life form over most of the southwest Amazon forests, including the ones where bamboo is very abundant. The trees generally comprise 50 % or more of the canopy area in a Landsat or MODIS pixel, even when the bamboo cohorts are at adult stage and dense (Carvalho et al., 2013). They also fully dominate the canopy during 30 % of the bamboo life cycle, while juvenile bamboo is confined to the forest understory (Smith and Nelson, 2011). Even though, the tree cover percent of bamboo-dominated forests was slightly smaller than the bamboo-free areas. We believe this might be related to (i) an increased gap opening associated with faster forest dynamics and tree mortality of these areas influenced by bamboo (Castro et al., 2013; Medeiros et al., 2013), or (ii) artifacts of the tree cover computation method that uses the pixels' reflectance from Hansen et al. (2013).

The MODIS NIR-1 reflectance was normally distributed over bamboo-free forests (Fig. 4Bb), while it showed a right skewed distribution over the bamboo-dominated forests (Fig. 4Cc). This result was expected considering that undisturbed old-growth bamboo-free forests are more or less stable over time while bamboo-dominated forests canopy undergo structural changes when the bamboo reach the height of tree crowns after 12 years of age (Smith and Nelson, 2011). This is supported by our

results ~~which shows that show~~ a continuous increase of NIR reflectance with bamboo age and an abrupt increase of NIR around the age of 12 years.

4.2 Automatic detection of bamboo die-off

The automatic detection of bamboo die-off performed very well with an accuracy above 79 % when estimating the exact year of bamboo death and a mean error of 0.5 years. When comparing the NIR-1 and NIR-2 bands, the leaf/canopy water sensitivity from NIR-2 might have contributed for a slightly better performance on bamboo die-off detection and the detection of different areas between the bands, which contributed for a larger coverage of the bamboo-dominated forests ~~(Fig. S3)~~. This different sensitivity to vegetation structure is specially highlighted in ~~the Figure Fig.~~ Fig. 7 where the NIR-2 remains at its lowest during ~~0-2~~ 0-2 years, explaining why NIR-2 band maps different areas than NIR-1.

Our die-off map is an improvement ~~from of~~ the current available ~~map-maps~~ from the literature, because the die-off detection conducted in previous works was solely based on the visual inspection of Landsat and MODIS color composites ~~from 2000-2008~~ during 2000-2008, thus leading ~~towards toward~~ the identification of big clusters of pixels that went through die-off (Table 1) (e.g., Nelson, 1994; Carvalho et al., 2013). Our method is automatic, easy to implement, and can detect relatively small patches because it runs on a per pixel basis. However, we do not advise to attempting detection of very small patches (e.g. < 10 km²) when using MODIS data due to limitations of the spatial resolution of the sensor (1 km). It is important to note that the detected bamboo die-off areas were not confounded with recently deforested areas, as the tree cover product did not point out forest losses in bamboo die-off areas. Since the method can detect bamboo die-off without a priori knowledge of the bamboo spatial distribution (Fig. 6), it could be used to better describe and understand the spatial organization of the bamboo stands that show synchronized die-off in forests around the world.

Our validation dataset was composed of 390 pixels visually detected in 78 bamboo patches during ~~2001-2017~~ 2001-2017. Therefore, we ~~can be are~~ confident that the sampling was representative to our study area given that we found 802 patches in the same time period, that is, the sample consisted in around 10 % patches. It is noted, however, that our visual analysis mostly sampled big patches that died-off, because those were the ones that we could be sure that were bamboo die-off. The high detection accuracy of bamboo die-off events also highlights the quality of the MODIS (MAIAC) data, which are suitable for bamboo-dominated forests mapping. The MAIAC algorithm improves the accuracy of cloud detection, aerosol retrieval and atmospheric correction compared to the standard MODIS product processing (Hilker et al., 2014). Combined with the appropriate normalization for sun-sensor-target geometry using BRDF modeling, the MAIAC contributed to minimize inter-annual artifacts in the time series for an accurate detection.

4.3 Spatial distribution of bamboo-dominated forests

A total of 155,159 km² (15.5 million ha) of bamboo-dominated forests were mapped in the southwestern Amazon by combining the automatic detection of die-off and live bamboo (Fig. 6). Most of the detected areas (72.5 %) were located inside the 16.5 million ha of the bamboo-dominated forests mapped by Carvalho et al. (2013), although covering only 68.8 % of the previous detected areas. This difference was ~~part~~ partially due to the increased land cover change in the region past-2010 ~~—period which~~

~~Carvalho et al. (2013) performed its analysis, areas which~~ period when Carvalho et al. (2013) performed their analysis, and areas where our method did not detect ~~as~~ bamboo-dominated forests. Despite the differences, we detected clusters of pixels that ~~are were~~ very likely bamboo-dominated patches outside of the previously mapped areas (e.g., 11.5°S, 70°W, and 13°S, 71°W, S, 70° W, and 13° S, 71° W). These areas should be further investigated in field to verify if they are indeed bamboo-dominated forests.

Compared to our results with 1 km spatial resolution, the map from Carvalho et al. (2013) (30 m spatial resolution) underestimated the bamboo-dominated forests in the order of 30 %. A possible explanation is that the authors considered live-adult bamboo and used only two Landsat mosaic images 10 years apart from each other (1990 and 2000) for mapping, thus not observing part of the bamboos that were at juvenile stage and hidden in the understory at that time. Another possibility is the limitation of visual interpretation and manual delineation of small bamboo patches. Our map was obtained on a per-pixel basis by assessing each pixel's spectral trajectory, thus reducing errors of omission by considering both live and dead bamboo for mapping, and by using a longer time series (18 years) for the detection.

The potential limitations of our map include the coarser spatial resolution (1 km) when compared to the previous map (30 m). In addition, we likely underestimated the true bamboo distribution because of the previously discussed uncertainties in detecting juvenile bamboos, given the limited temporal coverage of the MODIS (MAIAC) time series. A more accurate mapping of bamboo spatial distribution would require that all bamboo died-off during the time series (i.e. requiring at least 28 years of data). ~~At this moment~~ Currently, the only dataset that ~~have has~~ such temporal coverage ~~would be that comes~~ from the Landsat satellites ~~, which have a total of 33~~ with 47 years of data of variable spatial resolution (1972–2018) or 34 years of data , from 1985 to 2017. of 30 m spatial resolution (1985–2018). The challenge in applying such detection with Landsat imagery ~~would be to acquire a dataset relies in the dataset acquisition~~ of yearly time series of cloud- and aerosol-free images for the whole area, and ~~correct for inter-annual variations in the signal~~ signal normalization between images.

4.4 Bamboo cohort age and reflectance variability

When reconstructing the spectral response of the bamboo-dominated forest as a function of cohort age (Fig. 7), we found that two spectral bands, the NIR-1 and NIR-2, followed our initial assumption of overall reflectance increase with bamboo cohort age and of sharp decrease at the time of die-off.

Between 1 and 12 years of cohort age, the NIR-1 reflectance did not show a continuous increase (Fig. 7), while it presented strong correlation ($r = 0.41$) with bamboo-free forest (Fig. 8). The NIR-2 reflectance, however, showed a slight monotonical increase (Fig. 7) with weak correlation ($r = 0.19$) to bamboo-free forest (Fig. 9). Even though, the accuracy on detecting juvenile bamboos was poor (Fig. 9). Thus, it is very difficult to identify the bamboo dominated patches in this hidden juvenile age without identifying the prior death event, as reported in a previous study (Carvalho et al., 2013).

The NIR signal suddenly increased at ~~12-14~~ 12-14 years of age, which we believe had two possible explanations. First, there was a change in the density of leafy bamboo branches in the upper forest canopy, where they are visible to the satellite. This is supported by the field observations of Smith and Nelson (2011), in which juvenile bamboo cohorts reach the upper forest canopy by 10 years of age and accelerate in growth due to increased access to solar radiance. They observed that bamboo

density doubled (from 1000 to 2000 culms ha^{-1}) and basal area almost tripled (from 2.1 to 5 $\text{m}^2 \text{ha}^{-1}$) between 10 and 12 years of age. The second explanation could be an artifact of our unbalanced sampling for this set of cohort ages. The reflectance values collected for ~~12-15~~12-15 years of cohort age were only available from the extremes of our time series (2000 and 2017) due to the bamboo 28 years life cycle and the 18 years of MAIAC data availability.

5 From ~~14-27~~14-27 years, a smooth steady increase occurs only in the NIR-1 signal until the synchronous cohort death, while the NIR-2 signal seems to have saturated at about age 15 years maintaining a constant signal of 0.3 reflectance until it drops steeply at cohort death. Thus, NIR-1 should present better results for predicting the bamboo age of adult-live stands. Finally, the sharp decrease of NIR-1 and NIR-2 at ~~28-29~~28-29 years explain why our bilinear model performed well detecting the time of death. At the time of death, there is a high abundance of dead/dry bamboo branches in the canopy, which reflect less
10 amounts of NIR energy than leafy and photosynthetically active bamboo.

The increases in red reflectance at the die-off, as well as at 1 year of age (Fig. 7Aa), can also be related to the high abundance of dry bamboo with decreased leaf chlorophyll content and increased non-photosynthetic content. Dry, or dead, vegetation is non-photosynthetically active, and, thus, the incoming red energy near 672 nm is not absorbed by the plant's chlorophyll, that is, causing an increase in the red reflectance (Daughtry, 2000) The dry culms can take up a few years to decompose (Carvalho
15 et al., 2013), which may explain the reason for still observing an increased red signal at 1 year of age.

The curves also showed a large spectral variability in bamboo-dominated forests with age, which very likely occur due to different bamboo abundance and/or forest structure among the area, as well as the inter-annual variability in the signal. Even though, we were able to extract the annual changes in reflectance and predict bamboo ages with 2.92 and 4.25 years RMSE (Fig. 9) using NIR-1 and NIR-2, respectively. The data of each age class was merged from different year composites of the
20 whole time series, thus incorporating the noise in inter-annual variability. Three factors contributing to such noise could be the: (i) temporary formation of green leafy secondary forest, spectrally similar to adult bamboo, in large forest gaps left by the dead bamboo; (ii) semideciduous nature of the trees that are mixed in with bamboo, in the seasonally drier parts of the bamboo range; and (iii) death of bamboo revealed suppressed trees below the bamboo canopy. Nevertheless, because our detection and prediction methods were not based on absolute reflectance values, but on the correlation between the time series and a
25 reference, such as the bilinear model or the empirical curve, we do not believe that the large spectral variability should have a major impact on the detection/prediction.

4.5 Bamboo die-off prediction

By applying the empirical bamboo-age reflectance curves, we estimated the bamboo die-off year for all bamboo patches of the region providing a detailed map of ~~bamboo die-off year and ages~~the age structure of bamboo-dominated forest (Fig. 9) and
30 bamboo patch ~~size~~sizes description (Table 1). The estimated die-off events between 2000 and 2017 were similar to the ones detected using the bilinear model because of the abrupt spectral changes with die-off. Regarding predictions between 2018 and 2028, the estimate of the exact die-off year was not so accurate (at best 20 % accuracy) because those bamboo patches were mainly at the juvenile stage during the MODIS (MAIAC) time series period and did not die. However, we believe that the predictions using the NIR-1 were at acceptable levels (RMSE = 2.92 years) when considering that: (i) the Landsat validation

points based on visual interpretation can have a deviation of 1 year; and (ii) we assumed that every bamboo cohort had the same life cycle length of 28 years, while we know that it can vary between ~~27-32~~27-32 years (Carvalho et al., 2013). The validation dataset for the predictions (~~2017-2028~~2017-2028) corresponded to 175 pixels in 35 bamboo patches and represented 4.5 % of the 778 bamboo patches predicted for the ~~2018-2028~~2018-2028 time period.

5 We believe that knowing where and when the bamboo dies is an important information for future studies of the bamboo-dominated forests ecosystems, and the potential applications of the bamboo die-off year or age map are various. Since areas with dead bamboo are difficult to maintain trails and hinder the work of rubber trappers (Carvalho et al., 2013), it can be used in forest management planning in order to avoid areas where die-off year occurred in the last 3 years and dry culms are still not decomposed, or to avoid areas with likely future die-off. It can also be used for public policy planning regarding food and
10 human health security, for example, in bamboo forests in Southeast Asia, where the bamboo reproductive events cause huge rodent invasion and proliferation that then damage nearby crop plantations (Fava and Colombo, 2017). It could also be used to explore broader scientific questions on the ecology of bamboo-dominated forests such as studies on maintenance/expanse of bamboo patches, flowering waves, cross-pollination between patches, fauna habitat dynamics, impacts on short and long-term carbon dynamics.

15 **4.6 Fire occurrence and bamboo**

We ~~cannot support the ‘bamboo-fire hypothesis’~~could not support the bamboo-fire hypothesis from Keeley and Bond (1999) because fire occurred only in a small fraction of bamboo-dominated areas during the 16 years of fire analysis (Fig. 6), equivalent to 2371 km² of burnt area or 0.0955 % of the total bamboo area (155,159 km²) burning each year, ~~and~~. In addition, the statistical tests comparing dead and live bamboo fire frequency showed that dead bamboo did not burn more than live bamboo
20 (Fig. 11). Hence, we believe ~~that there should be in~~ other explanations for bamboo maintenance in the forest, such as bamboo itself being responsible for its maintenance in the forest due to the damage it causes in the trees while increasing tree mortality (Griscom and Ashton, 2003).

We also did not observe an overall increased fire probability over dead than live bamboo in non-drought years. However, our findings suggest that forests with recently dead bamboo exposed to severe drought are more susceptible to fire occurrence,
25 as there were 45 % higher area-normalized mean active fire detections in dead than live bamboo during severe drought years, such as 2005, 2010, 2015 and 2016. When considering the total fire occurrence, we did not observe an overall significant increase in fire occurrence during the 2005 and 2010 major droughts when compared to the other regular years (Brando et al., 2014). We believe that this is because we filtered the active fire occurring inside the bamboo-dominated areas and pixels with, theoretically, zero non-forested areas using the tree cover products (Hansen et al., 2013), thus excluding the areas of increased
30 fire occurrence in 2005 and 2010 that were reported in the literature (Brando et al., 2014).

The fire occurrence beyond 2 km inside the forest was probably underestimated because the forest canopy can obscure fires that occur only on the understorey, and, thus, are not detected by the MODIS/Aqua satellite (Roy et al., 2008). In addition, the MODIS active fire detections should be treated as a lower bound of fire occurrence, as it underestimates fire occurrences in the order of 5 % for small fires with less than 0.09 km², or 10 % of MODIS spatial resolution, due to the coarse spatial resolution,

high cloud cover, and when having high viewing angles (> 15 °) (Morissette et al., 2005). Nevertheless, we do not believe this might have an impact on rejecting the ~~'bamboo-fire hypothesis'~~ bamboo-fire hypothesis due to the minimal fraction of fire occurrences occurring over the large bamboo-dominated forests.

5 Large areas of bamboo die-off that burned occurred close to agricultural lands near Sena Madureira city in the state of Acre, Brazil, during 2015, 2016 and 2017. The combination of increased dry fuel material from bamboos and nearby ignition sources from land use might have contributed to this increased fire occurrence. This result supports the notion that bamboo die-off enhances fire probability by increasing the dry fuel material in the forest. As we observed in the red wavelength, the reflectance increase was probably associated with greater amounts of dry biomass or non-photosynthetic vegetation in the die-off year and up to 1 year of age (Fig. 7Aa).

10 The fire occurrences over bamboo-dominated forests were therefore associated with the proximity to ignition sources, as less than 1 % of forest fire events occurred more than 2 km apart of non-forested areas. This was expected because fire depends on both fuel and ignition to occur. Thus, areas closer to deforested areas, roads and rivers would have higher probability to burn, as probably occurred in 2015, 2016 and 2017. The study of (~~Kumar et al., 2014~~) Kumar et al. (2014) found that 50 % of MODIS active fire detections were found within 1 km of roads and rivers, and 95 % of the active fires were found within 10 km
15 of roads and rivers in Brazilian Amazon. Fire is known to be associated to deforestation and land use practices in Amazonia such as slash-and-burn and land preparation, where people remove trees of economic interest and then set the areas on fire in order to clear the land and implement crop plantations or pasture (e.g., Roy et al., 2008). Thus, ~~we believe that this reinforces a bamboo-human-fire~~ this reinforce a bamboo-human-fire association through the increased land use and cover change. This association is slightly different than it was in pre-Columbian times (McMichael et al., 2014), where geoglyph builders could
20 have used the bamboo die-off patches and fire as an easier way to clear the forest cover to build their monuments, but it should also favor increases in fire occurrence on the vicinities of bamboo-dominated areas, thus leading to potential bamboo expansion.

The higher fire probability in dead bamboo patches during drought events, ~~altogether along~~ with the increasing human influence, can favor increases in bamboo abundance and expansion ~~overtime~~ over time by assisting them in their competition
25 with trees. A previous study showed that fire favored the *Guadua* bamboo expansion in the region, because the bamboo individuals have faster responses to catastrophic disturbance such as fires than tree species (Smith and Nelson, 2011). Thus, when a fire occurs inside or close to a bamboo forest patch, it may favor the growth of bamboo seedlings ~~—~~ derived from the massive amount of seeds that have been launched during the reproductive phase and prior to death ~~—~~ and the vegetative expansion of the adult bamboo.

30 Our findings regarding bamboo die-off year being associated to fire occurrence, mainly in drought years, might have implications to fire control policies, such as in the state of Acre in Brazil, where many bamboo-dominated areas occur near human settlements and that these extreme climate events are occurring within 5 years' interval in Amazonia. By knowing where and when the die-offs are occurring, public policies can be made to avoid fire ignitions in such areas or prepare the fire brigades to attend to potential fires.

5 Conclusions

This study demonstrates that the NIR reflectance is more sensitive to the bamboo life cycle than the other spectral intervals and can be used to detect and map bamboo-dominated forests distribution, age structure, and death. The automatic bamboo die-off detection achieved an accuracy above 79 % by assessing the point of maximum correlation between the ~~near-infrared~~ NIR time series and a bilinear model of linearly increasing NIR with a sharp decrease at the end. After merging the die-off map with the live bamboo map, a total of 155,159 km² of bamboo-dominated forests was mapped in the region. It is noted, however, that this area was probably still underestimated due to the limited temporal coverage of the MODIS (MAIAC) time series. ~~The ‘bamboo-fire hypothesis’ restricted to the last two decades. The bamboo–fire hypothesis~~ was not supported by our results, because only a small fraction of bamboo areas burned during the analysis timescale, ~~and, in~~. In general, bamboo did not show higher fire probability after the reproductive event and die-off, meaning that fire should not be the driver for bamboo dominance. Nonetheless, ~~when~~ under severe droughts effects, forests with recently dead bamboo are more susceptible to fire than forests with live bamboo, being affected by 45 % more fire occurrence. The fire in these areas is mostly associated with ignition sources from land use, suggesting a ~~bamboo-human-fire~~ bamboo–human–fire association. The interaction of dead bamboos and ignitions cause increased fire occurrence that may contribute to the maintenance of bamboo, burn adjacent forested areas and promote tree mortality, and ultimately the expansion of bamboo into adjacent areas.

Further research related to bamboo dynamics can use the bamboo die-off map that we produced to pinpoint the location of reproductive and die-off events in space and time in order to support studies of bamboo maintenance and colonization, wildfire dynamics, carbon assimilation in trees and bamboos, tree mortality, fauna/flora demography and species distribution, etc. The mapping approach can be applied with other remote sensing data, such as Landsat data with better spatial resolution and longer time series, and tested with different spectral bands and attributes to further improve the detection. It can also be applied in other areas around the world that have bamboo-dominated forests. Using this approach, one can evaluate the temporal dynamics of the reproductive events (e.g. spreading of flowering waves) and map the bamboo-dominated areas.

Data availability. The processed MODIS (MAIAC) data and bamboo maps processed in this paper are freely available and published at: <http://doi.org/10.5281/zenodo.1229426>.

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