Dear editor, 1) we here reply to the third review of the reviewer. We updated the figure evaluating the rainfall seasonality and number of dry days with the TMPA dataset instead of CRUNCEP and find a better agreement between MPI-ESM and the observational dataset than previously. Although we don't agree that it is necessary to look at all other climate biases as with the multivariate analysis we already account for spatial biases in precipitation (which is the main driver of tree cover) we now show that bias in mean temperature and bias in mean shortwave radiation does not explain any of the tree cover bias (close to zero, non-significant correlation). We adjust the paragraph on the discussion of climate biases and moved it to the discussion section on "Limitations in the comparability between observations and modeled variables".

We are surprised about the reviewer's grading. Following the reviewer's advice of his second review apparently led to a degradation of the scientific significance. The reviewer's assessment of scientific quality dropped following the reviewer's advice of the first review. With this third review it remains largely unclear what exactly the reviewer wants us to change and especially how to make an end to this process.

Below we reply to the reviewer as positive as possible. Our replies are in italic. Our replies cited by the reviewer are set in bold.

1 Review

The authors have included new figure to determine if there is a bias in rainfall distribution simulated by ECHAM. This has helped rebalance the analysis across variables in their multivariate analysis. I do have some specific issues with the new figure, which I also feel could be used more in discussing weaknesses in the model performance. I also pick up on some of the author responses that could have some bearing for revision in the rest of the paper, and provide some examples of quick analysis to assess or rule out two remaining climate biases described in the last review.

Figure B1

1. The figure uses CRU-NCEP precip observations, whereas TMPA is used for observed precip elsewhere in the paper. The same climate observations should be used for both, especially as the new figure is used to diagnose differences in climate relationships between the two different climate axes in figures 2, and 4-7. Apologies if I implied in an earlier review that it would be okay to use different precip data for different parts of the analysis - I used fireMIP as an example of an offline JSBACH-SPITFIRE simulation, and thought that it would self evident that if used, observations should still be consistent across different parts of the analysis. While the authors may argue that choice of dataset might make little difference to the relationship, the disagreement in precipitation between observed datasets in notorious (Beck et al. 2017; Weedon et al. 2014). A quick plot of MAP vs no. dry days I conducted with CRU TS3.2 (Harris et al. 2013) (data I chose for no other reason that I already had it downloaded, not because I'm recommending it for use in the m/s) compared to CRU-NCEP used in figure B1 shows what I mean:Figure 1: CRUTS3.2 MAP vs no. dry days for tropics and Australia, based on coordinates provided in section 2. The relationship between MAP and no. drys days for CRU by itself is clearly different, and would actually agree more with ECHAM annual precip. TMPA may also show a significantly difference relationship as well.

2) We downloaded the daily version of the TMPA dataset (the one used in the manuscript is monthly) and redid the figures showing an even better agreement with the model and only small underestimation of seasonality or number of dry days, mostly for high rainfall regions which are not important to our conclusions. See also reply 1.

2. The authors already produces an excellent style of figure to diagnose burnt area vs precip in figure 3 which could have been used here with the x-axis displaying precip and the y-axis cumulative days at a given precip level. This would provide more information on rainfall distribution biases. However, there is nothing particularly wrong with the simple scatter plot used, so I'll leave this as a suggestion rather than a requirement.

3) We prefer to use the plot as it is.

3. If the author's choice to stick with the scatter plots, then please add a trend line.

4) See reply 3. We added a trend line and even the slope of the line.

4. Remember that, for SPITFIRE, impact of dry days in cumulative, so cumulative dry days might also be worth consider-

ing, especially as this is another area MPI has been shown to sometimes struggle with (Sillmann et al. 2013) . If the authors are able to use the variables already in figure B1 effectively though, then again this won't berequired.

5) As the burned area pattern shows a good relation with precipitation we don't see a need to include a third measure of rainfall seasonality.

5. The authors need to use this figure to help diagnose climate relationships in more detail. In their response, the authors state that " This analysis ... 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." If this relationship holds once the figure is redrawn with TMPA, then the "anti-drizzle" bias in MPI is surprising. However, it is still a climate bias that will affect simulated fire and possible vegetation, and should be discussed as such in the main text. If it turns out that MPI-ESM agrees with TMPA dry days, than the text will be fine as it is.

6) See reply 2 and 5. MPI-ESM agrees better with TMPA, especially the agreement in the dry regions, which we discuss the most, is good. We modified the text according to the new comparison.

Author responses

We cite our old response set in bold, the reviewers comments on it normal and our replies in italics.

main concern of the reviewer with respect to the climate biases is the seasonality of the rainfall.

I use seasonality as an example, and it was not the only or main concern.

7) OK.

Of courser biases always exist, here, however, it is important whether the climate biases could have such a strong effect as the reviewer claims.

This is correct. I have no idea how strong an affect the climate biases have. As the authors are presenting a new way of evaluating land surface in ESMs, they need to demonstrate that the impact of other climate biases is either negligible or can be accounted for.

8) See reply 1. The multivariate evalutation takes into account spatial biases of precipitation. We discuss the presence and impact of climate biases, include analysis on climate biases of precipitation seasonality, and now temperature and shortwave radiation. Our results show no influence of climate biases on the tree cover.

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.And Radiation could have a considerable influence on the productivity of PFTs, but is very unlikely to influence tree cover 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.

Was this test with just JSBACH, or for observed tree cover/climate as well? Obviously if SW does not have a significant effect on JSBACHs simulated tree cover but does on observed, then this would be a useful missing climate-vegetation relationship that would need to exploring. If it was tested for both model and observation, then the authors point stands.

9) We show that radiation has no influence of the modelled tree cover, therefore biases in radiation cannot have an influence on our results. We now additionally compute the correlation between the radiation bias and tree cover bias and find a zero, not significant correlation. See reply 1 and 8.

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 precipiation 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

Although the authors have only used burnt area for the fire axis, assessment and suggested improvements have borrowed a lot from previous model assessment and literature. In response to reviewer 1s comments, they also have started exploring fire intensity (figure C1). Obviously PFT fractions are always going to be grouped into just three (tree, grass, bare) fraction types for observational comparison, but each were assessed, which gave some grounding for suggested changes in vegetation dynamics, at least from the land surface bias side. Land use experiments also help explore this impact of changing anthropogenic land cover in JSBACH - again part of the vegetation axis. There is also extensive discussion of changes in plant physiological traits and vegetation dynamics and vegetation-fire feedbacks. And this maybe the key to the problem. i.e, the number observed datasets + number ofvariables assessed + past model evaluation + literature + suggested model deficiencies and potential development that has gone into the fire and vegetation axis is extensive, but there is much less detail on the climate axis. And that any mismatches in the multivariate pattern compared to observations are almost always assumed to be because of vegetation and fire biases and not climate. This can be properly balanced by proper discussion of figure B1, and/or reference to MPI climate assessment and climate biases.

10) We discuss that figure B1 does not show a concern that climate biases are important. We do not aim at discussing the impact of climate biases in the same way as the biases in the vegetation and fire parameters, as we aim to evaluate vegetation and fire not the climate. This disbalance is therefore intended, discussion on the biases in MPI-ESM forcing is included in the manuscript.

A reduction in tree cover would lead to an increase in burned area, therefore what we write is correct. Or vice versa the high burned fraction observed in Australia cannot be achieved with SPITFIRE if such a high tree cover is present.

The argument that burnt area would increase with reduced tree cover is fine. That the ESM needs to reduce simulated tree cover in Australia is also fine. The problem is the statement that " An improved response of vegetation cover dynamics to precipitation will therefore likely improve the patterns of burned area " has not been demonstrated. I suspect improved vegetation response would be useful, but I also suspect that biases in MPI climate also share some of the blame. If a change in vegetation cover dynamics is induced with is used to improve fire by compensating for any climate bias, then this is not an improved response but a pragmatic tuning and should be identified as such. Figure 1c shows too much rainfall in Northern Australia, so the authors could already use some of their original analysis to diagnose precip as one potential climate bias that would affect tree cover and burnt area. In terms of regional climate biases not taken into account by MAP, it might be that figure B1 isn't very helpful yet. In figure 1 in this review, for example, the slope of the fit line, spread of the data, and deviation from linear fit at low precips is different for Australia compared to the spread for the whole tropics.

11) We account for spatial biases in mean annual precipitation by evaluating tree cover and burned area for a given mean annual precipitation.
In Australia tree cover is too high, burned area is too low. We know that if tree cover decreases burned area increases in the model, therefore the burned area will increase. There is no further demonstration necessary. Our statement is correct and sufficiently supported by previous sensitivity analysis (Lasslop et al., 2016) and our knowledge of the model equations.
We modify the text to improve the clarity and include that observed climate might contribute to the improved pattern:
An improved response of vegetation cover dynamics to precipitation will reduce the underestimation of burned area as in SPITFIRE tree cover and burned area are closely related (Lasslop et al., 2016). Part of the better performance in the previous study might also be due to the use of observed climate forcing.

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, but the same would be true for any observational dataset used as model forcing.

Apologies for not providing references in the previous review. The authors may want look at and cite (Ahlström et al. 2017). Although exploring the carbon cycle rather than vegetation cover, they did show a significant impact of precip, temperature and SW biases on simulated vegetation in CMIP5 models. Focussing on the Amazon, (Ahlström et al. 2017) showed MAP, SW and temp climate biases explain most of the simulated GPP, above ground biomass and tree cover. (Ahlström et al. 2012) also showed similar results for disagreement in projected changes in different climate variables into the future. These are just the ones I can think of off the top of my head, there is probably many more. As GCMs have been around for a lot longer, there is of course extensive literature on climate biases that could potentially lead to problems with vegetation dynamics once enabled. (Sillmann et al. 2013) might be a good starting point. The authors could use (Li et al. 2013) to support their view that only MAP needs to be considered for tropical vegetation distribution, as they use observational constraints to show MAP is the main driver of disagreement in vegetation productivity across models in a region of similar extent to southern America used in this study. However, it should be noted that other climate biases appear to become more important at high MAPs, where vegetation productivity is predominantly limited by available radiation (Nemani et al. 2003). I don't know enough about vegetation dynamics (in model or real world) to know if this tipping point between MAP and SW limited production occurs when tree cover is already saturated. If it does, then maybe (Li et al. 2013) would suggest that other tree cover controls don't need to be considered, at least for this region. I'm not so sure about the impact of climate biases on fire, as this is a little outside my area of expertise. However, I get the impression that, even with wind speed limitation, SPITFIRE is sensitive to variations in windspeed, especially at lower speeds (Lasslop et al. 2014), which again, GCMs struggle to adequately simulate.

12) We already showed that radiation has no influence on the tree cover, this is already clear from the model equations. We now include the correlation between temperature and shortwave radiation bias with tree cover bias, which is close to zero and insignificant. See reply 1,8,9.

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.
Again, the authors need to back these statements up by showing in some way that other climate biases are not the issue here. As they are unable to run JSBACH with climateobservations, perhaps offline runs could be referenced in other papers. For example, JSBACH seems to simulate too much tree cover at low MAPs in the offline study by (Baudena et al. 2014). If this was an appropriate test with no fundamental developmental changes compared to the JSBACH configuration used in the m/s, then the authors could cite this study to back up their suggestion of improved vegetation dynamics at MAP. The authors should have a much better idea of published JSBACH and MPI experiments and evaluation, so might also be able to think of better examples.

13) Our statement is based on the knowledge of the model equations, it is impossible that climate biases affect the dominance of trees in regions without fire. We include a sentence in the model description to emphasize this more:
"In gridcells without disturbance and positive NPP trees prevail."
The cited study of Baudena et al. uses results from a coupled simulation. No comparable study with offline JSBACH and observations exists. We account for spatial biases by evaluating tree cover for a given mean precipitation. With our additional analysis we do not find any indications that the other climate biases affect our results. See reply 1,8,9, and 12

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.
I was just reinforcing that fact that the climate axis should be considered as much as the vegetation and fire axis. I meant "ESM setup" as a land surface model driven by ESM output that is emulating a full ESM, obviously without the land-atmosphere feedback (I'm not sure that makes it any clearer...?).

14) We do not intend to adress the climate axis in a similar detail as the vegetation parameters. The latter are the focus of this study.

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 point is more to show that the cause of low tree cover is fire feedback in the first place, and not other climate biases (though

the author are right that maybe the impact of climate biases on fire-feedbacks should also be a concern...?) If the authors can show climate biases beyond MAP isn't to blame, then the suggested changes fire-feedback are fine.

15) That fire is the reason can easily be seen from the figure 4 where fire and low tree cover are clearly related, most notably for Africa. Moreover, with the old fire model, that does not include a feedback between fire and vegetation the tree cover is higher, it is therefore caused by the different fire model. We could not identify any support of the reviewers idea that climate biases impact our results. see reply 1, 8,9,12 and 13

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.

I was more thinking of some like this: Figure 2 (Apologies for the messy style). The 2 left hand columns of the figure shows CRU TS3.2 cloud cover (roughly used a not-so-great inverse proxy for SW) vs MAP, middle shows MAT vsMAP, and the two right show number of wetdays vs MAP. Again, I'm not recommending CRU, but just using it as a readily available example. Green column 1 and 3 shows tree cover from VCF (Dimiceli et al. 2015) , and red coloured columns 2 and 4 show burnt area from GFED4s (van der Werf et al. 2017) . The regions (all tropics, Africa, Southern America, Asia and Australia) are the same used in the m/s. Even from this example, it is clear that MAP is important but not the only control on either variable. Tree cover does increase with MAP as expected, but the extent of the increase is modulated by temperature, with an ideal MAT occuring around 25 degrees C, and with a rapid drop off at warmer temperatures. The relationship can be exaggerated further in some regions. Australia in particularly has tree cover extending into very dry areas when it is cool enough. Number of wetdays also seems important for tree control in Asia and Australia. Although some of this might be explained by fire feedbacks, that only goes to show that these variables are important for the fire axis also. As I'm using different data to the authors, I won't dwell on the details in the figure above - but it is an example of using on of the technique the authors have already developed to account for more climate controls and identify which biases are appropriate to consider when. A figure like this does not need to be included in the m/s, but it could serve as a starting point to help identify important climate biases. The authors could also think about using spearman's rank or the multivariate regression they used with JBACH to rule out significant effects of short wave.

16) We agree that using regressions is a very interesting way of analysing model results. There is no evidence of an influence of cloud cover on tree cover literature to our knowledge. Knowing that cloud cover/short wave does not influence tree cover in the model we do not consider including a discussion useful. The reviewer mentions that such a figure does not need to be included, but we should use regressions or correlations. We computed the correlation between radiation bias and tree cover bias; as expected the correlation is not significant. We did the same for temperature and also found no indication that a temperature bias could help to explain tree cover differences. We indicate the lack of correlation/association between climate biases and tree cover biases in the manuscript now. See reply 1,8,9,12,13 and 15.

References

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

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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 robustness 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 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 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.

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.

Copyright statement.

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 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 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 suggested to be caused by a feedback between fire and vegetation. Although the reliability of remotely sensed tree cover sets to diagose 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).

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 Earth system.

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 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 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 (precipitation). Also the relationship

between 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. In gridcells without disturbance and positive NPP trees prevail. Land use is included following the protocol of Hurtt et al. (2011). The implementation is described in detail in (Reick et al., 2013). 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 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 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 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.

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 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). For an evaluation of the climate forcing, e.g. the precipitation seasonality, we use the daily TMPA dataset (Savtchenko and Greenbelt, 2016) .

2.2.4 Other climate parameters

As we are using modelled climate forcing we used the shortwave radiation and temperature of the CRU-NCEP v5 dataset reanalysis (Wei et al., 2014), which is commonly used as observation based model forcing dataset (Rabin et al., 2017), to investigate whether biases in the climate parameters might explain biases in tree cover. We compute the correlation between the difference in modelled and observed tree cover and MPI-ESM and CRU-NCEP for shortwave radiation and temperature.

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 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

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 influence 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

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 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-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 underestimation 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 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 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 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.

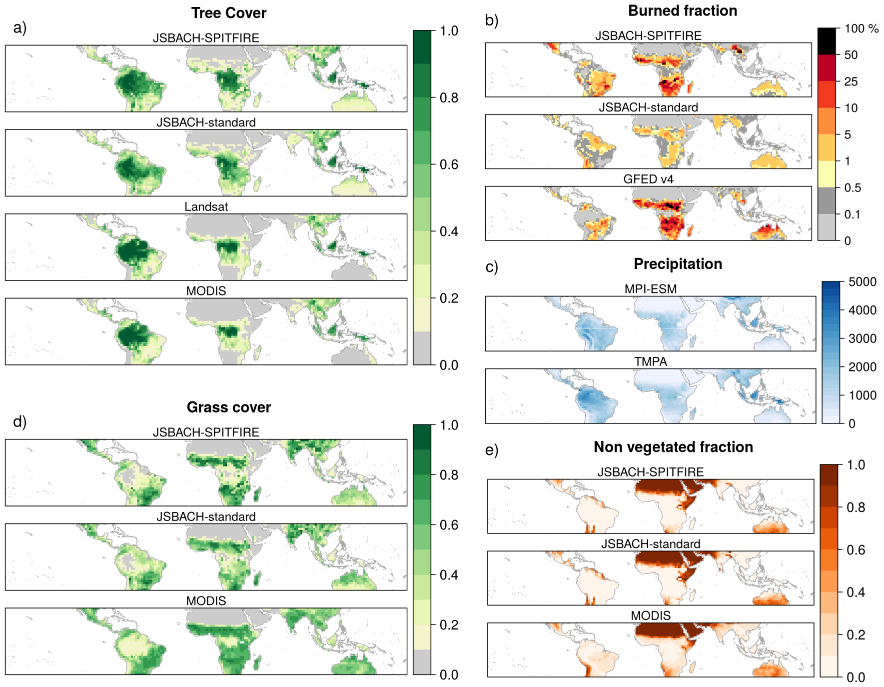

Figure 1. Spatial distribution of modelled and observed datasets used in this study. (a): Spatial distribution of tree cover fraction over the global tropics for the JSBACH-SPITFIRE and JSBACH-standard model simulation and the satellite data products from Landsat and MODIS. (b): Burned fraction [year^{-1}] 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.

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 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 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

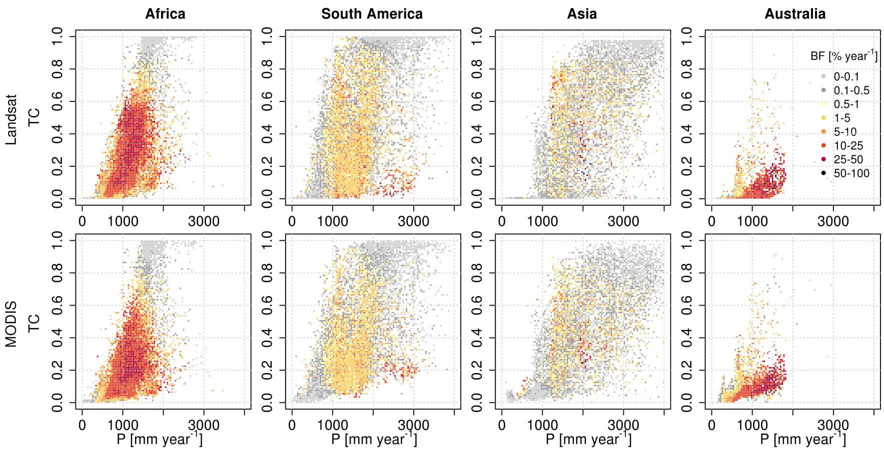

Figure 2. Tree cover (TC) versus precipitation [mm year^{-1}] with color coded burned fraction (BF) for different continents for the two satellite datasets. Burned area is averaged over data points with the same precipitation (40 mm steps) and tree cover (in steps of 0.01) to avoid over-plotting based on a spatial resolution of 0.25°. For Asia some higher precipitation values were cut off.

year^{-1}), where the maximum tree cover is very low in the observations and both models strongly overestimate the maximum tree cover (Figure 4).

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 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 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 fraction in Africa. In JSBACH-standard the difference in burned fraction between the continents is smaller than in JSBACH-SPITFIRE (Figure 4).

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 precipitation shows a saturation for high precipitation. For Australia maximum tree cover increases linearly with increasing precipitation for models

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

and observations, but the precipitation range also does not reach values where a clear saturation is reached for the other continents. 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 valuse 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 for South America compared to Africa (albeit the difference is stronger) for mean annual precipitation lower than 1000 mm, 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}, Figure 6). While the relationship between precipitation and non-vegetated fraction is similar between the continents, the re-

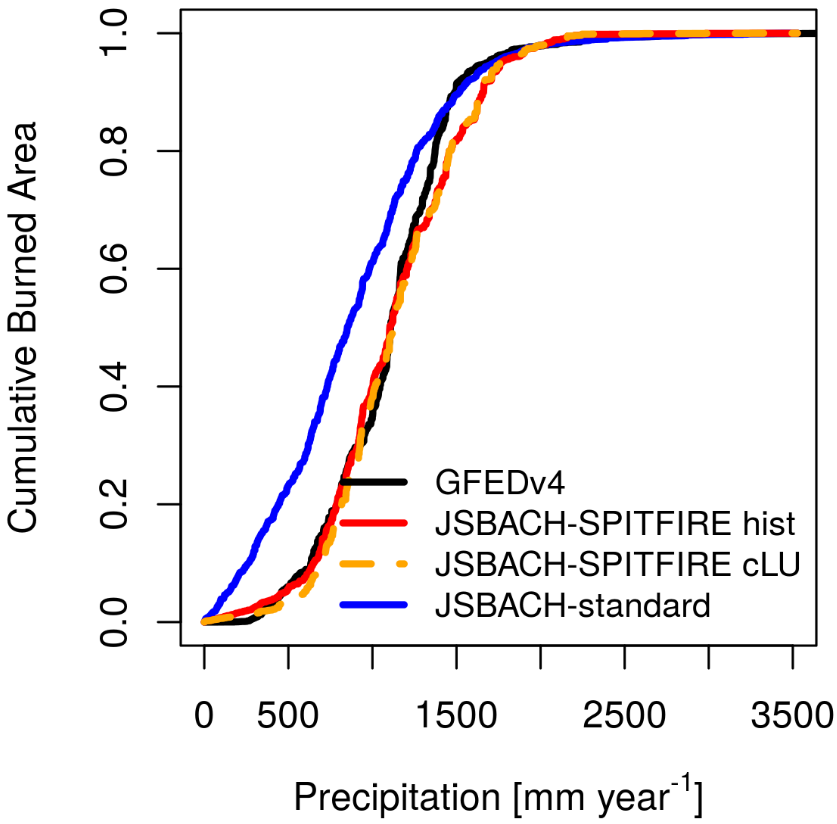

Figure 3. Cumulative burned area normalized with the total burned area for increasing precipitation. For the GFEDv4 burned area the TMPA dataset was used, for the model simulations the MPI-ESM precipitation was used.

lationship 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

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,

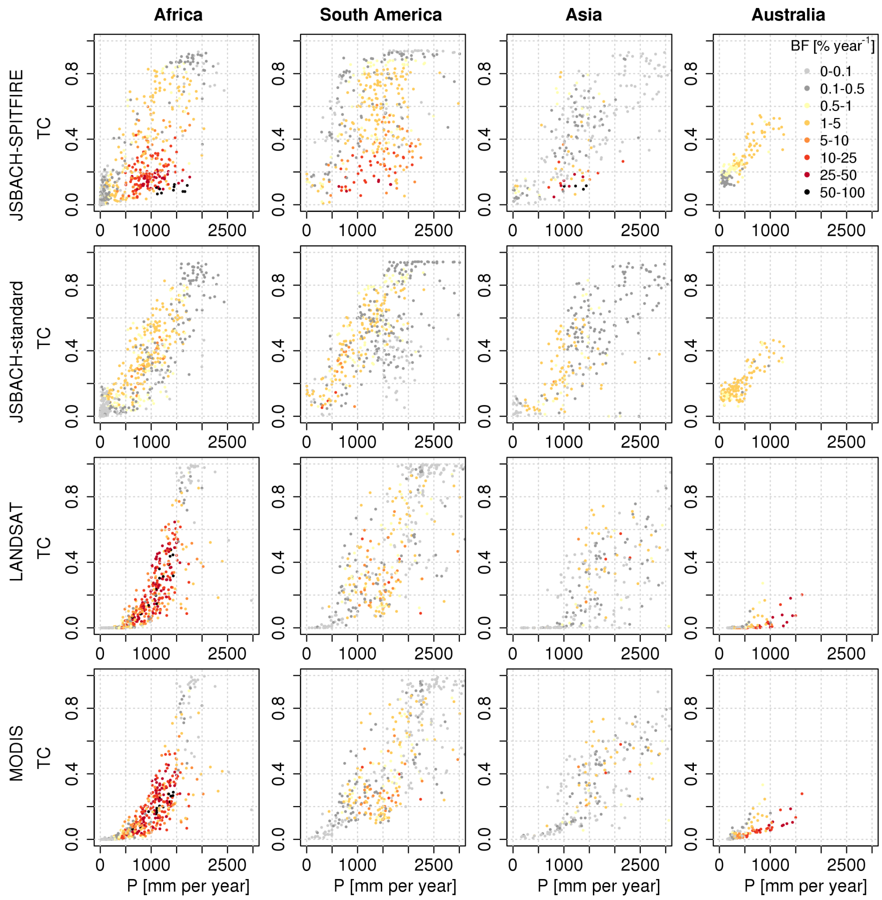

Figure 4. Modelled and observed tree cover (TC) versus precipitation (P), color coded burned area fraction (BF). Satellite datasets were aggregated to model grid resolution (1.875°).

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 historical simulation (Figure 7 compared to Figure 4).

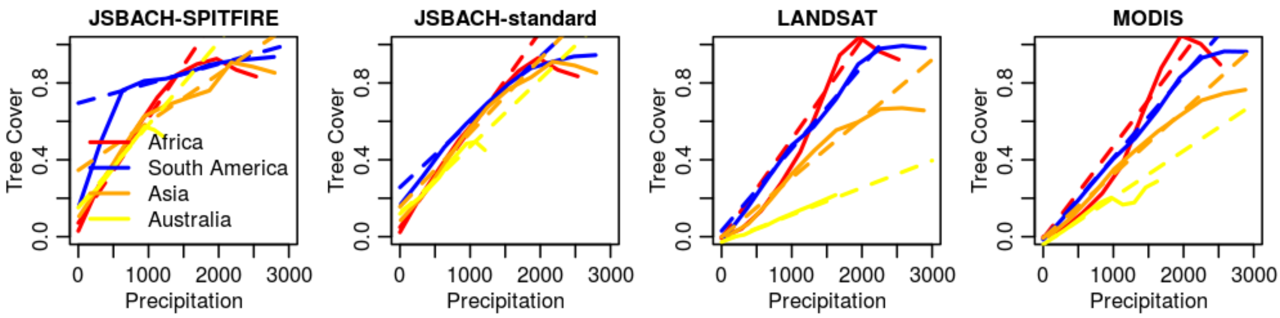

Figure 5. Modelled and observed relatioship between precipitation and maximum tree cover based on a linear quantile regression (dashed line) and a local quantile regression (solid line). Different colors indicate the different continents.

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 agreements in intercontinental differences and whether limitations of the observations might influence our findings.

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 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 year average of NPP turns negative, 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 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

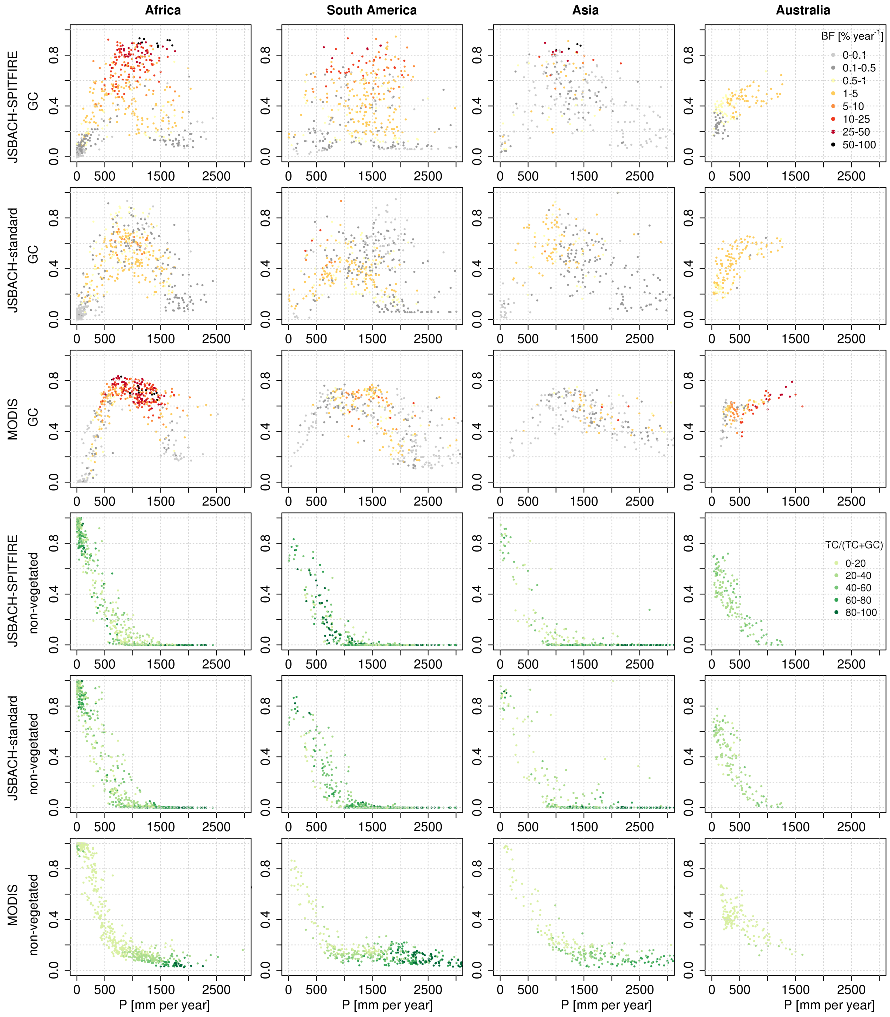

Figure 6. Modelled and observed grass cover (GC) and non-vegetated fraction over precipitation (P), with color coded burned area fraction (BF) for the grass cover and dominance of trees as (TC/total vegetation cover) for the non-vegetated fraction.

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.

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

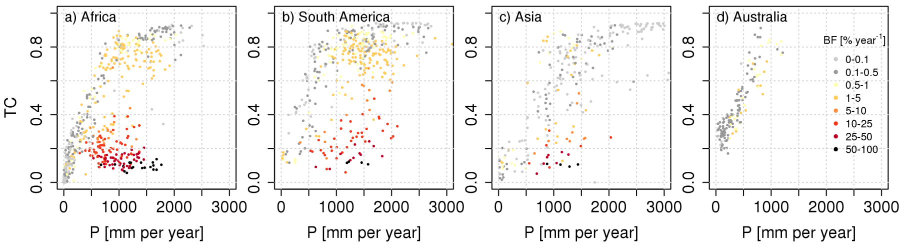

Figure 7. Same as Figure 4 for JSBACH-SPITFIRE but with preindustrial land use.

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. This is also observed in field studies where savanna species show a higher ratio of bark thickness to stem diameter and are more resistent to fire (Hoffmann et al., 2003). However, the modelled bark thickness does not adapt to the fire regime as observations indicate (Pellegrini et al., 2017). Kelley et al. (2014) included bark thickness as an adaptive trait in the LPX model, increasing bark thickness for high fire frequencies. This increased and improved the tree cover for Australia. Resprouting is an important plant characteristic that changes the balance between mortality and recovery and also led to an increase in tree cover in fire affected areas in a modelling study (Kelley et al., 2014). A third mechanism to decrease the strong 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. However there is no decrease in fire line intensity with incresing annual burned area (Figure C1). This feedback might therefore be too weak and 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 resistence. 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~~ reduce the underestimation of burned area as in SPITFIRE tree cover and burned area are closely related (Lasslop et al., 2016). Part of the better performance in the previous study might also be due to the use of observed climate forcing.

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 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 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.~~

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. 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 precipiation 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 explicitely 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.

By evaluating tree cover and fire for a given mean annual precipitation we account for biases in the MPI-ESM forcing of this parameter. Mean annual precipitation is a strong driver of vegetation patterns especially in the tropics, however other aspects of precipitation and other climatic parameters might be biased and influence our results. Many climate models have problems representing extremes (Sillmann et al., 2013), length of dry periods and tend to generate a permanent drizzle

(DeAngelis et al., 2013; Gutowski et al., 2003). Observed rainfall seasonality and number of dry days of the MPI-ESM forcing compares well between the TMPA observed dataset (see Figure B1), with a small underestimation of seasonality and number of dry days of the MPI-ESM mainly in regions with high rainfall. As we found mostly mismatches in regions with low rainfall, the mismatch between observed and MPI-ESM seasonality of rainfall is not concerning. With our approach we only include mean annual precipitation, other biases of the modelled climate could influence our results, such as temperature or radiation. We therefore explored the correlation between tree cover biases and biases in the two climate parameters. The biases in mean temperature and shortwave radiation however do not explain any of the variability of tree cover biases, e.g. the correlation is virtually zero and not significant on a 95% significance level (R=0.04, p-value=0.07945 for radiation and R=-0.004, p-value = 0.8842 for temperature). These two parameters were identified previously to explain the impact climate biases on the carbon cycle (Ahlström et al., 2017).

The interactions between climatic parameters are however difficult to disentangle, based on this simple analysis and other approaches such as multivariate regression or random forrest approaches (Forkel et al., 2017) might help to gain further insights on the effects of specific climate drivers.

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.

Code and data availability. The observational datasets are freely available. The processed data and model output as displayed in this publication and the processing scripts are available upon request to publications@mpimet.mpg.de.

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)~~ TMPA 3B42 daily dataset (Savtchenko and Greenbelt, 2016) 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 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, there is a small underestimation however and it is stronger in regions with high rainfall.

Appendix C: Relationship between modelled burned area and fire intensity

Author contributions. GL wrote the manuscript. GL and TM designed the study and performed the analysis. SH, DD, SK helped refine the analysis and to develop and shape the manuscript.

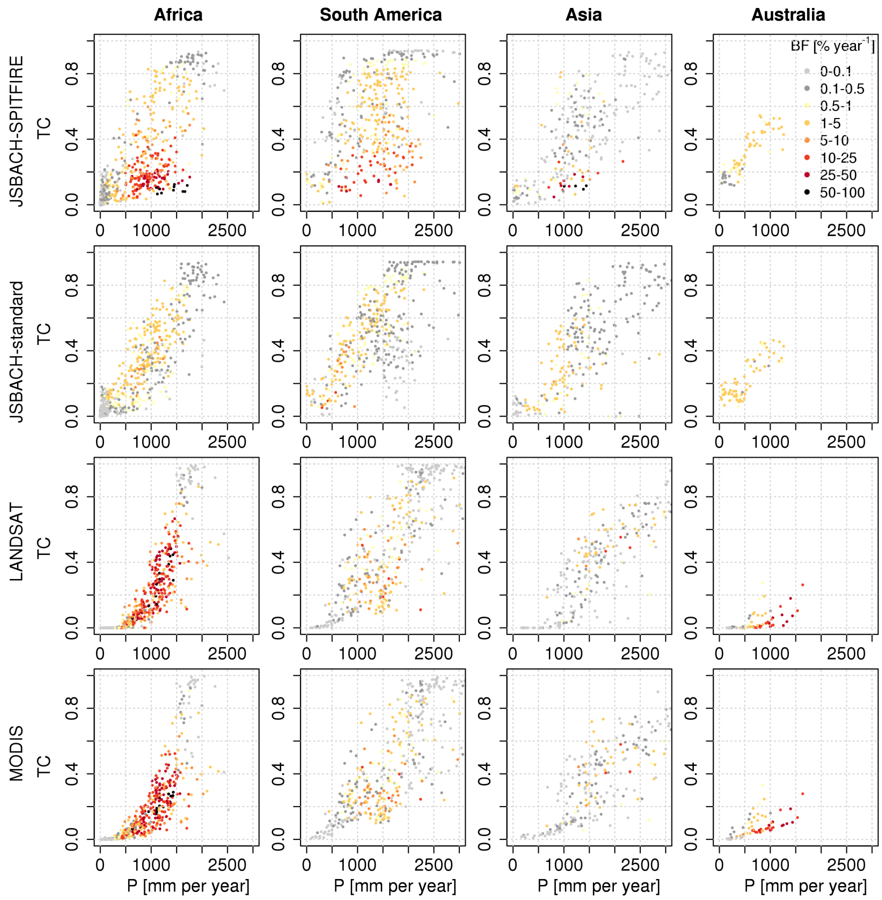

Figure A1. Same as figure 4 but tree cover filtered for the presence of shrub lands (using the MODIS open and closed shrub land classification). This indicates a low sensitivity of the fire-vegetation-climate relationships to shrub lands.

Competing interests. The authors have no competing interests

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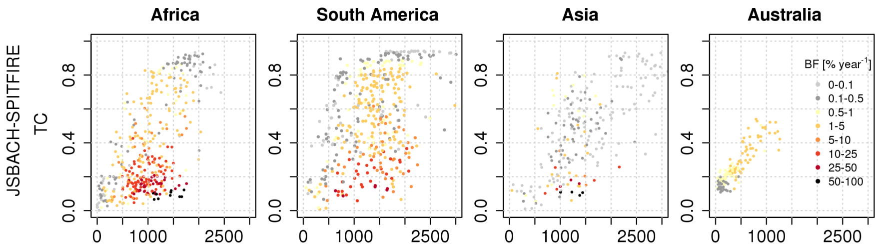

Figure A2. Modelled tree cover (TC) versus precipitation (P) [mm year-1]. Modelled tree cover was filtered for vegetation height of trees <5 m using the modelled vegetation height. This value is given as detection threshold for the satellite products. When filtering the model output with this threshold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

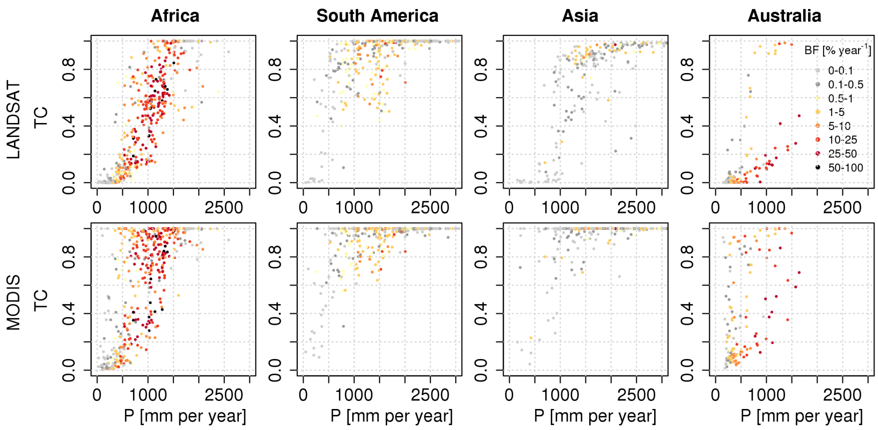

Figure A3. Tree cover (TC) versus precipitation (P) with color coded burned fraction (BF). Tree cover was here remapped from 0.05° resolution to 2° using the maximum value of the higher resolution instead of the mean.

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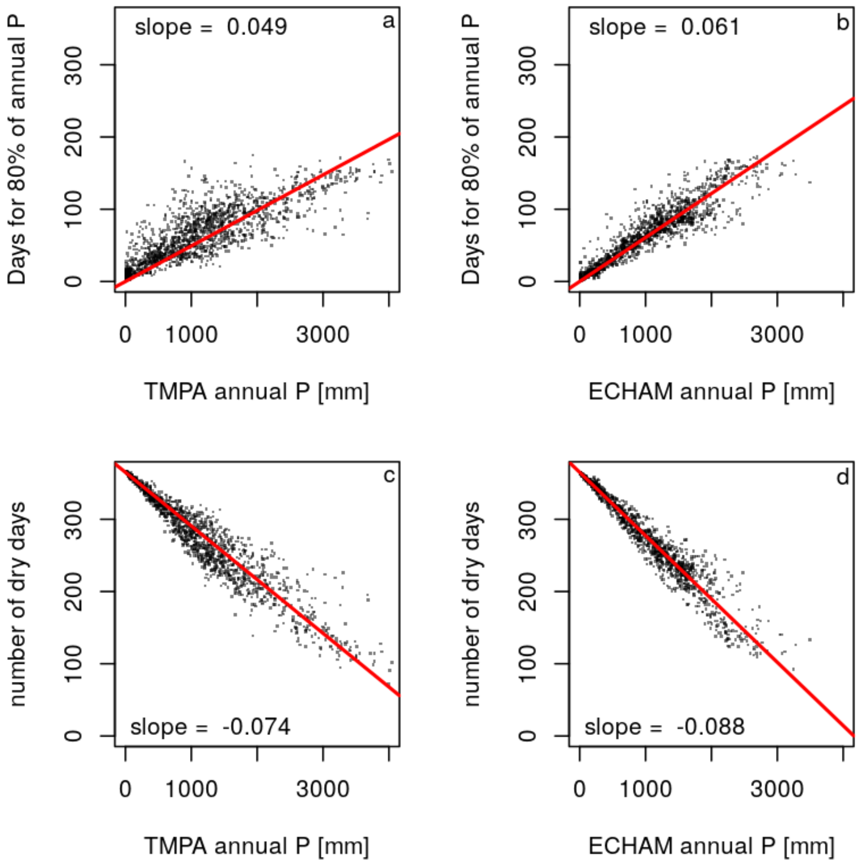

Figure B1. Relationship between annual precipitation and precipitation seasonality and number of dry days, respectively, for the ECHAM simulation used as meteorological forcing for the JSBACH simulations used here and the ~~CRU-NCEP~~ TMPA 3B42 daily dataset. Slope indicates the slope of the regression line.

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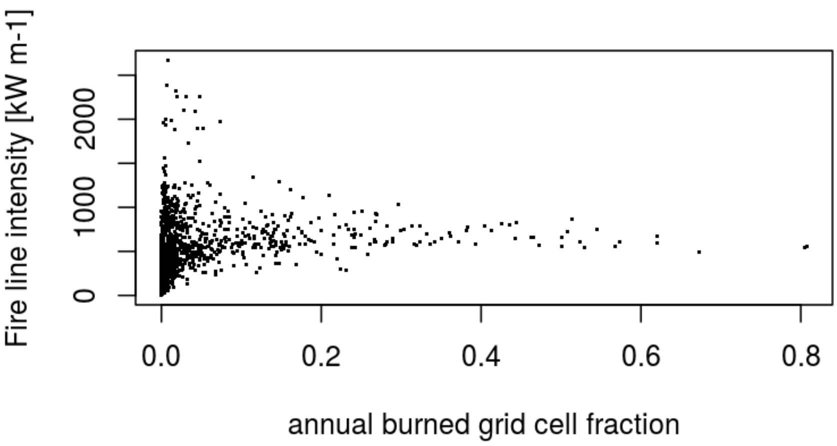

Figure C1. Relationship between annual burned area and fire line intensity. The expected decrease in fire line intensity for frequently burning areas due to the feedback between fire and fuel load is not found in the simulation results and might indicate that the feedback between fire occurrence, fuel load and fire intensity is too weak.

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