We thank the reviewers for taking the time to provide additional comments. Our reponses are inserted below the reviewer comments in italics.

1 Review 1

Page 14 line 10: Update to "NPP turns negative does drought effect the vegetation."
1) Updated to include the next comment.

Page 14 line 9-10: Add in how drought impacts the vegetation currently. What are the effects of drought that take effect after NPP turns negative for 5 years? Diminished productivity? Through percent reduction biomass? Total die-off?
2) NPP is the productivity, lower productivity of course also leads to lower biomass, the effect of five years negative NPP is that PFTs stop establishing. We changed the sentence, (also addresses previous comment) to:
...only if a 5 year average of NPP turns negative, PFTs stop to establish.

Page 14 line 11-12: "The excessive tree cover could be partly improved by improving the non-vegetated fraction which decreases too fast with increasing precipitation." The non-vegetated fraction decreases too quickly, implying that the vegetation increases and controlling this vegetation response is important to addressing the excessive tree cover. What could be a mechanism of improvement be for the drought response?
3) From this analysis it is not possible to draw conclusions about the mechanisms. The non-vegetated fraction depends on vegetation productivity, therefore improvements in productivity might help, also the hydrology is an important process for the drought response, we therefore mention the relation to these two processes as examples now:
This non-vegetated fraction depends on the productivity of vegetation. Further investigation of effects of the soil moisture memory not only on climate (Hagemann and Stacke, 2015) but also on the vegetation might also lead to useful insights.

Page 14 line 25: I think you mean "lower sensitivity to fire due to higher bark thickness and taller crown leading to lower probability of crown scorch." Update.
4) We removed the part on the crown, as the paragraph mostly focusses on the bark thickness.

Page 14 -15, pg14 lines 21 to pg 15 line 14. There are duplicate sentences and redundancies in this paragraph. Improve the organization of the paragraph and remove redundancies. Specifically, the sentence about JSBACH-SPITFIRE and bark thickness is duplicated.
5) We removed the duplicate sentence and restructured and shortened the paragraph.

Page 15 line 11: SPITFIRE quantifies fire intensity. Are the fires more frequent and of lower intensity once the tree cover has decreased?
6) Fire frequency increases with decreasing tree cover as seen here in Figure 4,6 and 7 and in Lasslop et al. 2015. Fire line intensity however does not decrease with increasing burned area (Figure 1. We add the figure to the supplement.

Page 15 line 15-21: Complete this paragraph with a concluding statement of how including saplings and adult long lived trees may impact the balance of tree cover to bare fraction or fire behavior in SPITFIRE.
7) We included:
Including a sapling state could therefore increase tree cover in frequently burned areas, while decreasing tree cover (as described above) in areas that are too dry to provide fuel for frequent burning.

Page 16 line 7: Update to "...climate models have problems representing extremes..."
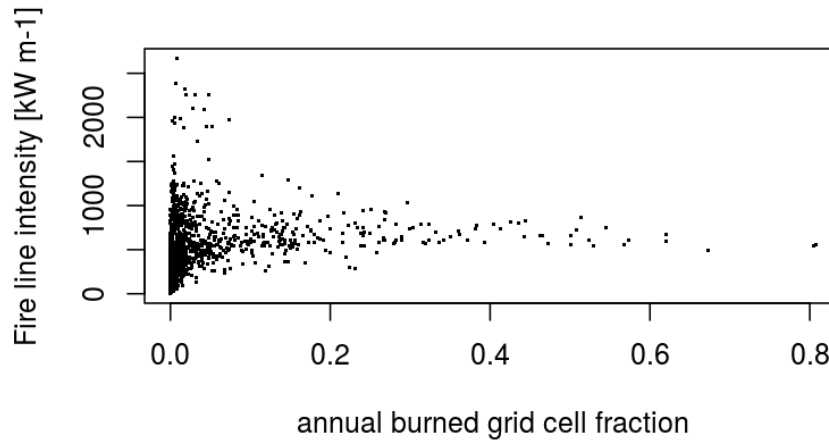*8) We updated the text as suggested.*

Figure 1. Relationship between annual burned area and fire line intensity. The expected decrease in fire line intensity for frequently burning areas is not found in the simulation results and might indicate that the feedback between fire occurrence, fuel load and fire intensity is too weak.

Page 16 line 15: " fire is quite sensitive to the length of dry seasons" add references supporting this statement.
9) change to number of dry days reference to Bistinas, also reference to correlation between dry days and mean precipitation in supplement.

5   Page 17 line 1-3: The evidence that increases in managed land leads to decreased burned area is supported in the recent literature as referenced in the manuscript. Remove the sentence about roads as a fire break or provide a citation recognizing this link within the tropics. Roads are often a source of ignitions that also impact the spatial variability of burned area (Loboda and Csiszar 2007 RSE; Syphard et al 2007 Eco. Appl.; Syphard et al 2008 Int J Wild Fire; Narayanaraj and Wimberly 2012 Appl. Geog; Faivre et al 2014 Int J Wild Fire).

10 Additionally, there is evidence that forest fragmentation due to land cover change by humans leads to increases in fires. This type of fragmentation is shown to alter micro-climate conditions within forest canopies and lead to increased understory ignitions and fires. (Morton et al 2013 Philos Trans R Soc; Brando et al 2014 PNAS; Soares-Filho B et al. 2012 Landscape Ecol.) This connection is not well represented in models, but, as detailed in these references, representation of forest fragmentation specifically is an important component of capturing the relationship between humans, land use and fire. Further, as demon-

15 strated by and detailed within these references there is an expanding understanding of the relationships between humans, land use and fire. Acknowledge that this research is progressing, alongside the need to improve this representation in models.
10) We remove the sentence about roads. The studies mentioned here are on a much smaller scale than our simulations, global large scale analysis so far only support the decrease of burned area due to humans. We mention that work on local scale helps to increase the understanding, however a generalization to the large scale is still needed to be able to represent it in global

20 *models. As this is not the working scale of our model we do not include all 8 additional references, but only the most recent ones:*
The mechanism behind the reduction in burned area due to croplands is however likely a fragmentation of the landscape, which is not explicitly accounted for in the model. On local scale understanding on these relationships is increasing, for instance the relation between fire and roads (Faivre et al., 2014; Narayanaraj and Wimberly, 2012) or between fire and land management

25 *(Morton et al., 2013; Brando et al., 2014). However, a generalization to an approach that would be suitable for global models*

is still missing.

2 Review 2

We only include the points where the reviewer disagrees to shorten the text and time needed to read it.

The remaining main concern of the reviewer is summarized in the beginning of the review:
However, I remain concerned about the response to the "choice of JSBACH driving data", although after clarification on the aims of the analysis, I am no longer sure if the this is an issue with using ESM model output itself or the way this is used to infer areas for improvement of JSBACH.

11) The main concern of the reviewer with respect to the climate biases is the seasonality of the rainfall. We therefore performed an additional analysis comparing the number of dry days and the rainfall seasonality of the forcing data used here to the CRUNCEP observational model forcing dataset (used in the FireMIP simulations, a setup that was suggested by the reviewer). We define rainfall seasonality as the number of days needed to reach 80% of the annual precipitation, and dry days as days with less rainfall than 3 mm. The CRUNCEP dataset is a reanalysis dataset commonly used in offline model comparisons (Rabin et al., 2017). This analysis (, now a figure in the supplement) shows that the number of dry days in dry regions is well comparable between model and CRUNCEP, for moister regions the number of dry days is even higher in the forcing dataset (MPI-ESM output) used here. We therefore confirm that our conclusions are unlikely affected by biases of rainfall seasonality. The reviewer now also mentions existing biases in shortwave radiation. Of courser biases always exist, here, however, it is important whether the climate biases could have such a strong effect as the reviewer claims. Shortwave radiation does not affect the tree cover in JSBACH, we quickly tested it by applying a multivariate regression, precipitation is highly significant, radiation is not significant if only these two variables are used in a multivariate linear regression. As so far there is no discussion on shortwave radiation and how it influences the model in the paper, we did not include this in the manuscript as it would require several paragraphs to be added.

Choice of JSBACH driving data

The authors have clarified the three aims:

1. Develop a simple multivariate technique to explore the difference between modelled and observed vegetation, fire and climate.

2. Use these differences to evaluate the simulation of, and coupling between, tree cover and burnt area in JSBACH

3. To do this within the MPI-ESM framework, achieved by driving JSBACH offline but with MPI-ESM model output.

There is nothing wrong with the aims, and I like that the authors attempt to at keep the methodology relatively simple. Driving the JSBACH as configured for use in MPI-ESM, offline with ESM output also makes sense, and in their response and suggested changes to the manuscript, the authors have justified the choice of driving data. The authors also discuss the weaknesses associated with this method in the revision of section 4.1, which is also a welcome addition to the paper. However, to critique solely the land surface component in an ESM setup such as this, as if it were independent of other potential climate model biases seems to contradicts the 3rd aim above and introduces the methodological inconsistency which I don't feel have been adequately addressed. To phrase in terms of the multivariate approach, the authors have diagnosed the vegetation cover and fire axis, but not the climate axis.

12) We also already mentioned climate biases in the revised version of the manuscript in more detail. The expected drizzle, which seems to be the main concern of the reviewer, however, is not present in our climate forcing as our new analysis shows. See also reply 11. Our proposed method clearly goes beyond the normal variable by variable comparison. Including all variables that might be important in the coupled system of fire, vegetation and climate would be optimal in a certain sense but would then suffer from the complexity of the necessary approach and difficulties in interpretation. As stated in the manuscript we use precipitation as a proxy for climate and precipitation is included as one of the axis. The same critisim, that there could be biases not in the mean but in another characteristic of precipitation, could apply to fire and vegetation cover. We simply use annual burned area as a proxy for the fire regime, but fire intensity and seasonality and extremes can be important characteristics too. For tree and grass cover we also summarized two PFTs into one variable. This is the compromise we did to allow a
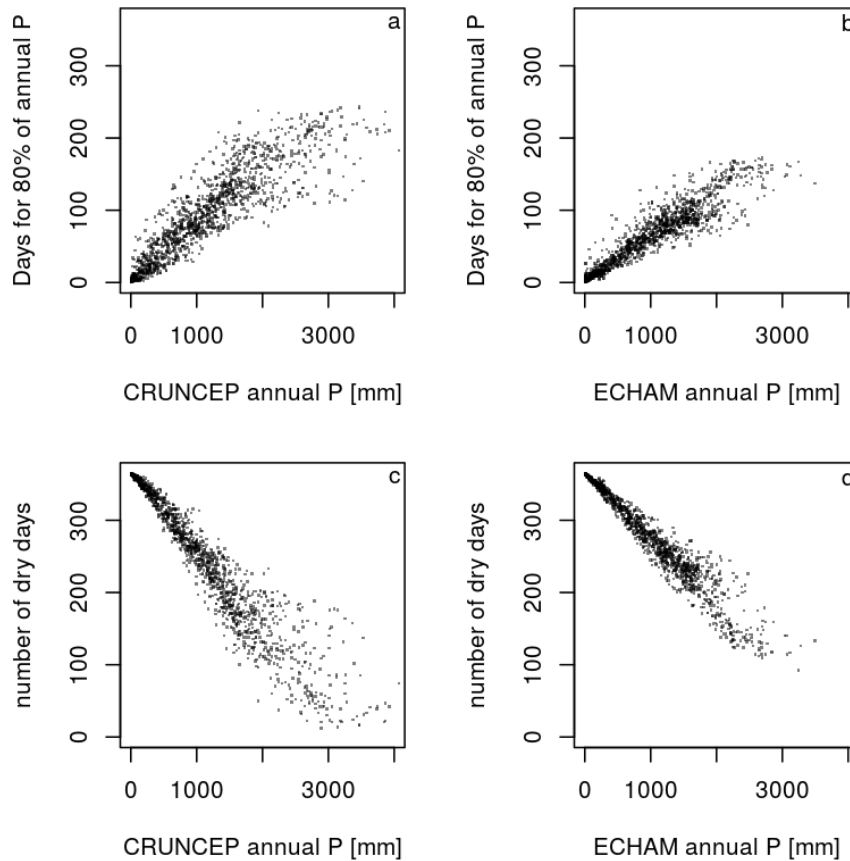
Figure 2. Relationship between annual precipitation and precipitation seasonality and number of dry days for the ECHAM simulation used as meteorological forcing for the JSBACH simulations used here and the CRUNCEP dataset.

simple interpretable approch.

The authors state in their response that "regarding the conclusions we draw from our comparison we don't see a strong point that they would be strongly affected." Here are just some examples from the (revised) paper where climate biases could
5   potentially affect either the results, discussion and/or conclusion:
1. Surprisingly the observations show a higher Spearman correlation between tree cover and precipitation than the models (Table 1). The lower correlation of the modelled relationship most likely originates from the lower precipitation regions (<500 mm year-1 where the maximum tree cover is very low in the observations and both models strongly overestimate the maximum tree cover (Figure 4).
10   The correlation between MAP and other climate variables that influence tree cover could also break down in the MPI-ESM driving JSBACH. As already noted, length of dry seasons are likely to be shorter in seasonal climates. Most GCMS models (although I don't know if MPI-ESM is amongst them) also suffer from biases in downward SW (Li et al. 2013) which could influence tree cover, particularly at the higher tree cover range, where figure 5 also indicates mismatches beetween model and observation in some continents, particularly Asia.
15   *13) Radiation could have a considerable influence on the productivity of PFTs, but is very unlikely to influence tree cover*

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in JSBACH for the tropics based on the way the model is build. We tested this also quickly with a multivariate regression TC=a1*P+a2*R for the modelled variables where the influence of radiation is not significant. It is therefore unlikely that biases in radiation would show up in tree cover. We now show that the number of dry days is not less in the ECHAM forcing. See also reply 11 and 12.

5 2. JSBACH overestimates tree cover for low precipitation on all tropical continents. The drizzle problem already discussed seems like an obvious candidate to affect vegetation cover at low precipitations, either through decreasing the length of dry periods or due to associated changes in cloud cover changing evaporative demand and hence available moisture. Despite not ruling out additional climate problems, the authors use this simulated mismatch at low tree covers to justify planned changes
10 to tree to vegetation dynamics: only if a 5 year average of NPP turns negative, drought effects on the dynamic vegetation take effect. Other models require a minimum of 100 mm year-1 precipitation for sapling establishment (Sitch et al., 2003). The too high excessive tree cover could be partly improved by improving the non-vegetated fraction which decreases too fast with increasing precipitation and Tree-grass competition for water could for example be improved in the model by introducing the a sapling stage of trees, which are competitively inferior to grasses (D'Onofrio et al., 2015). Including this mechanism could
15 improve the balance between tree and grass cover, but it could also reduce the establishment rate of trees and therefore the tree cover in the dry regions with excessive tree cover. Including a PFT-specific rooting depth of vegetation would be an important extension of the model to improve the competition for water between grasses saplings and adult trees. These three fundamental changes to the dynamics of JSBACH are suggested without establishing that the problem is with JSBACH itself. While it is often necessary reparameterize components of ESMs to compensate for biases in other model components, this should always
20 been done in the knowledge that it is to compensate for other these other biases, and the suggested changes to JSBACH above go beyond a standard re-parameterization.

14) Our analysis shows that there is no drizzle problem see reply 11. The suggestions made here are also based on the too strong dominance of trees in dry regions, grasses can only exist if fire is present, effects of climate on productivity would not make a difference about this in the model. Even if there were other climate biases or other problems in the model, the processes
25 *discussed here are known to be crucial for the vegetation composition in dry areas, therefore suggesting that including them could help the model be better is in our opinion reasonable. We add in the manuscript:*

The suggested processes are known to be important for the vegetation distribution and it seems plausible that they can help to improve the vegetation distribution.

30 3.For Australia underestimation of burned area for both fire models is strong (Figure 4). In a previous evaluation where the model was forced with observed climate and vegetation cover was prescribed (in contrast to the dynamic vegetation cover and climate modelled by the MPI-ESM) JSBACH-SPITFIRE showed better results for Australia (Hantson et al., 2015). An improved response of vegetation cover dynamics to precipitation will therefore likely improve the patterns of burned area. The better simulation of fire in Hantson et al. 2015 could also be due to better representation of rainfall timing and distribution,
35 temperatures or any number of climate factors from being driven by observed climate. Also, better representation of vegetation cover would hopefully have been achieved in Hantson et al. 2015 with observed rather than simulated climate. Again, parameterization of either JSBACH or SPITFIRE to account for additional climate biases may be necessary in an Earth System model, but here the author imply the the problem is with JSBACH itself.

15) A reduction in tree cover would lead to an increase in burned area, therefore what we write is correct. Or vice versa the
40 *high burned fraction observed in Australia cannot be achieved with SPITFIRE if such a high tree cover is present. The JSBACH model is parameterized for the coupled setting not for the observational dataset. The model shows between 10 and 30% tree cover for any precipitation below 500mm per year, while the observations a maximum of 10%. The discrepancy is rather large and it seems unlikely that a different distribution of rainfall can explain the difference. Also the reviewer does not give any references that climate model biases can have such a big effect. Of course any of the climate parameters used can be wrong,*
45 *but the same would be true for any observational dataset used as model forcing.*

 4.This indicates that not an improvement of the fire model but improved modelling of drought effects on the vegetation dynamics will improve the response of vegetation to climate in dry regions. Again, another likely explanation is MPI-ESM rainfall distribution or the impact of other climate factors on available moisture etc.

16) In regions where fire is absent trees always win the competition in JSBACH, it is therefore impossible that other climate factors can solve this, the only reasonable reason is the absence of drought effects on vegetation cover in the model.

5. Intercontinental variation in the relationship between precipitation and maximum tree cover is much smaller for the models compared to the observations. Known variations in vegetation are not sufficiently understood to be represented in models. However our finding that models do show differences in the fire-vegetation-climate relationships between continents shows that further exploration why models show differences can be helpful to better understand causes for intercontinental differences. If this is meant purely for land surface modelling, then there is little in the results of this paper to justify this statement. That there is a modelled difference in fire-vegetation-climate relationships between continents would be more valid if the authors made it clear that this statement is about the ESM setup as a whole.

17) This comment is unclear, the variations that are mentioned are observed and the model also shows some variations. We do not see how the ESM setup as a whole comes in here.

6. Overall the multivariate model evaluation highlights the potential for more targeted model improvements with respect to the interactions between climate vegetation and fire, which are crucial for our understanding of future vegetation projections. Again, this is fine as a statement about the ESM setup as a whole, but not focusing solely on the land surface component. Of course, there are more suggest model improvements in the manuscript where inherent climate biases from MPI-ESM have (to my mind at least) no obvious impact. However, even in these cases, the authors should be careful at presenting potential new model processes without first checking for the influence in other climate biases. The apparently stronger correlation between fire and tree cover compared to observations, for example, is used to suggest inclusion of resprouting and adaptive bark thickness or fuel feedbacks that might influence fire intensity and hence tree mortality. Again, there are no end of climate biases that could affect intensity which would not be picked up by a straight MAP-tree cover-bunt area comparison. And again, these changes go far beyond standard reparameterization of a land surface model in an ESM. To be fair to the authors, they have included the statement "exact parameterization and needs to be tested with stepwise model development and factorial simulations" which does help mitigate some concern with model changes such as this.

18) Climate biases can clearly influence the burned area, and its spatial patterns, but I do not see a way that climate biases will turn around the impact of fire on tree cover that much in SPITFIRE, except for the fire-fuel feedback mentioned by the reviewer here. This feedback is already included in the model and different climate forcing leading to different fuel loads could maybe strengthen the feedback. However, in that case it would make sense to reparameterize the model to strengthen the feedback in the Earth system model setting.

The authors suggest in their response that only way to address this contradiction is the do detailed assessment of the atmospheric component of the model, or perform complex experiments or analysis using additional model driving data. This is almost certainly not the case, and it would be a shame if further revisions did make the analysis more complicated. However, some additional, simple analysis might resolve the issue. Here are some examples based on the author responses:

We use the standard JSBACH setup, which is the combination of JSBACH with MPI-ESM meteorology. As the fire is sensitive to a number of variables, evaluation of the model in a different setup wouldn't help to guide model development for a model that is almost only run in the coupled setup.

A run with observed climate obviously wouldn't be used as a basis for further model development if your aiming to improve JSBACH when driven with ESM meteorology. But it would help the authors determine if the deficiencies already identified are due to simulated climate biases or due to the vegetation component, and would place their discussion on much firmer ground. This is part of the justification for offline land surface model runs required for MIPs associated with CMIP6, e.g (van den Hurk et al. 2016; Lawrence et al. 2016).

19) Using observed climate is obviously most useful when looking at the spatial patterns, which we avoid with our method. It is certainly an important approach, our aim here was to evaluate the model for the Earth system model setup.

our motivation here is to evaluate the land surface model, a detailed evaluation of climate biases in the ECHAM model is therefore out of scope

There is no need to do a detailed evaluation of climate biases in ECHAM (which would indeed be out of the scope of this

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paper). However, the authors should ascertain if problems in land surface simulation are caused by either problems in the simulation of the land surface or problems with the information it receives from the atmospheric component - a rather basic first order assessment of any land surface model within an earth system framework. I was able to give a few pointer to potential climate biases from my limited knowledge of climate intermodel comparison literature in my last review. The authors should be able to identify other MPI-specific climate biases that they could at least discuss if not to test. As stated in the last review, there are two of instances where climate model deficiencies are discussed (i.e, when explaining discrepancies in simulated spatial patterns and when discussing calculation of lightning ignitions). At the very least, these types of discussions should be included when critiquing the rest of JSBACH.

20) We adressed the problem of the drizzle now, showing that the seasonality and number of dry days is comparable in ECHAM and a observational model forcing dataset. We already discuss model deficiencies in the revised version in appropriate sections, more specifically in the section where discuss potential model improvements, repeating these in more parts would lead to redundancies.

Understanding potential influences of certain climate biases (such as extremes) on the simulation would require specific factorial experiments

and

While certainly more parameters influence tree cover distribution an increasing number of variables included to explain patterns would require a totally different appraoch

Not necessarily. A first step could be to simply show if other climate information (no. dry days, downward SW etc) are causing some of the relationships you see using the exact same approach used for MAP. It may well be that this shows that using MAP alone does do a sufficient enough job as a proxy for climate space, which will then support the rest of the papers discussion. If not, then any additional climate variable that explains some discrepancy could be included in the same way that grass and tree cover are interchanged at various stages in the manuscript.

21) Precipitation is the main driver of vegetation cover in the tropics. Removing the main driver from this analysis and exchanging it with other potential climatic drivers that are correlation with Precipitation would likely lead to correlations between vegetation and the climatic driver mainly because of the correlation between the two drivers. The relationship would then still be caused by precipitation. We do not see a way for a useful interpretation of such relationships without removing the effect of precipitation, which would require a more complex approach. Exchanging tree and grass cover is different as both are mainly driven by precipitation and fire.

Mean annual precipitation explains a large part of the tree cover variability and therefore is a useful proxy for climate

Obviously not enough in JSBACH when driven by MPI climate data - the range of TC at a given MAP is one of the features JSBACH as driven by MPI data does not replicate, and there is no other result to help indicate how much of this discrepancy is due to simulation of vegetation cover or other climate biases. While I do not expect the authors to address all these points in the manuscript (that would be a very long paper!), I hope that I have demonstrated they are certainly not without options. Picking up on one or two of these point, or anything else which can either show MAP really is enough by itself to account for all other climate biases or that can truly attribute problems with model performance to either JSBACH or MPI-ESM climate, will be sufficient.

22) The reviewer agrees that JSBACH is not enough driven by mean annual precipitation, our previous comment cited here refered to observed relationships (although this may have been not exactly clear). He also agrees that adressing all his comments is outside of the scope of this paper or would make the paper too long. We hope that the additional analysis with the number of dry days, which supports that our main discrepancy between model and observations (the overestimation of tree cover for dry regions is a problem of JSBACH not the forcing data, adresses most of the reviewers concerns.

As the authors are only able to use MPI-ESM model output till 2005 to drive JSBACH, they have to make a rather awkward choice about comparison time periods, as identified in the last review. An ideal solution to this would be to run MPI-ESM beyond 2005, something that could be happening as part of CMIP6 simulations? However, I realise that this is probably not possible, and the MPI-ESM may well be configured differently for CMIP6 simulations. I would like to hear to authors thoughts changing the comparison periods though. The authors state that "Using only the overlapping period (2001-2005) would de-

crease the robustness of the mean fire regime and climate characterization". This is certainly true for fire regime. However, tree cover is normally more stable, and as trees take a few years to establish, the cover found during 2001-2005 would of also be a consequence of burnt area and climate before this period. Perhaps a better choice is to split comparison periods based on variable rather then on model/observation. i.e, when performing analysis, take modelled and observed burnt area and climate
5 from 1996-2005 (climate data, MPI and GFED overlap) and tree cover from 2001-2005. While this is still a rather pragmatic solution to the mismatch in modelled and observed time periods, it might make more sense then the pragmatic solution outlined in the manuscript?

23) We prefer to keep the same averaging periods for all variables. If the goal was to only evaluate tree cover it would likely be a good idea. The goal here is however to evaluate the interactions. Tree cover influences the fire regime therefore having the
10 *same averaging period for these two variables seems plausible to us. Also the GFED data have more problems for the earlier years and are more reliable from 2001 on.*

I am happy with all changes except for a couple of small details:

39 and 45) Kelley and Harrison 2014 should probably be changed to Kelley et al. 2014:
15 Kelley, D. I., Sandy P. Harrison, and I. C. Prentice. "Improved simulation of fire–vegetation interactions in the Land surface Processes and eXchanges dynamic global vegetation model (LPX-Mv1)." Geoscientific Model Development 7.5 (2014): 2411-2433.

Kelley and Harrison 2014 looks at future changes in fire, whereas Kelley et al. 2014 is the paper describing model development and benchmarking.
20 *24) We thank the reviewer for finding this mistake, the reference is corrected.*

42) Was the "minor shifts between woody PFTs in a few cells" quantified? Quantifying equilibrium during spin-up should really be a requirement for any modelling study, and if authors did quantify equilibrium in any way, then it would help the cause to state how this was assessed. However, I do understand that quantifying equilibrium is unfortunately not standard practice,
25 and finding a way to do so is well outside the scope of this paper. So if it was not quantified, then leave this sentence as is.

25) The minor shifts were not used to quantify equilibrium. We therefore leave the sentence as is.

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Tropical climate-vegetation-fire relationships: multivariate evaluation of the land surface model JSBACH

Gitta Lasslop[1,2], Thomas Moeller[1], Donatella D'Onofrio[3], Stijn Hantson[4], and Silvia Kloster[1]

[1]Max-Planck Insitute for Meteorology, Bundesstraße 53, 20146 Hamburg, Germany
[2]Senckenberg Biodiversity and Climate Research Centre, Senckenberganlage 25, 60325 Frankfurt am Main, Germany
[3]Institute of Atmospheric Sciences and Climate (ISAC-CNR), Torino, Italy
[4]Karlsruhe Institute of Technology, Institute of Meteorology and Climate research, Atmospheric Environmental Research, 82467 Garmisch-Partenkirchen, Germany

Correspondence: Gitta Lasslop (gitta.lasslop@senckenberg.de)

Abstract. The interactions between climate, vegetation and fire can strongly influence the future trajectories of vegetation in Earth system models. We evaluate the relationships between tropical climate, vegetation and fire in the global vegetation model JSBACH, using a simple fire scheme and the complex fire model SPITFIRE with the aim to identify potential for model improvement. We use two remote sensing products (based on MODIS and Landsat) in different resolutions to assess the ro-

5   bustness of the obtained observed relationships. We evaluate the model using a multivariate comparison that allows to focus on the interactions between climate, vegetation and fire and test the influence of land use change on the modelled patterns. Climate-vegetation-fire relationships are known to differ between continents we therefore perform the analysis for each continent separately.

The observed relationships are similar in the two satellite datasets, but maximum tree cover is reached at higher precipitation

10   values for coarser resolution. The model captures the broad spatial patterns with regional differences, which are partly due to the climate forcing derived from an Earth system model. SPITFIRE strongly improves the spatial pattern of burned area and the distribution of burned area along increasing precipitation compared to the simple fire scheme. Surprisingly the correlation between precipitation and tree cover is higher in the observations than in the largely climate driven vegetation model, with both fire models. The multivariate comparison identifies an excessive tree cover in low precipitation areas and a too strong

15   relationship between high fire occurrence and low tree cover for the complex fire model. We therefore suggest that drought effects on tree cover and the impact of burned area on tree cover or the adaptation of trees to fire can be improved.

The observed variation of the relationship between precipitation and maximum tree cover is higher than the modelled variation. Land use contributes to the intercontinental differences in fire regimes with SPITFIRE and strongly overprints the modelled multimodality of tree cover with SPITFIRE.

20   The multivariate model-data comparison used here has several advantages: it improves the attribution of model-data mismatches to model processes, it reduces the impact of biases in the meteorological forcing on the evaluation and it allows to evaluate not only a specific target variable but also the interactions.

1 Introduction

Capturing the interactions of vegetation cover and composition with the climatic drivers and related disturbances in Earth system models is crucial to provide reliable changes of vegetation for a changing climate. Climate is the main driver of global
5 vegetation patterns, but also vegetation has crucial impacts on the Earth system, due to its influence on the surface albedo and the water cycle (Bonan, 2008; Brovkin et al., 2009). The importance of vegetation type has been assessed in various studies: when compared to grasslands, forests in tropical areas cool the climate due to higher evapotranspiration while in boreal regions, forests warm the climate due to a reduction of the albedo (Bathiany et al., 2010). The relevance of vegetation also shows when contrasting vegetated and non-vegetated surfaces: in the Sahel region this difference is of major importance for the climatic
10 conditions (Brovkin et al., 1998).

Interactions between vegetation, fire and climate are particularly important to understand the spatial patterns in tropical vegetation, which is characterized by strong gradients from deserts to tropical rainforests. Remotely sensed tropical tree cover shows a bimodality between forest (T>60%) and savanna (T<60%) states for grid cells with similar climate. Intermediate tree cover fractions (e.g. 60%) are virtually absent (Hirota et al., 2011; Staver et al., 2011b). The occurrence of this "gap" in tree cover was
15 suggested to be caused by a feedback between fire and vegetation. Although the reliability of remotely sensed tree cover sets to diagnose this "gap" was recently questioned (Gerard et al., 2017), the bimodality in the distribution is also confirmed by canopy height (Xu et al., 2016) or biomass (Yin et al., 2014). The occurrence of both forest and savanna states under similar climate conditions due to a feedback between fire and vegetation is supported by conceptual (Staver et al., 2011a) and process-based models (Higgins and Scheiter, 2012; Moncrieff et al., 2014; Lasslop et al., 2016) .
20 While data analysis can provide insights on driving factors for certain variables, process-based models summarize the process understanding and allow us to perform experiments that are impossible in reality. Dynamic global vegetation models (DGVMs) were developed to understand ecosystem dynamics, the carbon cycle and biosphere-atmosphere interactions (Sitch et al., 2003). Many of them are part of Earth system models (ESMs), to represent the dynamics of the land surface within the climate system. It is therefore important that DGVMs include appropriate representations of vegetation to obtain reliable simulations of the
25 Earth system(e.g. Baudena et al., 2015).

The development of remotely sensed global burned area products facilitated the implementation and evaluation of complex fire models within DGVMs (Hantson et al., 2016). Over the recent years these models were applied to address the impact of fire on the carbon cycle (Li et al., 2014; Yue et al., 2016), the land surface temperature (Li et al., 2017) or the sensitivity of the fire model to driving factors (Kloster et al., 2010; Lasslop and Kloster, 2015). Evaluation of fire models mostly focused on
30 evaluating the burned area and carbon emissions, but also the importance of benchmarking effects on vegetation has been noted (Hantson et al., 2016) and applied in model development studies (Kelley and Harrison, 2014; Lasslop et al., 2014)(Kelley et al., 2013). The evaluation, however, is based on comparing variables one by one and not the relationships between them. Baudena et al. (2015) go beyond the geographic comparison by analyzing the relationship between tree cover and the main climatic driver

2

(precipitation). Also the relationship between ~~precipitation and climate~~ climate and fire was evaluated in previous studies (Prentice et al., 2011). However, to our knowledge, climate, vegetation and fire have not been combined in a multivariate model-observation comparison.

Here, we aim 1) to assess the robustness of observed climate-vegetation-fire relationships across the tropical continents based on two remotely sensed tree cover datasets; 2) to test a multivariate model evaluation to identify opportunities for model improvements in JSBACH, the vegetation model used within the MPI Earth system model, and 3) to test the contribution of land use change on the obtained relationships.

2 Model and Data

To investigate the climate-fire-vegetation relationships in the tropical regions we represent climate by the mean annual precipitation (P), vegetation by the tree (TC), grass (GC) and non-vegetated cover and fire as the burned fraction (BF).

We define the tropical region as between -30° and 30° latitude. As continental limits we chose -20° to 60° longitude and -30° to 30° latitude for Africa, -130° to -30° longitude and -30° to 30° latitude for South America, 60° to 160° longitude and -10° to 30° latitude for Asia and 100° to 160° longitude and -30° to -10° latitude for Australia.

2.1 Model and simulation description

We use the JSBACH land surface model (Reick et al., 2013), which is the land component of the MPI Earth system model (MPI-ESM) (Giorgetta et al., 2013). JSBACH simulates the terrestrial carbon and water cycle in a process based way. We use two fire algorithms, a simple empirical model (Brovkin et al., 2009; Reick et al., 2013) and the process-based fire model SPITFIRE (Lasslop et al., 2014; Thonicke et al., 2010). Results referring to simulations with the complex SPITFIRE model are referred to as JSBACH-SPITFIRE, simulations with the simple JSBACH standard fire scheme are indicated as JSBACH-standard. These two approaches span the range of complexity of currently used global scale fire models (Hantson et al., 2016). The JSBACH-standard fire computes burned area based on a minimum burned fraction which increases as a function of the litter carbon pools and relative humidity averaged over the last three weeks. It was tuned to yield reasonable global emission estimates (around 2PG carbon) and to improve the tree cover, which is clearly too high without fire. SPITFIRE computes burned area based on human and lightning ignitions, fire spread rate and a fire duration. SPITFIRE distinguishes between different fuel particle sizes and uses a combination of minimum and maximum temperature, precipitation and soil moisture to determine the fuel moisture. Both fire models interact with the vegetation model as follows: JSBACH provides fuel amounts, vegetation composition and soil moisture as inputs to the fire model. The fire model in turn reduces the carbon pools of JSBACH according to the simulated carbon combustion of vegetation fires and reduces the cover fractions of burned vegetation. In the JSBACH-standard fire scheme the burned area directly translates into a reduction of the cover fractions of the plant functional types (PFTs) (100% of the cover fractions on burned area are removed). Whereas in SPITFIRE the mortality of woody vegetation depends on the fire intensity, fire residence time, the vegetation height and bark thickness. The model's plant functional types for the tropics include C3 and C4 grass, tropical evergreen and deciduous trees, and rain green shrubs.

Shrubs and trees compete according to their net primary productivity. Grasses and shrubs have an advantage compared to trees in regions with disturbances due to their lower establishment time scale (Reick et al., 2013, grasses: 1 year, shrubs: 12 years, tropical trees: 30 years). PFTs do not establish if the 5 years running mean net primary productivity (NPP) turns negative. Land use is included following the protocol of Hurtt et al. (2011). The implementation is described in detail in (Reick et al., 2013).

5 Croplands are excluded from fire occurrence while pastures are treated as natural grasslands with a higher fuel bulk density within JSBACH-SPITFIRE (Rabin et al., 2017). The JSBACH-standard fire excludes fire occurrence on both anthropogenic land cover types. JSBACH-SPITFIRE shows a reasonable agreement with remotely sensed data products for present day burned area and carbon emissions for simulations with prescribed land cover (Lasslop et al., 2014). The present setup with dynamic biogeography has been evaluated along the human dimensions population density and cropland fraction. The model tends to

10 overestimate burned fraction for high cropland fractions and underestimates burned fraction for very low and high population densities (Lasslop and Kloster, 2017).

2.1.1 Simulation setup

JSBACH was forced with meteorological data extracted from a coupled simulation with the MPI-ESM version 1.1 for the historical period 1850-2005. The SPITFIRE model additionally uses a population density dataset (Klein Goldewijk, 2001) with

15 decadal resolution and a monthly lightning climatology (LIS/OTD product of the LIS/OTD Science Team, http://ghrc.msfc.nasa.gov) as input for the computation of ignitions. The model's spatial resolution is 1.875° x 1.875°. The time step for plant productivity and hydrology is 30 minutes, while the disturbance routine is called once per day. During the 1000 year spinup period the first 28 years of forcing (1850-1877) were recycled and CO_2 concentration fixed at the value of 1850 (284.725 ppm). At the end of the 1000 years PFT distribution was largely in equilibrium with only minor shifts between woody PFTs in few grid

20 cells. The subsequent transient historical simulation (Hist) from 1850-2005 accounts for the changes in atmospheric CO_2, climate, population density and land use. A complementary simulation accounting only for the rise in atmospheric CO_2, transient climate and population density but using the land use of 1850 for the whole period (cLU) is used to isolate the effect of land use change on the climate - vegetation - fire relationships. When comparing the model output to observations, the averaging period for the model simulations was 1996-2005, as the forcing was only available until 2005.

25 ## 2.2 Datasets for model evaluation

We averaged the remote sensing datasets over the years that were covered by all datasets (2001-2010). Model output is only available until the year 2005. Using only the overlapping period (2001-2005) would decrease the robustness of the mean fire regime and climate characterization. We therefore use different averaging periods for model (1996-2005) and observations (2001-2010). The presentation of the relationship between precipitation, tree cover and burned fraction based on remote sensing

30 data is based on 0.25° resolution and for the comparison with the model the datasets were aggregated to the model resolution (1.875°x1.875°).

2.2.1 Vegetation and land cover

We use two tree cover datasets based on satellite data, one based on the MODIS (moderate-resolution imaging spectroradiometer) sensor (Townsend et al., 2011), the other on the Landsat satellite (Hansen et al., 2013). Additionally we use the non-tree vegetation cover and non-vegetation cover of the MOD44B product version 051 (downloaded 6/February 2017, using the R modis package (Mattiuzzi and Detsch, 2018)). The datasets rely on different sensors, however, the algorithms to derive vegetation cover are very similar and the datasets are therefore not completely independent. Nevertheless using the two datasets can give a first insight on the robustness of the investigated patterns.

The maximum tree cover in the MODIS dataset is 80%. This however corresponds to 100% crown cover (Hansen et al., 2003). The modelled cover fractions represent rather the crown cover with a 100% maximum, we therefore linearly rescaled the tree cover data to improve the consistency between model and observations. The second dataset based on Landsat data builds on a high spatial resolution of 30m (Hansen et al., 2013). The dataset provides annual forest gain and loss over the period from 2000-2012. Alkama and Cescatti (2016) reconstructed the annual tree cover and aggregated the dataset to 0.05° . Here, we used the mean over their reconstructed annual tree cover values from 2001-2010.

The MODIS collection 5 land cover dataset (Friedl et al., 2010) was used to test the influence of shrub lands (open and closed shrub lands), as the tree cover data have a higher uncertainty for shrublands. The filtering was applied on 0.05° spatial resolution. This dataset is distributed by the Land Processes Distributed Active Archive Center (LP DAAC), located at the U.S. Geological Survey (USGS) Earth Resources Observation and Science (EROS) Center (lpdaac.usgs.gov), distributed in netCDF format by the Integrated Climate Data Center (ICDC, http://icdc.cen.uni-hamburg.de) University of Hamburg, Hamburg, Germany in 0.05° spatial resolution and annual time step.

2.2.2 Fire

The global fire emissions database (GFED, http://www.globalfiredata.org/) provides globally gridded monthly burned area based on the MODIS sensor. We used the version 4 of the dataset (Giglio et al., 2013).

2.2.3 Precipitation

The "TRMM and Other Data Precipitation Data Set" (TMPA) is based on the Version 7 TRMM Multi-satellite Precipitation Analysis algorithm (Huffman et al., 2007, 2010). The product has near global coverage from 50° north to 50° south. The precipitation estimate (including rain, drizzle, snow, graupel and hail) is based on a combination of multiple data sources including precipitation gauges. The dataset is available online (http://disc.sci.gsfc.nasa.gov/gesNews/trmm_v7_multisat_precip).

2.3 Quantile regression

We use quantile regressions to characterize the relationship between precipitation and maximum tree cover. The quantile regressions were computed with the R package quantreg (Koenker, 2018). We use the local quantile regression to characterize the shape of the increase in maxmimum tree cover for increasing precipitation. Moreover we quantify the deviation from a

5

linear increase by also including the linear qunantile regression. Both regressions were computed for the 0.9 quantile. For the local quantile regression the bandwidth parameter was set to 300 and the number of points where the function was estimated was set to 10.

3   Results

5   We first give an overview over the geographical distribution of the used observation and model output datasets. The comparison of geographical patterns is an important assessment of model performance, it is however difficult to assess whether the interactions between precipitation, fire and tree cover are well captured. Moreover as the JSBACH model is usually used as a land surface model for the MPI-ESM and therefore also here forced with MPI-ESM output, biases in model forcing can cause geographical biases of vegetation and fire variables even with a perfect fire and vegetation model. To reduce the in-
10   fluence of biases in forcing data on the model-data comparison and allow to more closely evaluate the interactions between model components we propose a multivariate evaluation of climate-fire-vegetation relationships. We assess the robustness of observed relationships for two tree cover datasets and two spatial resolutions and compare them to the model simulations. The last paragraph of this section adresses the influence of land use change on the simulated relationships.

3.1   Spatial distribution of vegetation cover, area burnt and precipitation in the tropics

15   The two observational satellite based tree cover datasets are consistent and show only small differences in their spatial pattern (Figure 1a). The overall clear pattern in tree cover is a transition from very high tree cover in moist rain forest regions to low tree cover in the drier savannas to the absence of trees in the desert regions. Both models reproduce this overall observed pattern, although with marked local differences. Both model versions overestimate tree cover in northern Australia to a similar extent. In the North-Eastern Amazon region the simulations underestimate tree cover compared to the observations. This
20   underestimation is much smaller for JSBACH-SPITFIRE. The simulations overestimate tree cover in Southern Hemisphere Africa, this overestimation is again smaller for JSBACH-SPITFIRE. The simulated grass cover has higher maximum values, but generally is often lower than observed by satellite (Figure 1 d). The non-vegetated fraction is captured well by the models (Figure 1 e).

Generally JSBACH-standard strongly underestimates the total area burnt and the spatial variability (Figure 1 b). JSBACH-
25   SPITFIRE improves the capability to represent fire regimes with high fire occurrences. The tropical average burned area per year is for JSBACH-standard 65 Mha, for JSBACH-SPITFIRE 242 Mha and for the satellite dataset 315 Mha. In South America spatial patterns in JSBACH-standard are inconsistent with the observations (most burning in the Northeast). JSBACH-SPITFIRE overestimates fire occurrence in South America but the spatial patterns are more similar to observations. In Africa we find reasonable agreement between JSBACH-SPITFIRE and the observations. JSBACH-standard shows a strong underes-
30   timation of the burned fraction (max. 10% of the grid cell area year^{-1}, while the observations show up to 100%). In Australia JSBACH-SPITFIRE and JSBACH-standard show similar patterns and both strongly underestimate the burned fraction.

Precipitation of the MPI-ESM forcing shows a dry bias in the East and central Amazon region, a dry bias in Asia, and moister
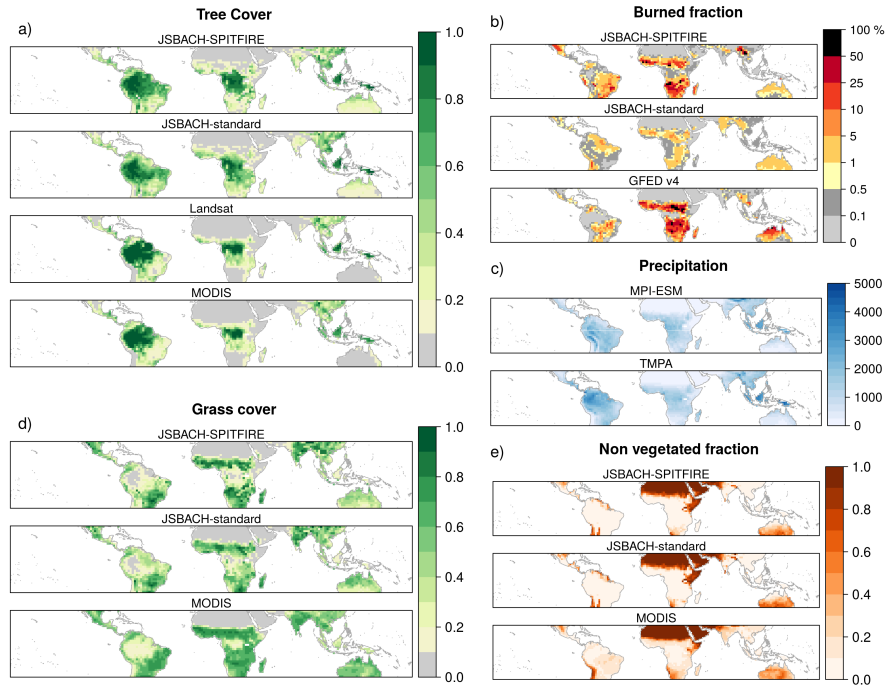
Figure 1. Spatial distribution of modelled and observed datasets used in this study. (a): Spatial distribution of tree cover fraction over the global tropics for the JSBACH-SPITFIRE and JSBACH-standard model simulation and the satellite data products from Landsat and MODIS. (b): Burned fraction [year^{-1}] as modeled by JSBACH-SPITFIRE and JSBACH-standard and the GFED v4 satellite product. (c): Precipitation in mm year^{-1} of the MPI-ESM and the TMPA dataset. (d): Grass cover fraction, and (e): non-vegetated fraction of the grid cell for the models and the MODIS satellite product. All datasets were remapped to the 1.875° model resolution.

conditions in the western part of southern hemisphere Africa (Figure 1 c). The dry bias in South America and Asia is known from previous ECHAM model versions (Hagemann et al., 2013; Stevens et al., 2013). The dry bias in precipiation in the Amazon may for instance explain the high bias in burned fraction in that region.

3.2 Climate-fire-vegetation relationships: comparison of observation datasets

Maximum tree cover shows an increase along the precipitation gradient across all continents, with trees being absent until a certain threshold (300-500 mm year^{-1}), increasing maximum tree cover and saturation of maximum tree cover for high precipitation (between 1500 and 2000 mm year^{-1}). The two remotely sensed tree cover datasets are consistent in their variation along the precipitation gradient (Figure 2). Fire occurrence is much higher for the African and Australian continent compared to South America and Asia. Burned fraction increases with increasing precipitation until around 1000mm mean annual precipitation, due to the increasing availability of fuels. For tree cover fractions higher than 0.8, fire is virtually absent. Beyond
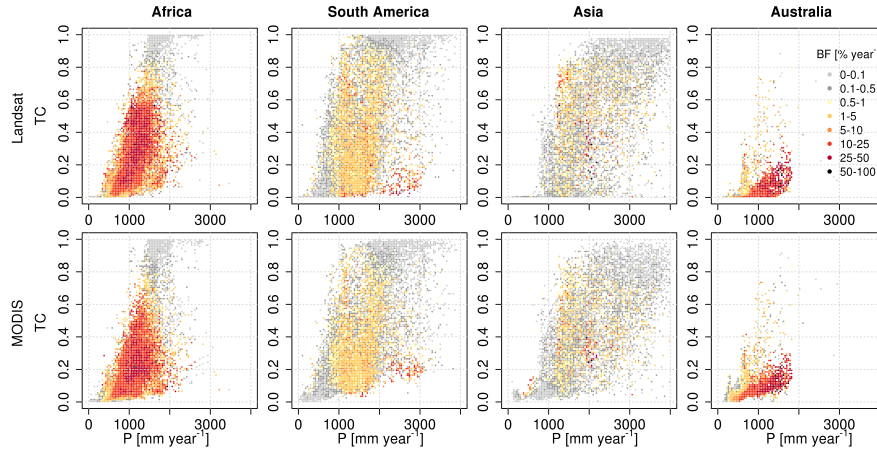
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Figure 2. Tree cover (TC) versus precipitation [mm year^{-1}] with color coded burned fraction (BF) for different continents for the two satellite datasets. Burned area is averaged over data points with the same precipitation (40 mm steps) and tree cover (in steps of 0.01) to avoid over-plotting based on a spatial resolution of 0.25°. For Asia some higher precipitation values were cut off.

this distinction there is no visually clear increase in burned fraction for decreasing tree cover at a given precipitation value. The Spearman rank correlation between burned fraction and tree cover for grid cells with mean annual precipitation higher than 1000mm and tree cover lower than 0.8 is, however, significant for both datasets in the 0.25° resolution, in the model resolution only the correlation with the MODIS dataset is significant. This correlation is much stronger for the MODIS tree cover ~~compare~~ compared to the LANDSAT tree cover (Table 1). For Australia and Africa fire occurrence is very low below a mean annual precipitation of 300 mm year^{-1}, for South America and Asia already below 500 mm year^{-1}.

The Spearman rank correlation between precipitation and tree cover is very similar for both tree cover datasets (Table 1). The statistical precipitation thresholds for low (but higher than 0) and high tree cover differ by less than 100 mm. The aggregation to the model resolution shows the strongest effect on the precipitation threshold for high tree cover and shifts this value to higher precipitation. The association between precipitation and burned area is less sensitive to the aggregation: 80% of the global burned area occurs in regions with precipitation between 609 and 1518 mm on 0.25° resolution and between 635 and 1495 mm in 1.875° resolution.

3.3 Climate-fire-vegetation relationships: Evaluation of model results

In the tropics the observed burned area is strongly constrained by precipitation, around 80% of the burned area is observed in regions with mean annual precipitation between 600 and 1500 mm year^{-1} (Table 1). This precipitation range is slightly larger for the model simulations (Table 1). JSBACH-SPITFIRE reproduces the increase in burned area for low precipitation, but slightly overestimates the contribution of grid cells with precipitation higher than ca. 1300 mm year^{-1} to the total burned

Table 1. Spearman rank correlation (R) between precipitation (P) and tree cover (TC), and rank correlation between burned fraction (BF) and TC for data points with mean annual precipitation higher than 1000mm and tree cover less than 0.8. The required precipitation [mm year^{-1}] for $0.05 < TC < 0.15$ and $0.85 < TC < 0.95$, estimated as 0.05 quantile of precipitation for grid cells with the specific TC only, and precipitation value [mm year^{-1}] where 10% and 90% of the burned area (BA) originates from areas with lower precipitation. For the remote sensing datasets TMPA was used as precipitation, for the simulations (Hist, cLU, and JSBACH-standard) the MPI-ESM precipitation was used. Model results are all in 1.875° resolution.

Data	R(P,TC)	R(BF,TC)	0.05 quantile of P for $0.05 < TC < 0.15$	0.05 quantile of P for $0.85 < TC < 0.95$	10% of BA has lower P	90% of BA has lower P
Landsat 0.25°	0.90	-0.05	568	1417		
Landsat 1.875°	0.91	-0.08	569	1596		
MODIS 0.25°	0.91	-0.26	425	1514		
MODIS 1.875°	0.93	-0.4	462	1644		
GFED v4 0.25°					607	1517
GFED v4 1.875°					635	1489
JSBACH-SPITFIRE Hist	0.79	-0.5	31	1268	652	1663
JSBACH-SPITFIRE cLU	0.78	-0.64	13	1000	700	1654
JSBACH-standard	0.87	0.17	34	1597	266	1519

area (Figure 3). JSBACH-standard overestimates the contribution of areas with low precipitation, but agrees well on the contribution of areas with high precipitation (>1300 mm year^{-1}) when compared to the satellite observations. Fire occurrence is limited in regions with low precipitation due to low fuel availability (Krawchuk and Moritz, 2011). This low fire occurrence is well reproduced by JSBACH-SPITFIRE and for most continents also by JSBACH-standard with the exception of Australia

5 where the burned fraction of JSBACH-standard shows almost no variability (Figure 4).

Surprisingly the observations show a higher Spearman correlation between tree cover and precipitation than the models (Table 1). The lower correlation of the modelled relationship most likely originates from the lower precipitation regions (< 500 mm year^{-1}), where the maximum tree cover is very low in the observations and both models strongly overestimate the maximum tree cover (Figure 4).

10 Models and observations generally agree on the absence of fire for very high tree cover (>0.8) and on the decrease of burned fraction for mean annual precipitation decreasing below 1000mm. However for regions with tree cover < 0.8 and mean annual precipitation > 1000mm we find strong differences. JSBACH-SPITFIRE shows a strong negative Spearman rank correlation
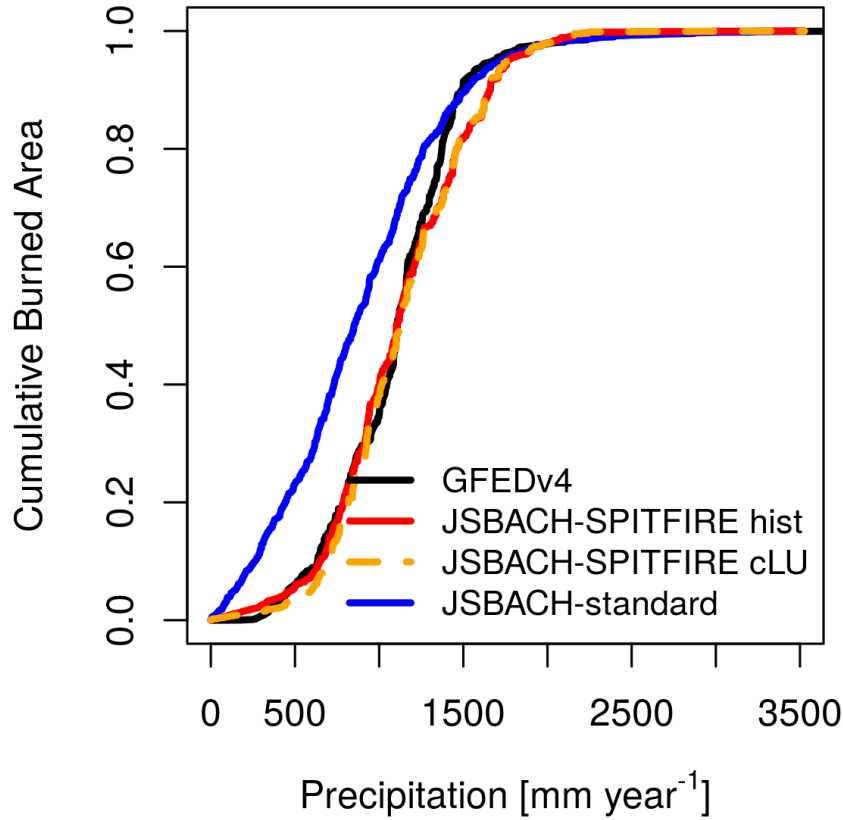
Figure 3. Cumulative burned area normalized with the total burned area for increasing precipitation. For the GFEDv4 burned area the TMPA dataset was used, for the model simulations the MPI-ESM precipitation was used.

between burned fraction and tree cover, the observations show a weaker negative correlation, and JSBACH-standard shows a positive correlation (Table 1). This can also be seen in Figure 4 where for the JSBACH-SPITFIRE simulation the highest burned fractions ($> 50\%$ of grid cells year^{-1}) are found in Africa for the lowest tree covers (0.1) and for precipitation between 1000-2000 mm year^{-1}. JSBACH-standard in many grid cells shows low fire occurrence for low tree cover, especially for

5 South America (Figure 4), these grid cells have a high fraction of crops or pasture, which both are excluded from burning in JSBACH-standard (in SPITFIRE only crops are excluded). The observations (also Figure 4) show highest values of the burned fraction for tree cover values up to 0.3 for MODIS and up to 0.5 for LANDSAT.

Burned fraction is much lower in Asia and South America compared to Australia and Africa in the observations. Both models show an underestimation of the fire occurrence in Australia. SPITFIRE reproduces the fire regime with high annual burned

10 fraction in Africa. In JSBACH-standard the difference in burned fraction between the continents is smaller than in JSBACH-SPITFIRE (Figure 4).
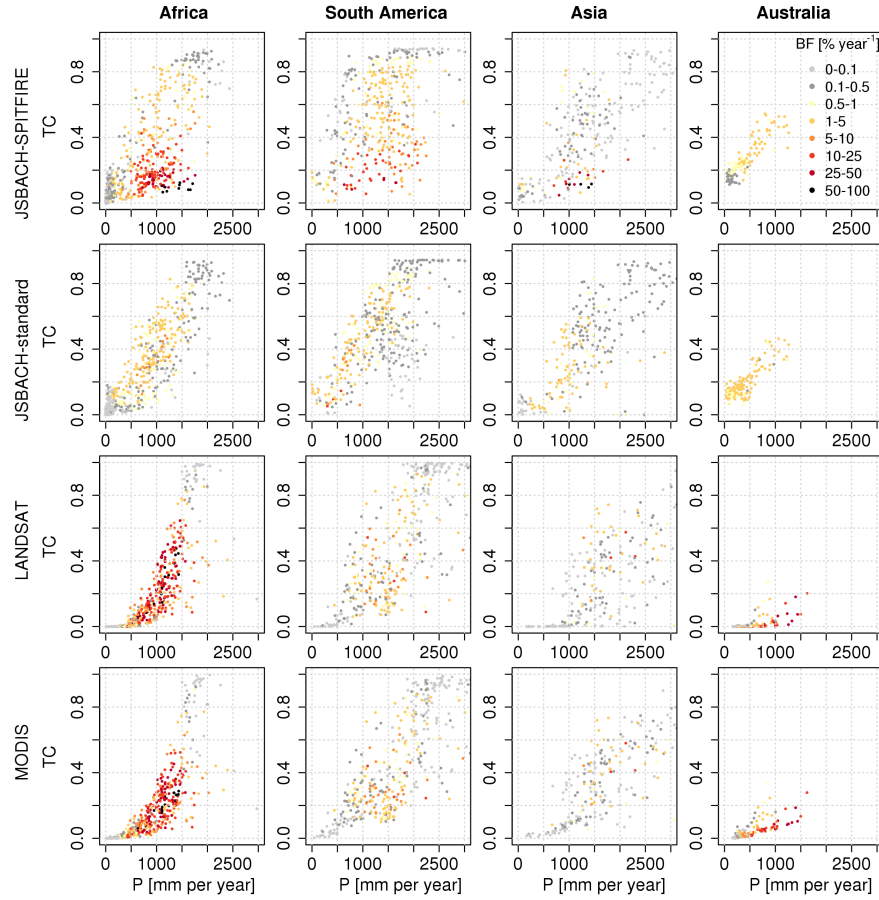
Figure 4. Modelled and observed tree cover (TC) versus precipitation (P), color coded burned area fraction (BF). Satellite datasets were aggregated to model grid resolution (1.875°).

Models and observations show differences between continents in the relationship between precipitation and maximum tree cover (Figure 5). For Africa, South America and Asia the relationship between maximum tree cover and precipiation shows a saturation for high precipitation. For Australia maximum tree cover increases linearly with increasing precipitation for models and observations, but the precipitation range also does not reach values where a clear saturation is reached for the other con-

5   tinents. For JSBACH-standard the curves are very similar for the different continents. JSBACH-SPITFIRE shows a stronger variation, this must be due to the differences in fire as the model is otherwise the same. The observations show an even stronger variation between continent, with clearly lower tree cover value for Australia followed by Asia. For Africa local quantile regression clearly differs from the linear quantile regression for the satellite data, indicating a sigmoid shape, while the other continents show a rather linear increase until the saturation (Figure 5). JSBACH-SPITFIRE reproduces the higher tree cover

10   for South America compared to Africa (albeit the difference is stronger) for mean annual precipitation lower than 1000 mm,
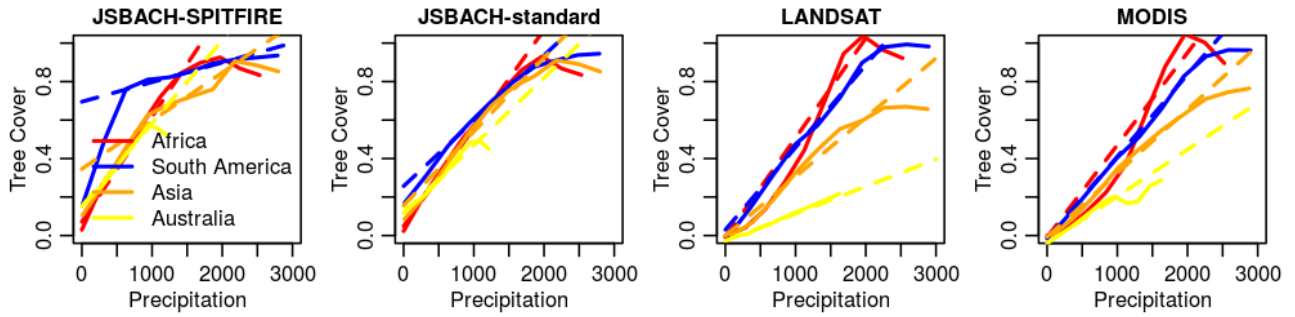
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Figure 5. Modelled and observed relatioship between precipitation and maximum tree cover based on a linear quantile regression (dashed line) and a local quantile regression (solid line). Different colors indicate the different continents.

but also JSBACH-standard shows a small difference.

The grass cover has a much higher variability in the model compared to the MODIS data (Figure 6). The modelled non-vegetated fraction decreases faster with increasing precipitation compared to the observations (Figure 6). The dominance of trees (computed as TC/total vegetation cover) is strongly overestimated in the model for low precipitation (<500 mm year^{-1},

5   Figure 6). While the relationship between precipitation and non-vegetated fraction is similar between the continents, the relationship for grass cover differs (Figure 6). For Australia observations and modelled grass cover increases with increasing precipitation. In Africa, South America and Asia grass cover first increases and then decreases with increasing precipitation.

3.4   Climate-fire-vegetation relationships: Influences of land use change

10   The simulation with preindustrial land use represents a state with low influence of land use change. The comparison to the historical simulation allows to assess the influence of land use change since 1850. The impact of fire on tree cover, as quantified by the Spearman rank correlation, between burned fraction and tree cover is higher for the simulation with preindustrial land use (Table 1). Land use change did not affect the rank correlation between precipitation and tree cover. The precipitation range for 80% of the burned area is only slightly narrower for the simulation including land use change (Table 1). Tree cover,

15   however, is even higher for low precipiation and reaches canopy closure for lower precipitation (Table 1 and Figure 7 compared to Figure 4). The simulation with land use of 1850 shows a strong gap between the savanna systems (TC < 40%) and closed forests (TC > 70%) for Africa and less strong for South America (Figure 7). For Australia and Asia the simulation does not show this pattern. In the historical simulation land use overprints this gap of the natural vegetation dynamics. The difference in fire occurrence between Africa and South America is smaller for the simulation with preindustrial land use compared to the

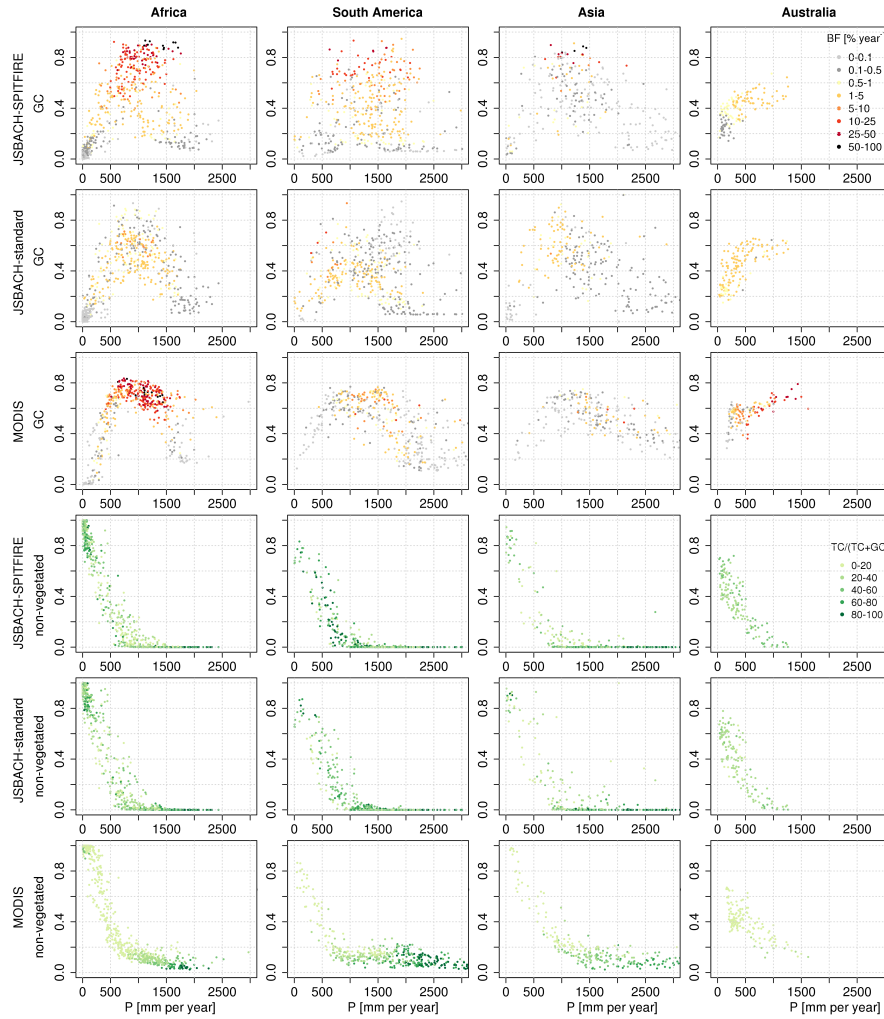20   historical simulation (Figure 7 compared to Figure 4).

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Figure 6. Modelled and observed grass cover (GC) and non-vegetated fraction over precipitation (P), with color coded burned area fraction (BF) for the grass cover and dominance of trees as (TC/total vegetation cover) for the non-vegetated fraction.

4 Discussion

The multivariate model-data comparison identified differences and agreements between modelled and observed interactions between fire, vegetation and climate. It goes beyond spatial comparisons by providing better guidance on which processes in the model need improvement. Here we discuss which model improvements can help to address the differences, what causes
5 agreements in intercontinental differences and whether limitations of the observations might influence our findings.
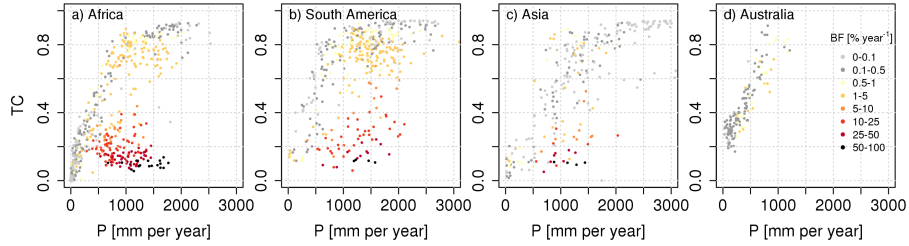
Figure 7. Same as Figure 4 for JSBACH-SPITFIRE but with preindustrial land use.

4.1 Opportunities for model improvements

JSBACH overestimates tree cover for low precipitation on all tropical continents. In these dry regions no or only very low burned fractions are observed, and SPITFIRE shows a good response to precipitation while JSBACH-standard already overestimates the burned area (Figure 3). The improved burned area pattern of SPITFIRE did not lead to an improvement in tree cover

5 for these dry regions. It is therefore unlikely that further improvements in burned fraction will improve this model-data mismatch for tree cover in dry regions, satellite data however indicate that the intensity of fires increases in these regions and might help to explain the disappearance of trees (Hantson et al., 2017). The mechanisms however are not sufficiently understood to be included in a model. The productivity of vegetation in the JSBACH model depends on the availability of water and is therefore sensitive to drought. The establishment time scale of trees, however, is a constant (30 years for tropical PFTs) and only if a 5

10 year average of NPP turns negative, ~~drought effects on the dynamic vegetation take effect~~PFTs stop to establish. Other models require a minimum of 100 mm year^{-1} precipitation for sapling establishment (Sitch et al., 2003). The excessive tree cover could be partly improved by improving the non-vegetated fraction which decreases too fast with increasing precipitation. This non-vegetated fraction depends on the productivity of vegetation. Further investigation of effects of the soil moisture memory not only on climate (Hagemann and Stacke, 2015) but also on the vegetation might also lead to useful insights. The excessive

15 dominance of trees (Figure 5) however indicates that also the tree-grass competition is not well represented in the model. Tree-grass competition for water could for example be improved in the model by introducing a sapling stage of trees, which are competitively inferior to grasses (D'Onofrio et al., 2015). Including this mechanism could improve the balance between tree and grass cover, but it could also reduce the establishment rate of trees and therefore, the tree cover in the dry regions with excessive tree cover. Including a PFT-specific rooting depth of vegetation would be an important extension of the model

20 to improve the competition for water between grasses, saplings and adult trees.
The absence of fire for closed canopies is captured well by JSBACH-SPITFIRE, the modelled strong relationship between higher burned fraction and lower tree cover for open canopies (Figure 4, with the exception of Australia, Table 1), however, is not found in the observations (Figure 2, 4, Table 1). Many general processes determining the savanna-forest boundary are included in the JSBACH-SPITFIRE model: Increased tree cover leads to a suppression of fire by excluding grasses,

25 higher flammability of grasses leads to increases in fire occurrence with increasing grass biomass (Hoffmann et al., 2012). In

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JSBACH-SPITFIRE bark thickness is PFT specific and depends on the biomass. Tropical trees are represented by two PFTs one of them has a lower sensitivity to fire due to a higher bark thickness~~and a higher stem leading to a lower probability of crown scorch~~. This is also observed in field studies where savanna species show a higher ratio of bark thickness to stem diameter ~~(Hoffmann et al., 2003). Inclusion or improvement of several ecological processes might improve the modelled relationship. Bark thickness is a key property of trees for the fire-related mortality. In JSBACH-SPITFIRE bark thickness is PFT specific and depends on the biomass. The adaptation of trees to frequent fires by increased bark thickness, and therefore higher resistance of trees to fire (Pellegrini et al., 2017) would increase the tree cover in regions with high burned fraction. This could be implemented in the model with more specific PFTs or by modifying the bark thickness according~~ and are more resistent to fire (Hoffmann et al., 2003). However, the modelled bark thickness does not adapt to the fire regime ~~.~~ ~~Kelley and Harrison (2014)~~ as observations indicate (Pellegrini et al., 2017). Kelley et al. (2014) included bark thickness as an adaptive trait in the LPX model, ~~which~~ increasing bark thickness for high fire frequencies. This increased and improved the tree cover for Australia. Resprouting is ~~another important mechanism~~ an important plant characteristic that changes the balance between mortality and recovery and also ~~leads~~ led to an increase in tree cover in fire affected areas in a modelling study ~~(Kelley and Harrison, 2014). A second option~~ (Kelley et al., 2014). A third mechanism to decrease the strong ~~associating~~ association between high burned area and tree cover could be a negative feedback between fire occurrence and tree mortality: frequent fire occurrence leads to low fuel loads and low fuel loads allow only low intensity fires with associated lower mortality of trees. In consequence a high burning frequency could lead to lower tree mortality and therefore higher tree cover. This feedback between fire, fuel load, fire intensity and tree mortality is included in the SPITFIRE model~~, but might~~. However there is no decrease in fire line intensity with incresing annual burned area (Figure C1). This feedback might therefore be too weak and ~~therefore~~ result in the stronger correlation between burned fraction and tree cover (Table 1).

A more detailed representation of vegetation structure including a sapling state of trees that is more sensitive to fire (e.g. Higgins et al., 2000) and a long-lived adult tree state could also increase the survival of trees. The "fire trap" describes a mechanism where in regions with frequent fires topkill of saplings maintains them in a nonreproductive state (Hoffmann et al., 2009). It explains the importance of the fire free intervals to allow accumulation of sufficient bark to gain sufficient fire resistance. The JSBACH model does not represent the age structure of vegetation, therefore fire always affects the average tree while in reality only trees that did not accumulate sufficient bark are affected (Hoffmann et al., 2012). Moreover, fire does not influence the tree establishment in JSBACH, it can only lead to mortality. Including a sapling state could therefore increase tree cover in frequently burned areas, while decreasing tree cover (as described above) in areas that are too dry to provide fuel for frequent burning.

For Australia underestimation of burned area for both fire models is strong (Figure 4). In a previous evaluation where the model was forced with observed climate and vegetation cover was prescribed (in contrast to the dynamic vegetation cover and climate modelled by the MPI-ESM) JSBACH-SPITFIRE showed better results for Australia (Hantson et al., 2015). An improved response of vegetation cover dynamics to precipitation will therefore likely improve the patterns of burned area.

The rank correlation between precipitation and tree cover is higher for the observations compared to the model outputs (Table 1). One reason might be the lower maximum tree cover for low precipitation in the observations which limits the range

of tree cover values in these regions. In JSBACH-standard the correlation between tree cover and precipitation is stronger than in JSBACH-SPITFIRE. In the JSBACH-standard model, fire is only driven by meteorological variables and vegetation properties (which also largely follow climatic gradients). JSBACH-SPITFIRE, however, also uses population density and lightning datasets as input, which are potentially inconsistent with the meteorological forcing derived from the MPI-ESM output. This decoupling between climate and ignitions might cause the lower correlation for JSBACH-SPITFIRE compared to the JSBACH-standard simulation. For instance in the Northeast Amazon region precipitation of the MPI-ESM is too low, leading to a decrease in tree cover in regions with closed canopy with the JSBACH-standard fire model. The very low ignitions in JSBACH-SPITFIRE in that region contribute to a low fire occurrence compared to JSBACH-standard and in consequence to higher tree cover (Figure 1). Lightning can be computed within climate models (Krause et al., 2014) and using these lightning datasets based on the model not on observations would ensure consistency between meteorological forcing and the ignitions used in the fire model (Felsberg et al., 2018).

The suggested processes are known to be important for the vegetation distribution and it seems plausible that they can help to improve the vegetation distribution. How exactly these plausible modifications would change the patterns of tree cover, fire and their relation to climate likely strongly depends on the exact parameterization and needs to be tested with stepwise model development and factorial simulations.

Many climate models have problems ~~to represent~~ representing extremes, length of dry periods and tend to generate a permanent drizzle (DeAngelis et al., 2013; Gutowski et al., 2003). We did not find this problem for the driving data used here (see Figure B1). With our approach we only include mean annual precipitation, other aspects of the modelled climate are neglected but might contribute to model-data mismatches in the relationship between precipitation and other variables. Mean annual precipitation is however a strong driver of vegetation patterns especially in the tropics and including more climate parameters would require ~~an entirely different~~ a more complex approach and possibly limit visualization and interpretation of the results. Including more climatic parameters could especially help to interpret more of the variability for mean annual precipitation amounts that allow tree establishment but do not lead to complete canopy closure. ~~The reasonable relationship of mean annual precipitation and burned area however indicates either, that additional climate biases are not important as fire is quite sensitive to the length of dry seasons, or that the fire model cancels out additional climate biases.~~

4.2 Difference between continents

We find differences in the climate-vegetation-fire relationships between continents in the satellite products as well as in the model simulations with JSBACH-SPITFIRE and the JSBACH standard model. Differences in the climate-vegetation-fire relationships have been described based on site level datasets (Lehmann et al., 2014). They find that the response of tree basal area to growth conditions (climate and nutrients) and disturbances differs between continents. The study suggests that the one climate–one vegetation paradigm which is an under-pinning of many global vegetation models cannot lead to vegetation patterns that differ between continents under the same climatic conditions as the patterns depend on past environmental conditions and evolution. Evolution is not accounted for in common vegetation models. In simulations with changing climatic forcing, however, the vegetation is a function of previous environmental conditions and adapts to changes in climate with constant

PFT specific time scales. Additionally the human dimension is more and more included in DGVMs, primarily by including anthropogenic land cover change. Moreover, in recent global fire models population density is a commonly used driver for human ignitions and suppression of fires (Hantson et al., 2016).

Our model simulations show that also global vegetation models models can have differences in climate-vegetation-fire relationships between continents. We seperated the effect of land use change by comparing the historical simulation to a simulation with preindustrial land use. We find that land cover change is influencing the differences in the modelled fire regime between Africa and South America. Land cover change influences simulated fire occurrence as cropland areas are excluded from burning and pastures have a higher fuel bulk density in the JSBACH-SPITFIRE model. A reduction in burned area due to increases in croplands is well supported by statistical analysis of satellite data for Africa (Andela and van der Werf, 2014) and globally (Bistinas et al., 2014; Andela et al., 2017). The mechanism behind the reduction in burned area due to croplands is however likely a fragmentation of the landscape, which is not explicitly accounted for in the model. ~~Fragmentation of the landscape by for instance roads, can act as a fire break and therefore reduce the potential fire size. The exact relationships between humans, land use and vegetation fires are still unknown and therefore not well represented in models~~ On local scale understanding on these relationships is increasing, for instance the relation between fire and roads (Faivre et al., 2014; Narayanaraj and Wimberly, 2012) or between fire and land management (Morton et al., 2013; Brando et al., 2014). However, a generalization to an approach that would be suitable for global models is still missing.

Vegetation in the MPI Earth system model including SPITFIRE is not only a function of climate but also depends on the history of previous vegetation due to the feedback between fire and vegetation (Lasslop et al., 2016). We did not isolate the effect of the multi-stability in this study but initialized the model with the standard vegetation initialization of the MPI-ESM for the year 1850. The SPITFIRE model also takes into account differences in the fire regime through spatially varying ignitions. In addition to the effect of land use on the differences between continents these spatial differences in ignitions might be important and might explain the smaller differences for the purely climate and land use driven JSBACH-standard model.

The comparison of the increase in maximum tree cover with increasing precipitation shows that although the model shows some variability between continents, it misses a large part of the observed variation. Finding the correct balance of the many influencing factors, e.g. climate, fire, land use, evolutionary differences, will remain a challenge for the future.

4.3 Limitations in the comparability between observations and modeled variables

We use two remotely sensed tree cover products, which show coherent patterns. Although these products are derived from imagery with different spectral, temporal and spatial characteristics (MODIS and Landsat), they cannot be considered totally independent because both are derived using a similar classification and regression tree method as well as reference data. The observational tree cover datasets are limited to trees taller than 5 m and do not include shrubs. For the model however we included shrubs and all trees. Previously differences in the threshold where maximum tree cover is reached were attributed to different precipitation datasets and ex- or inclusion of shrub cover (Devine et al., 2017). Filtering modelled and observed tree cover based on the presence of shrubs in the MODIS land cover product leads to only small differences in the relationship between tree cover and precipitation (Figure A1). Excluding grid cells where biomass indicates that the vegetation height is

smaller than 5 m according to the allometric relationship used in SPITFIRE-JSBACH (Lasslop et al., 2014) did not lead to substantially different relationships (Figure A2). Our conclusions are therefore not affected by the limitation of the datasets to observe only trees taller than 5 m.

Compared to the satellite datasets, an African site level dataset shows lower thresholds of precipitation for the absence of trees (ca. 100 mm year^{-1}) and for reaching the highest tree cover values (>650 mm year^{-1}) (Sankaran et al., 2005). The remote sensing datasets show for Africa an absence of tree cover for precipitation less than ca. 300 mm and canopy closure for 1500 mm year^{-1} in the model resolution (Figure 4). However, the general absence of trees for very low precipitation and increase until a certain threshold is similar to the remote sensing datasets.

The maximum value of a variable can decrease due to spatial averaging. We tested this effect by not using the mean when aggregating the satellite tree cover to the resolution of the precipitation dataset but instead using the maximum value of the underlying 0.05° grid cells of tree cover. Canopy closure can then be reached for all continents for mean precipitation values around 500-1000 mm year^{-1} (Figure A3), which is more consistent with a published site level dataset (Sankaran et al., 2005). This is consistent with the figures in (Hirota et al., 2011) where the MODIS tree cover is shown in 1km resolution. The scale at which maximum tree covers are observed and the spatial scale of the model application therefore needs to be considered. Moreover, as the thresholds found for the model are closer to the ones found for site-level and high resolution satellite datasets the model performance could improve if the spatial resolution of the model is increased.

Tree cover seems to be a clearly defined variable, but already varies between the two satellite datasets, the MODIS tree cover dataset defines a maximum tree cover of 80%, while the LANDSAT tree cover dataset allows a cover of 100%. In the observations not fully closed canopies due to low foliar biomass might be tracked as a reduced tree cover. In the model, however, tree cover and biomass are two rather independent variables, meaning that tree cover can be high in spite of a low biomass. Biomass datasets might therefore give additional valuable insights and pan-tropical datasets are available (Saatchi et al., 2011; Baccini et al., 2012; Avitabile et al., 2016).

The latest release of the GFED burned area and emissions datasets includes an extension for small fires (Randerson et al., 2012). However these small fires are often related to cropland fires or deforestation fires. Neither of these fire types are modelled explicitly in our model approaches and therefore could cause an unwanted mismatch. Cropland fires are not expected to strongly influence the vegetation cover, while deforestation is prescribed as described in the model and simulation paragraphs and therefore the influence on vegetation cover is considered. Burned area datasets are generally uncertain mainly due to the limited spatial and temporal resolution (Padilla et al., 2015), the difference in global burned area between the dataset including small fires and the one not including small fires is 25%. The spatial patterns are less affected, but missed burned areas due to high cloud cover certainly introduces also spatial biases. How important such errors are for a comparison as present here is unknown.

5 Conclusions

This study combines two satellite datasets with model simulations using a simple and a complex fire algorithm to investigate relationships between fire, vegetation and climate. Our analysis shows that the two satellite datasets are consistent in terms of the relationship between tree cover, precipitation and fire occurrence, but the spatial scale needs to be considered as some statistical characteristics change with the resolution.

Our analysis showed the strength of the multivariate comparison to detect model inconsistencies and guide model development. It goes beyond the insights gained by standard spatial comparisons. For JSBACH, independent of the fire model used, we find an overestimation of tree cover for low precipitation where typically fire occurrence is low due to limited fuel availability. The response of burned area to precipitation was captured well for SPITFIRE, but the simple fire scheme showed an overestimation of burned area for dry regions. This indicates that not an improvement of the fire model but improved modelling of drought effects on the vegetation dynamics will improve the response of vegetation to climate in dry regions. Dry regions often show a strong coupling between land and atmosphere (Koster et al., 2006), such an improvement has therefore also a high potential to improve the performance of the coupled Earth system model.

While fire occurrence and vegetation patterns are well observed by remote sensing, the impact of fire on vegetation is much less constrained by satellite observations limiting the possibilities of evaluating that part of fire models. The multivariate comparison revealed a too strong impact of fire on tree cover for gridcells with very high fire occurrence, which leads to too low tree cover. To boost the tree cover in exactly these regions with high fire occurrence possible model modifications are an adaptation of trees to fire, by increasing bark thickness in reponse to high fire frequencies, or a stronger negative feedback between fire occurrence and fuel load. This stronger feedback should then reduce fire intensity and consequently fire mortality.

The complex fire model SPITFIRE improves the difference in fire regimes between the continents, especially Africa and South America, compared to the simple fire model. The intercontinental variation in the relationship between precipitation and maximum tree cover is much smaller for the models compared to the observations. Known variations in vegetation are not sufficiently understood to be represented in models. However, our finding that models do show differences in the fire-vegetation-climate relationships between continents shows that further exploration why models show differences can be helpful to better understand causes for intercontinental differences.

Overall the multivariate model evaluation highlights the potential for more targeted model improvements with respect to the interactions between climate, vegetation and fire, which are crucial for our understanding of future vegetation projections.
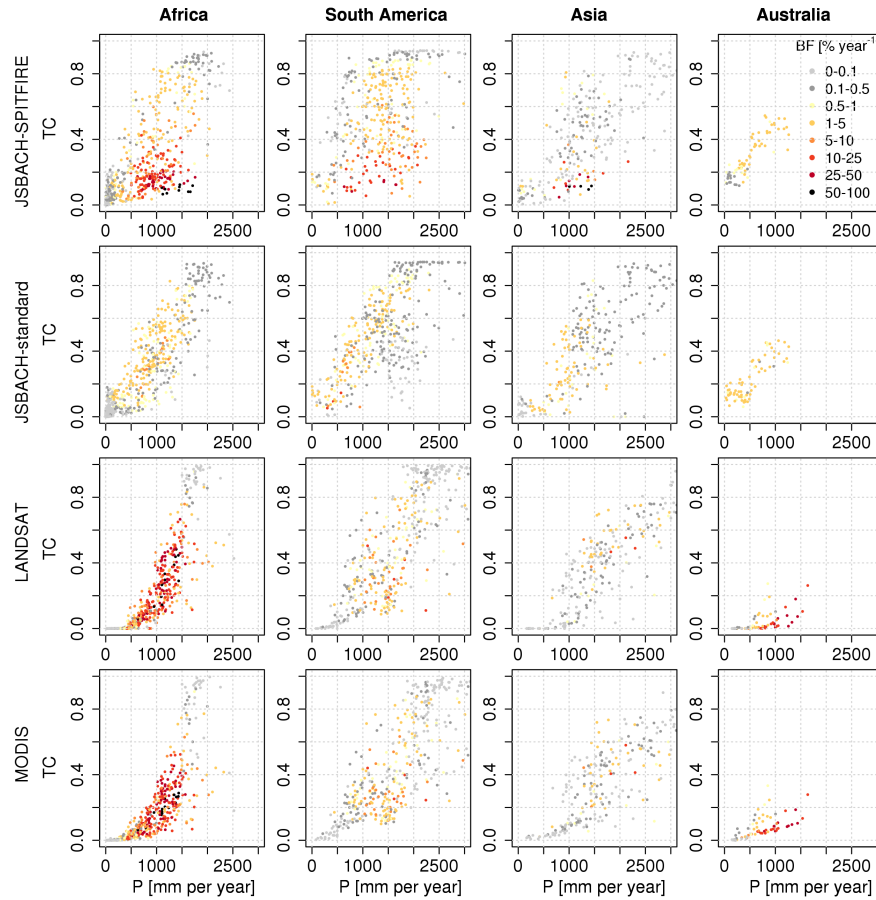
19

Figure A1. Same as figure 4 but tree cover filtered for the presence of shrub lands (using the MODIS open and closed shrub land classification). This indicates a low sensitivity of the fire-vegetation-climate relationships to shrub lands.

Appendix A: Sensitivity of climate-vegetation-fire relationships to remapping, presence of shrubs and modelled tree height

Appendix B: Evaluation of precipitation forcing

Additionally to the total amount of rainfall the seasonality can play role for vegetation or the length of dry periods. We therefore assess here whether the rainfall seasonality and the number of dry days are reasonable in our climatic forcing. We use the CRU-NCEP v5 dataset (Wei et al., 2014) as a reference and define rainfall seasonality as the number of days needed to reach 80% of the annual precipitation, and dry days as days with less rainfall than 3 mm. A low number of days need to reach the 80% rainfall indicates a strong seasonality, a high number of days a low seasonality. The CRU-NCEP dataset is a reanalysis dataset

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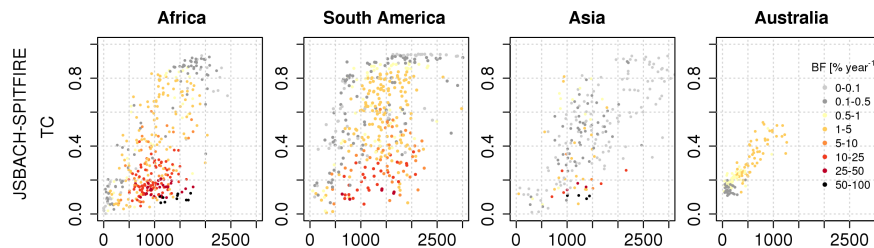
Figure A2. Modelled tree cover (TC) versus precipitation (P) [mm year-1]. Modelled tree cover was filtered for vegetation height of trees <5 m using the modelled vegetation height. This value is given as detection threshold for the satellite products. When filtering the model output with this threshold the differences to the unfiltered dataset are very small (compare with Figure 4, panels for JSBACH-SPITFIRE).
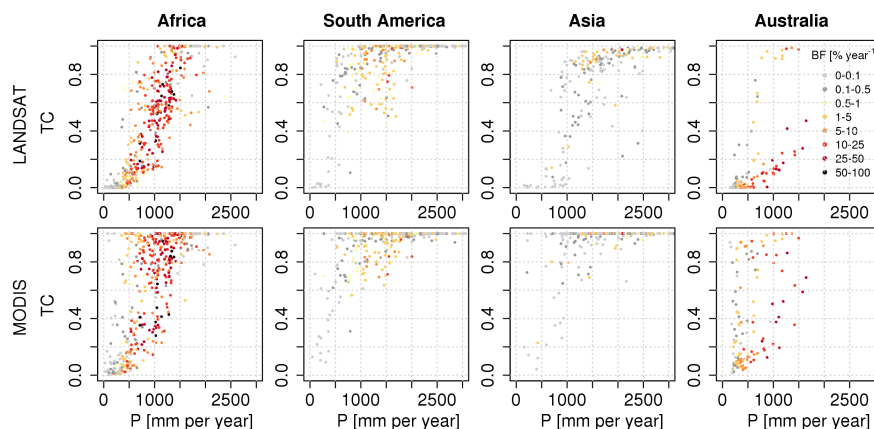

Figure A3. Tree cover (TC) versus precipitation (P) with color coded burned fraction (BF). Tree cover was here remapped from 0.05° resolution to 2° using the maximum value of the higher resolution instead of the mean.

commonly used in offline model comparisons (Rabin et al., 2017). The MPI-ESM does not show a concerning underestimation of dry days or too low seasonality.

Appendix C: Relationship between modelled burned area and fire intensity

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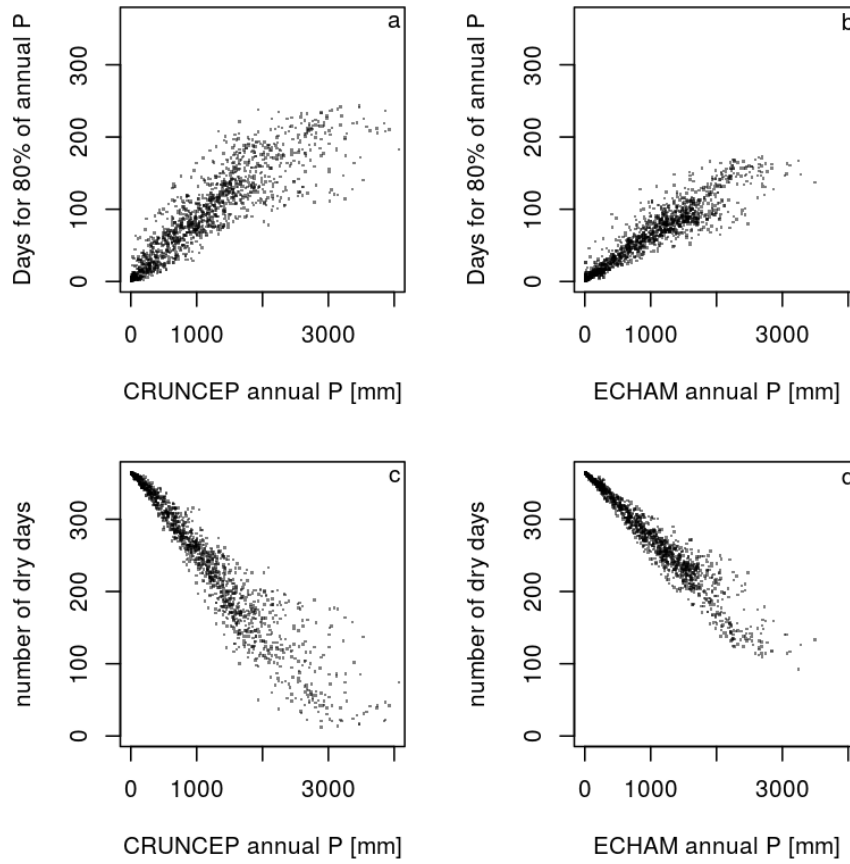
Figure B1. Relationship between annual precipitation and precipitation seasonality and number of dry days for the ECHAM simulation used as meteorological forcing for the JSBACH simulations used here and the CRU-NCEP dataset.
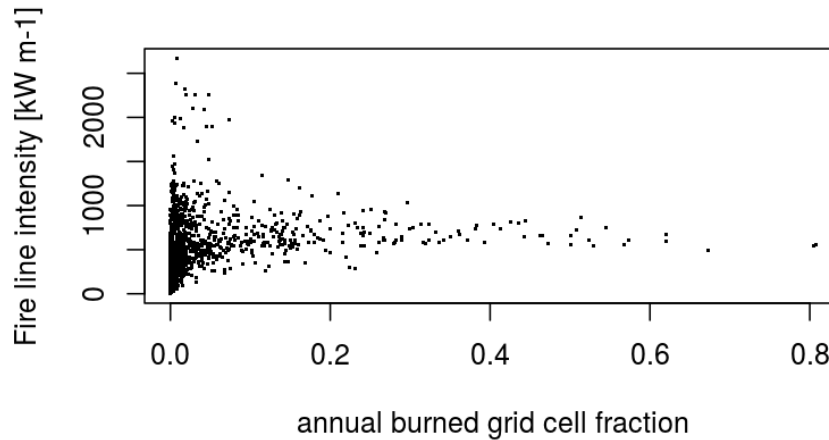
Figure C1. Relationship between annual burned area and fire line intensity. The expected decrease in fire line intensity for frequently burning areas due to the feedback between fire and fuel load is not found in the simulation results and might indicate that the feedback between fire occurrence, fuel load and fire intensity is too weak.

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