**Dear editor and referees,**

We want to thank you for your thoughts and comments on this manuscript. The reviews helped to clarify and improve the methodology, and reflect on the novel conclusions from this study compared to previous findings.

The major changes to the manuscript therefore are:

- A better explanation of the scope and novelty of this study (in the introduction, the discussion and conclusion sections)
- A clarification of the analysis of the trend in burned area and improved consistency between the different forcing factors

We below address the reviewer's comments point by point. We add *our replies in italic* and highlight suggested modifications in the manuscript in red. We number our replies and cross-refer to them to reduce the text if points had already been addressed before.

Referee #1

The manuscript "Sensitivity of simulated historical burned area to environmental and anthropogenic controls: A comparison of seven fire models" by Teckentrup et al compares several global fire schemes implemented in different global land surface models in a controlled setup (based on FireMIP), to analyze which processes and parameterizations cause differences between models. To this end, the authors perform a sensitivity analysis, where five different factors (CO2, population density, land use, lightning and climate) are individually modified. The authors identify land use as the most important factor for differences between models and discuss several potential routes to improve global fire models. The manuscript represents a significant contribution to attempts to improve the parameterizations of Earth system models. It is well written and relatively easy to understand. I have, however, one major concern regarding the setup of the sensitivity analysis, which also effects a part of the findings presented in the manuscript (see comments below). This point should be accounted for before submitting a revised version.

General comments:
In my opinion, the design of the sensitivity analysis is not sufficient to support all conclusions made in the manuscript. The setup is suitable to analyze differences between models with respect to one factor (e.g. CO2). This is the case, because the modification of the factor (e.g. keep at constant value) is the same for all models, so differences between models have to result from the shape of the relation between

this factor and the examined variable, burned area, which is implemented in the model. This is nicely explored in the manuscript by additional analyses of how the respective factors affect processes in the model. However, the setup is not suitable to compare the relative effects, meaning the relative importance, of different factors, e.g. population dynamics and climate. The reason is that the factors show trends of different strength over the examined period (1900-2013). It is not clear to me how the authors separate the effect of the trend from the effect of the relation between factor and the simulated burned area (see specific comments below). For example, let us assume that both $CO_2$ and climate have a similar effect on burned area in the models. However, $CO_2$ shows a strong trend in the period 1900-2013, while climate does not. This is enhanced in the setup of the sensitivity analysis by choosing a low value for $CO_2$ for the experiment, but average values of climate variables. Consequently, the slope of the relative difference in burned area (e.g. Fig. 2) will be larger for $CO_2$ than for climate, although both factors are (hypothetically) equally important in the model. This also affects the relative differences between models: If the general effect of $CO_2$ is amplified compared to climate in our hypothetical case, also the differences between models will be larger for $CO_2$ than for climate. The authors need to clarify this, both in the methods and discussion section of the manuscript.

1) *We thank the reviewer for their assessment and the acknowledgement of our contributions. We address the methodological concerns by three points:*
    - *We agree with the reviewer that we do not separate the effect of the trend in the driver from the effect of the relation between factor and simulated burned area. We used the word term sensitivity loosely to mean the net response to the forcing, while the reviewer interprets it more formally as a change in response variable per unit change in forcing. To avoid confusion we adopt the reviewer's definition and thus have changed the title to "Response of simulated burned area to historical changes in environmental and anthropogenic factors: A comparison of seven fire models". As our goal was to understand which factors cause the response of burned area over the historical period we therefore need to look at the response given the present trends. Finding a high sensitivity for a forcing factor that has no trend would not directly help to understand the response over the historical period. We now reword the appropriate text passages accordingly and address which factors influenced the burned area over the historical period. Further, we highlight that response in burned area are caused by both: the sensitivity of the model and the imposed trend in the forcing. We also add the trends of the forcing datasets in the table 4 and include three sentences 'Response of simulated burned area to individual drivers' section:*

*The population density forcing dataset has the strongest trend in the relative differences between the transient forcing and the year 1920 value followed by the land-use and land cover change dataset. The trend in atmospheric CO2 concentration is higher than the trend in the lightning dataset, which is more than twice as strong as in the air temperature. Wind speed shows the lowest trend of all investigated driving factors (see tab. 4).*

- *The reviewer notes that we use an average of the climate variables. This is not exactly what we did. We recycle the 20 first years that are available as climatic forcing (1900-1920) in the climate sensitivity simulations. However the reviewer is right that due to this there is no difference between the reference and the sensitivity simulation in the first 20 years of our comparison. We therefore now compute the trends of the in burned area between reference and sensitivity simulation starting in 1920 until the end of the simulation (2013). As we investigate the trend of differences with a consistent starting point for all factors (not simply the differences between sensitivity and reference simulation) we can now also compare the importance between the factors for the simulated historical changes of burned area.*

  *We add in the manuscript in the Methods:*
  *The resulting difference in burned area between the simulations is then a combination of the changes in the forcing and the sensitivity of the model to that forcing factor.*

  *and in the Response of simulated burned area to individual drivers section (see also reply 21):*
  *The response of burned area to the individual factors is determined by the changes in the driving factors and the sensitivity of the model to these changes.*

*We use the word sensitivity now only in these places and for "sensitivity experiment". In other places sensitivity has been replaced with "response of simulated burned area to" .*

- *As a second change we now use the absolute differences instead of relative differences. As the CO2 concentration for instance was fixed at the value of 1750, for some models the burned area that is used to normalized is much smaller than it would be if the value was set to the value of 1900. All models have a comparable magnitude of burned area for present day therefore the absolute changes are also comparable and the comparison between models is not strongly influenced. The reviewer did not directly request this but we think that*

*this increases the comparability between the factors. Our conclusions are not affected by this change but the quantification of trends is more meaningful. We add in the Methods section*
*Two of the models (CLASS--CTEM and CLM) started the simulations later than the others (1861 and 1850, respectively) and due to limitations in data availability the reference year of the forcings used in the spin-up varies (see tab. 1). We account for these differences in starting years between models and of the forcing factors by limiting our analysis to the period where all factors are different from the ones used in the spin-up (after 1921). These differences still influence the absolute differences, we therefore quantify the strength of the impact through the slope of a regression line and do not interpret the offset.*

Specific comments:
P 2 L 7 Please replace 'regularly' by a more detailed description, such as 'at least once in 100 years' or similar. Does that mean that at least 60% of the land surface are never affected by fire?

*2) The descriptions in the literature were not hat precise, thus we have removed the sentence.*

P 2 L 12 Please put the 5.6 ppm $CO_2$ into context: Which percentage of the total feedback per degree of warming does this correspond to?

*3) We now include the strength of the global land climate-carbon-cycle feedback (17.5 ppm K-1) as a context. It corresponds to a percentage of approximately 32%.*
*Analyses based on observations of the pre-industrial period suggest that the contribution of fire to the overall climate–carbon-cycle feedback is substantial with 5.6 ± 3.2 ppm K-1 $CO_2$ (Harrison et al., 2018) while the strength of the global land climate–carbon-cycle feedback estimated from Earth system simulations (Arora et al., 2013) is 17.5 ppm K-1 (Harrison et al., 2018). However, comparing potential fire-induced losses from terrestrial carbon pools and stocks of solid pyrogenic carbon in soils and ocean, fire may also be a net sink of carbon and Earth system simulations show a negative effect of fire on radiative forcing (Lasslop et al., 2019).*

P 2 L 26 Please explain the term 'woody thickening' shortly. How does vegetation composition change?

*4) We modified the manuscript as follows:*
*It can lead to an increase in the abundance of woody plants ('woody thickening'; Wigley et al., 2010; Bond and Midgley, 2012; Buitenwerf et al., 2012) [...]*

P 2 L 28 Why does reduced stomata conductance lead to increased fuel moisture? Is it assumed that plants take up water from the litter layer? Please explain this shortly.

*5) It is assumed that the water saving increases soil moisture and in consequence fuel moisture, including the living biomass contribution to the fuel load and the amount of litter on the soil surface.*

*On the other hand, decreased stomatal conductance and lower transpiration can lead to enhanced water conservation in plants. This increases the moisture content of soil as well as vegetation moisture content and consequently live and dead fuel moisture contents, which decreases flammability and in consequence reduces burned area.*

P 3 L 6 It is quite difficult to understand this sentence. Please start with the end (nr offires times size) and may be split into two sentences.

*6) We rephrased the sentence:*

*Burned area can be expressed as the number of fires multiplied by their fire size. The increase in burned area due to changes in ignitions is expected to differ between regions with varying population density as the largest fires occur in unpopulated areas (Hantson et al., 2015a).*

P 4 L 21 Does the around 150 year shorter spin-up for two of the models have effects on the fuel amount? Or is the turnover of the fuel fast enough to exclude that the models with shorter spin-up have less fuel?

7) The described simulations start from a spinup simulation where carbon pools were equilibrated. We add a sentence to describe this point in the Methods section:

*The baseline FireMIP experiment (SF1) is a transient simulation from 1700-2013, in which atmospheric CO2 concentration, population density, land-use, lightning, and climate change through time according to prescribed datasets. The baseline and sensitivity simulations start from the end of a spin-up simulation with equilibrated carbon pools (see Rabin et al. (2017a) for details of the experimental protocol).*

P 5 Tab1 Why are only low values of $CO_2$, population density and land use(?) included in the sensitivity analysis? Would it not make more sense to either use intermediate values, similar to climate and lightning, or, alternatively, test high values in addition to the low ones?

*8) See also reply 1. The experiments were designed to understand the influence of the historical variation in the driving factors on the simulated burned area. Therefore all factors were individually held constant at the initial conditions, e.g. the conditions that were used in the spin-up. Lightning and* *climate varied in the historical baseline simulation from 1900 and were set to the first twenty years before, as no forcing dataset is available before that time and because the interannual variability in climate is important (so using only one year is not an option). We now compute the trends starting with the year 1920, when all factors vary. Results may be slightly different when fixing the forcing at values of different years, but as we are interested in how the historical changes influenced the historical simulations in burned area we think the interpretation of the high values would be less direct. The sensitivity simulations now start with a state that existed in the past (neglecting, of course, any existing errors in the models and forcing datasets). Starting the simulation with the high values would be a hypothetical case, as the models also slightly depend on their history. Technically this would also mean that the sensitivity simulations all require a separate spin-up. They would start from different initial conditions and although they would end with the same forcing the model state would likely be different as for present day ecosystems are not in equilibrium due to global change.*

P 6 L 11 Please add a short description of how these data sets differ, beyond the retrieval algorithms, since this is important to understand the results (e.g. agricultural fires in GFED4s)

*9) We now include an improved description how these datasets differ.*

*To evaluate the simulations of burned area, we compare the simulated burned area with remote sensing data products. Global burned area observations from satellites still suffer from substantial uncertainty, as reflected by the considerable differences in spatial and temporal patterns between different data products (Humber et al., 2018; Hantson et al., 2016a; Chuvieco et al., 2018; van der Werf et al., 2017). Using multiple satellite products in model benchmarking is one approach to take into account these observational uncertainties (Rabin et al., 2017a). In this study, we use three satellite products: GFED4 (Giglio et al., 2013), GFED4s (van der Werf et al., 2017) and FireCCI50 (Chuvieco et al., 2018). GFED4 is a gridded version of the MODIS Collection 5.1 MCD64 burned area product. It is known that this product strongly underestimates small fires, including cropland fires (e.g.Hall et al. (2016)). In GFED4s, burned area due to small fires is estimated based on MODIS active fire (AF) detections and added to GFED4 burned area. However, this methodology may introduce significant errors related to erroneous AF detections (Zhang et al., 2018). As a complementary product, FireCCI50 was developed using MODIS spectral bands with higher spatial resolution than MCD64. A higher resolution enhances the ability to detect smaller fires; however, this improvement is partially offset by suboptimal spectral properties of the bands. Both GFED4s and FireCCI50 have larger burned area than GFED4. Since all three products are based on MODIS data, the inter-product* *differences probably underestimate uncertainties associated with these products. A recent mapping of burned area for Africa using higher resolution Sentinel-2 observations indicates that all three products substantially underestimate burned area (Roteta et al., 2019). For the model evaluation we use temporally averaged burned area fraction for the years 2001–2013, the interval common to all three satellite products and the model simulations.*

*Hall, J. V., T. V. Loboda, L. Giglio and G. W. McCarty (2016). "A MODIS-based burned area assessment for Russian croplands: Mapping requirements and challenges." Remote sensing of environment 184: 506-521.*

*Roteta, E., A. Bastarrika, M. Padilla, T. Storm and E. Chuvieco (2019). "Development of a Sentinel-2 burned area algorithm: Generation of a small fire database for sub-Saharan Africa." Remote Sensing of Environment 222: 1-17.*

*Zhang, T., Wooster, M., de Jong, M., and Xu, W.: How Well Does the 'Small Fire Boost' Methodology Used within the GFED4.1s Fire Emissions Database Represent the Timing, Location and Magnitude of Agricultural Burning?, Remote Sensing, 10, 823, https://doi.org/10.3390/rs10060823, 2018.*

P 6 L 16 In which direction is the distribution skewed? Does the model resolution have an effect on the shape of the distribution?

*10) The distribution of burned area has a very large fraction of 0 and small burned area, high fractions of burned area have a very low frequency. We add a plot indicating the influence of individual datapoint in the comparison between GFED4 and FireCCI50 in the supplement. Without transformation a very small fraction of the data points determines the correlation, this is improved with the squareroot transformation and would be further improved using a log transformation, but that would mean that grid cells with 0 would be excluded. As the correlation should provide a global evaluation of the model a much higher influence of individual grid cells is not desirable. As the models are all aggregated to the same spatial resolution the model resolution does not have an influence on the distribution.*

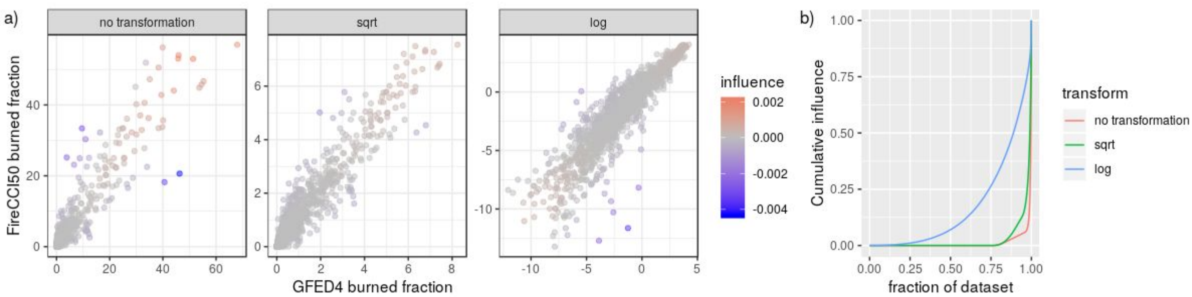


*Figure A9: Scatter plots for the GFED4 and FireCCI50 dataset without transformation, square root transformation and log transformation (a), the color* *indicates the influence of individual data points on the correlation (computed as the difference in the correlation with and without that datapoint). Cumulative influence of data points in the dataset on the correlation (b). Without transformation a very small fraction has a strong influence on the correlation, these are grid cells with high burned area fraction (as can be seen in a).*

*We also modify the text in the main paper:*
*We quantify the agreement between models and observations by providing the global burned area and the Pearson correlation coefficient for the between grid cell variation (see tab. 3). We choose the Pearson correlation as it quantifies the covariation of the spatial patterns, and is less sensitive to the highly uncertain absolute burned area values. Burned area has a strongly skewed distribution, with few high values and many small values close to, or equal to, zero. These few high values have a much higher contribution to the overall correlation (see figure A9 in Appendix) and therefore the metric is strongly determined by the performance of the model in areas with high burning. Square root or logarithmic transformation leads to more normally distributed values, that reduce this bias (see figure A9 in Appendix). As the logarithm transformation excludes grid cells with zero burned area, we adopt the square root transformation.*

P 6 L 21 The values 0.01 and 0.2 refer to the GFED4 and FireCCI50 data sets, I assume? Please make this clear.

*11) We clarify in the manuscript*
*[...] yields uncertainty estimates of 0.01% (GFED4) and 0.2% (Fire CCI50)*

P 8 L 9 - P 9 L 2 I think this part should be shifted to the discussion.

*12) We did not separate Results and Discussion but directly discuss the results following the presentation. We shortened the indicated paragraphs slightly to have more emphasis on the results and moved part of it to the "Implications for model development and applications" section.*

P 9 L 4ff I do not understand the line of argument: In the first three experiments ($CO_2$,population,land use), relatively strong trends and large model differences throughout the 20th century are reported. In the other two experiments, the trends are weaker. However, this result may be influenced from the setup of the sensitivity analysis, since there are trends in $CO_2$, land use and population density over the 20th century. Population density, for instance, is kept at the low value of 1900 in the experiment, so it is logical that the rel. diff. BA increases over the 20th century for models, which assume a positive effect of population density on BA (e.g. LPJ-GUESS-SPITFIRE), due to the trend in population density. For models which

assume a negative effect of population density on BA (e.g. LPJ-GUESS-SIMFIRE-BLAZE), the opposite is the case.
However, it is not described how the effect of the trends (e.g. increase in population density) is separated from the effect of the factor in the model (e.g. effect of population density on fire).

> *13) See also reply 1). Population density is kept at the value of 1700. We now use the absolute differences. The initial values of land use, CO2 and climate stem from different years. This is because climate data were only available from 1900 onwards. We now compute the trends starting in 1920 when all factors vary, with low influence on the results. Fig. 2 already showed the strong interannual variability of climate and lightning and the absence of trends over the whole period. Qualitatively the spread between models for population density is logical considering the different assumptions in the models, but note that most models assume a curve with a maximum and therefore include positive and negative effects. Quantification of the net effect and also the magnitude of the effect therefore requires the sensitivity simulations provided in this study. As we aim to quantify the effect of forcing factors over the simulation period we quantify the response in burned area given the historical trend. Quantification of the burned area response with a hypothetical trend (for instance a doubling) would not allow to understand the historical simulated trends.*

Figure 2 and Table 4 are only suitable to compare the relative effect of one factor between models, but not the relative importance of different factors. Maybe the relations between rel.diff. BA and lightning, and also rel.diff. BA and climate, are weak because the trends over the 20th century are not as pronounced as for the other factors, and also average values (1901-1920) are used for the experiments. In this case, the mean values of baseline scenario and the experiments would be very similar to each other, and variations would be randomly distributed over the 20th century, which is partly consistent with Fig. 2. Therefore, I am not convinced that the slope of the rel. diff. BA over the 20th century (Tab 4, Fig 2) is a good measure of the strength or importance of a certain factor in the model, compared to other factors.

> *14) We now use the absolute differences, see reply 1. We assume this may also again relate to the fact that we did not separate out the strength of the trend in the driving factor. See previous comment and reply 1 and 8. We now clarify that we are interested to understand which factors cause the simulated trends over the historical period. Note that the climate was not averaged over the 1900-1920 period but recycled. We now compute the trends for the absolute differences and for the period 1920 to 2013 for which all factors vary.*

P 12 L 11 Please add ’concentrations,’ after ’CO2’.

*15) We replaced all occurrences of 'CO2' with 'atmospheric CO2 concentration' to be precise.*

P 16 L 3 Please explain shortly why the presence of lightning always leads to a net suppression of fire by humans.

*16) The effect of increasing human ignitions is strongest if no other ignitions are present. If lightning already ignited a fire and additional human ignition has little effect. This was tested with the CTEM model, which is also part of this intercomparison study. We include in the text:*

*The presence of lightning ignitions reduces the limiting effect of a lack of human ignitions on burned area. For the CLASS-CTEM model as soon as lightning ignitions are present, the net effect of humans is to suppress fires, even though the underlying relationship assumes an increase in ignitions with population density (Arora and Melton, 2018, supplement). This may explain why global models assuming an increase of ignitions with increases in population density are able to capture the burned area variation along population density gradients (Lasslop and Kloster, 2017; Arora and Melton, 2018) and why global statistical analyses find a net human suppression also for low population density (Bistinas et al., 2014).*

P 18 L 15ff From the listed parameters, only the first two (precipitation and temperature) are climate variables. The others are dependent variables, which are also influenced by other factors (e.g. CO2). Please explain why you include them in the test. Moreover,I would like to see an analysis of the effects of wind speed. Is there a trend in wind speed from 1900 to 2013 ?

17) *We include the vegetation parameters in addition to the climate parameters as climate influences fire not only directly but also through its influence on vegetation. We modify the included explanation: "The influence of climate on burned area is complex; it influences burned area through the meteorological conditions and through effects on vegetation conditions that influence fuel load and fuel characteristics (Scott et al., 2014). We therefore correlated for each grid cell changes in physical parameters (precipitation, temperature, wind speed and soil moisture) and vegetation parameters (litter, vegetation carbon and grass biomass) with changes in burned area."*
*Note that CO2 is not different between the simulations compared here, only climate differs. In addition, we add the linear regression slope and the standard deviation for wind speed in table 4; over 1921 - 2013, the relative difference in wind speed has a significant negative linear regression slope (-0.012 +- 0.006). We add 'Wind speed shows the lowest trend of all investigated driving factors (see tab. 4).'*

P 18 L 30 The word 'is' occurs one time too often.

*18) Removed.*

P 19 L 10-12 I am not sure that this statement is valid, given my concerns on the setup of the sensitivity analysis above.

*19) See reply 1, 8, 13, 14. This refers to "Representing human influence on fire is the major challenge for long-term projections. Our analyses of the controls on the variability of fire suggest that human activities drive the long term (decadal to centennial) trajectories, while considering climate variability may be sufficient for short-term projections."*

*We have now improved the computation of trends. To assess the importance of certain factors in trajectories the underlying trend is important, a separation of the trend in forcing from the sensitivity of the model would therefore not improve the assessment. However changes in the trends of the forcing factors for future can change the results we therefore included:*

*Changes in the trends of the driving factors may change this balance. For instance, stronger changes in climate into the future may increase the relative importance of climate for long term fire projections in the future.*

P 19 L 32 The word 'Table' is missing in the brackets.

*20) It is included now.*

P 21 L 14 How strong is the trend in changing climate compared to other trends, e.g.population density and CO2?

*21) We now quantify the trends in the forcing factors. It is however questionable how comparable these changes are between factors. Also the global increases in CO2 are more meaningful than global changes in temperature as CO2 is fairly similar in different locations while the changes in temperature vary regionally. For text modifications, see reply 1.*

**Dear editor and referees,**

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The major changes to the manuscript therefore are:

- A better explanation of the scope and novelty of this study (in the introduction, the discussion and conclusion sections)
- A clarification of the analysis of the trend in burned area and improved consistency between the different forcing factors

We below address the reviewer's comments point by point. We add *our replies in italic* and highlight suggested modifications in the manuscript in red. We number our replies and cross-refer to them to reduce the text if points had already been addressed before.

Referee #2

General comments

The study is a useful compilation of the analysis of sensitivity experiments in the FireMIP output, but it is largely a technical report of the sensitivity of FireMIP model simulations of burned area since 1900. Philosophically, there is nothing really offered by the authors in terms of specific testing of improvements/changes needed with firemodels beyond what has been pointed out in the literature in papers such as Van Marle et al 2017 and Andela et al 2017, and hinted at in the Hantson et al 2016 FireMIP overview paper and the Forkel et al 2019 paper. While I appreciate the depth of the dissection of the causes for the discrepancies among FireMIP models in this study, I find myself with no questions about FireMIP that have new or interesting answers, which is a concerning lack of momentum from the initially promising FireMIP effort. For example, did the FireMIP sensitivity experiments produce knowledge that the modeling groups could leverage for specific technical advances on, say, a future set of experiments? If anything, this paper makes me increasingly skeptical about the utility of FireMIP other than to show precisely what these authors stated in their conclusions: "Although burned area in most models compares reasonably well with satellite observations, there is a huge spread in transient simulations before the satellite era and a huge spread in the influence of the driving factors between models." Again, however, many FireMIP related papers have already pointed this out.I recommend that the paper be published and I think that my comments fall somewhere between a minor and major revision, so I labeled it as minor revisions even though some of my comments might require some major discussion amongst the authors in terms of structuring a reply or rebuttal. The challenge that I offer to the authors is this: I do not see what we gain beyond now knowing that the sensitivity experiments areas confusingly inconclusive as the core experiments. If I were re-formulating my firemodel and looking to this study, I would have little idea as to what the focus point should be other than simply acknowledging weaknesses such as the representation of human use of fire or needed better data for model parameterizations. The authors may need to make their case more clearly for this paper to stand out beyond being a technical report out.

*1) We thank the reviewer for the critical review and take the chance to reflect and rework our conclusions. We include improvements in the Introduction, the discussion and the conclusions to clarify the novelty of our study.*

*In the introduction we clarify how our work relates to previous work:*

*Fire-enabled vegetation models simulate fire regimes in response to the combination of individual forcings, including atmospheric CO2 concentration, population density, land-use change, lightning and climate.*

*Individual fire-enabled vegetation models have been shown to simulate observed global patterns of burned area and fire emissions reasonably well (Kloster et al., 2010; Prentice et al., 2011; Li et al., 2012; Lasslop et al., 2014; Yue et al., 2014), but there are large differences between models in terms of regional patterns, fire seasonality and interannual variability, historical trends (Kelley et al., 2013; Andela et al., 2017) and responses to individual factors (Kloster et al., 2010; Knorr et al., 2014, 2016; Lasslop and Kloster, 2017, 2015). The fire model intercomparison project (FireMIP, Hantson et al., 2016a; Rabin et al., 2017a) provides a systematic framework to consistently analyse and understand the causes of these differences and to relate them to differences in the treatment of key drivers of fire in individual models. The FireMIP project provides simulations for a systematic comparison of fire-model behaviour based on outputs of a large range of models with identical forcing inputs. In addition to a reference historical simulation, sensitivity simulations were conducted for individual forcings, specifically atmospheric CO2 concentration, population density, land-use change, lightning and climate. A recent evaluation of the FireMIP models indicates that the relationship with climatic parameters is captured well by models, the response to human factors is captured by some models and the response to vegetation productivity or the allocation of carbon to fuels needs refinement for most models (Forkel et al., 2019a). Comparisons of the FireMIP historical simulations found differences in transient model behaviour in the 20th century (Andela et al., 2017; van Marle et al., 2017). The causes of the differences and the reasons why different models show different responses are not yet understood.*

*Our study shows in detail which model responses of burned area to environmental factors can be understood, how these are related to the model equations and how these translate into certain trends of burned area. The understanding on how certain model assumptions lead to trends in burned area is novel, the need for this was emphasized by the previous publications (but they do not provide it) and the recently detected trends in the satellite data. We improved the sections discussing the new possibilities for model reparameterization:*
*The main concern for model applications is the large spread of the historical simulated burned area. It remains difficult to evaluate and optimize the transient burned area simulations as the period observed by satellites is still short and the trends are not robust (Forkel et al., 2019b). Fire proxies (charcoal and ice-cores) give information on biomass burning over longer time scales. They do not confirm the recent decrease in burned area detected by satellites, but also only contain very few datapoints for that period (Marlon et al., 2016). For a valid comparison with the long term fire proxies, including estimates of deforestation fires in the models will be crucial, as land-use change fire emissions likely have a strong contribution to the signal (Marlon et al., 2008). An improved understanding of uncertainties in observed trends of fire regimes is therefore necessary. Only robust information should be included in models.*
*Our analysis shows which parts of the models are particularly important to simulate changes in burned area and need additional observational constraints or improved process understanding. In line with previous research (Bistinas et al., 2014; Hantson et al., 2016a, b; Andela et al., 2017), the large divergence in the response to human activities between the FireMIP models shows that the human impact on fires is still insufficiently understood and therefore not constrained in current models.*

*specifically for the effect of land-use change on burned area:*
*We identify land-use change as the major cause of inter-model spread. Only one model explicitly includes fires associated with land-use and land cover change (cropland and deforestation fires), all the other models only include such effects through changes in vegetation parameters and structure. The inclusion of cropland fires is certainly important to understand and project changes in emissions, air pollution and the carbon cycle (Li et al., 2018; Arora and Melton, 2018). Cropland fires are, due to their small extent and low intensity, still a major uncertainty in our current understanding of global burned area (Randerson et al., 2012). Biases in the spatial patterns of burned area and the relationship between cropland fraction and burned area can therefore be expected. High resolution remote sensing may help to improve the detection (Hall et al., 2016). Moreover, understanding why and when humans*

*burn croplands on a regional scale may help to find an adequate representation of cropland fires within models and avoid overfitting to observational datasets. As croplands are simply excluded from burning in most models (except two), the spread of the other models is likely related to the treatment of pastures. Fires on pasturelands have been estimated to contribute over 40% of the global burned area (Rabin et al., 2015). Pasture fires are not treated explicitly in any of the models, although some models slightly modify the vegetation on pastures by harvesting or changing the fuel bulk density (see tab. 5). Expansion of pastures is mostly implemented by simply increasing the area of grasslands. Information on how fuel properties differ between pastures and natural grasslands could therefore help to improve model parametrisations. Prescribing fires on anthropogenic land covers can be a solution for certain applications of fire models (Rabin et al., 2018). Grazing intensity was found to be related to decreases in burned area (Andela et al., 2017). Models so far represent the area that is converted due to land cover change but not the intensity of land-use. This was partly due to the lack of global data regarding land use intensity which is now becoming available and provides new opportunities for fire model development (e.g. the LUH2 dataset; Hurtt et al., 2017). In the sensitivity simulations shown here, even models that decrease burned area due to land-use and land cover change do not show a further decrease over the last decade. This indicates that model input datasets, explicit in time and space, for land-use intensity and grazing intensity are necessary for fire projections. The level of socioeconomic development also modifies the relationship between humans and burned area (Andela et al., 2017; Forkel et al., 2017). Regional analysis of remote sensing data could be highly useful, as a global relationship between burned area and individual human factors as assumed in many models and also statistical analysis is not likely. Assumptions on how different human groups (hunter-gatherers, pastoralists, and farmers) use fire have been included in a paleofire model (Pfeiffer et al., 2013). The development of such an approach for modern times would be highly valuable for fire models that aim to model the recent decades and future.*

*for the effect of CO2 on burned area:*

*We show that, although all models show an overall increase in biomass as a consequence of increasing atmospheric CO2 concentration, models disagree about whether this results in an increase or decrease in burned area. The disagreement reflects the complex ways in which changes in atmospheric CO2 concentration influence vegetation properties, which results in different responses in different ecosystems. For LPJ-GUESS-SPITFIRE and JSBACH-SPITFIRE the CO2 fertilization effect considerably contributed to an increase in burned area. Such an effect is so far only supported for fuel limited* *areas (Forkel et al., 2019b). The assumption that the influence of higher fuel load on burned area levels off for high fuel loads as used in other models could help to reduce this increase in burned area in regions with higher fuel load.*

*for the effect of climate and lightning on burned area in general:*
*Climate and lightning have a much lower effect on the trends than the other factors. While this study focuses on the trends, research on the short term variability and extreme events will be highly useful to investigate fire risks. The influence of climate and lightning on fire are therefore important research topics even if we find a comparably low influence on the long term trends. Moreover the trends in climate parameters may increase for the future and therefore the influence on burned area might increase.*

*and for the effect of lightning on burned area specifically:*
*But not only spatial patterns of lightning are important, the co-variation with climate as well as the temporal resolution of the input dataset determine the influence on burned area (Felsberg et al., 2018). Although we do not detect large signals in global burned area due to changes in lightning, lightning is known to be an important cause of ignitions regionally and is potentially involved in more complex interactions between fire, vegetation and climate, which can speed up the northward expansion of trees to the north in boreal regions (Veraverbeke et al., 2017). Thus, although our results suggest that the influence of increasing lightning is negligible at a global scale, it is a potentially important factor for process-based models that aim to model interactions between fire, vegetation and climate.*

*In addition, we point to datasets that can be used for model evaluation:*
*Recent advances in remote sensing products have high potential to support model development. However, remotely sensed burned area datasets alone are not a sufficient basis to evaluate fire models as many model structures can lead to reasonable burned area patterns. The emergence of longer records of burned area and the increasing availability of information on other aspects of the fire regime considerably improve opportunities to evaluate and improve our models. The FRY database (Laurent et al., 2018) and the global fire atlas (Andela et al., 2018), for example provide information on fire size, numbers of fire, rate of spread, and the characteristics of fire patches. These datasets will be useful to, for instance, separate effects of ignition and suppression. Rate of spread equations in global fire models are at present either very simple empirical representations tuned to improve burned area or based on laboratory experiments (Hantson et al., 2016). The mentioned datasets now offer the opportunity to derive parameters for rate of spread*

*equations at the spatial scales these models operate on. Fire size and rate of spread are important target variables besides burned area that can determine the impacts of fire. The effects on vegetation (combustion of biomass and tree mortality; Williams et al., 1999; Wooster et al., 2005) and on the atmosphere (Veira et al., 2016) are a function of fire intensity, which is also included in the FRY database (Laurent et al., 2018). A better evaluation of such parameters can enhance the usability of fire model simulations.*
*The specific model application has a strong influence on judging the validity of a model. Our analyses of the controls on the variability of fire suggest that human activities drive the long term (decadal to centennial) trajectories, while considering climate variability may be sufficient for short-term projections. Changes in the trends of the driving factors may change this balance. For instance, stronger changes in climate into the future may increase the relative importance of climate for long term fire projections in the future.*

*We change our Summary and conclusions to:*
*This comprehensive analysis of the influences of climate, lightning, CO2, population density and land-use and land cover change provides improved understanding of the relation between simulated historical trends in burned area and process representations in the models. It shows in detail which model responses of burned area to environmental factors can be understood, how these are related to the model equations, and how these translate into trends of burned area for the historical period.*

*Followed by the summary of insights for the individual factors. We add for the effect of population density:*
*It would be useful to develop an approach that represents local human-fire relationships, but this will likely remain a long term challenge and requires the synthesis of knowledge from various research fields.*

*We add for the effect of land use and land cover change:*
*Improved knowledge on the effects of land-use intensity on burned area and the development of appropriate forcing datasets could strongly support model development.*

*And end with:*
*The uncertainties in global fire models need to be taken into account in model applications, for instance if model simulations are to be used to support climate adaptation strategies. Model ensemble simulations can give indications of such uncertainties. Therefore the results of this study provide a basis to interpret uncertainties in global fire modelling studies. The spatial patterns of burned area and its drivers are already well explored and*

*understood. We here provide a summary of which model assumptions need additional constraints to efficiently reduce the uncertainty in temporal trends.*

Specific comments

Figures in the Supplement – please make larger versions of the maps in figures a1-a8. Another improvement would be to include a continuous rather than binary scale of values of the correlation coefficient in a2-a8. Painting the world with binary correlation coefficients would mask areas of potential weak and strong linear correlation. The strength of this study is the technical report-out of FireMIP sensitivity studies, so by making figures a1-a8 so hard to read, the authors are undermining the very purpose of the work. Read another way, the community may gain more with more detail in the manuscript.

*2) Figure a2-a8 are not correlations but the slope coefficients. It only shows significant changes to identify regions with weak relationships. We wanted to emphasize the spatial distribution of decreases and increases and therefore chose this color scale. We now provide the graphs with the more detailed color scale and larger versions of the maps, because, as the reviewer suggests, it will be useful for the community.*

Page 6 line 16-17 – authors stated they used a square root transformation to reduce the skewness of the distribution, but it is unclear why. Please expand on both the reasons and what this transformation accomplishes. Perhaps a supplemental figure?

*3) See also reply 10 for reviewer 1. The correlation coefficient is most useful for normally distributed variables. The burned area varies over several orders of magnitude and the skewed distribution gives the highest importance to values with very high burned area. We transformed the data to improve the applicability of the metric. We include now a figure illustrating the influence of individual data points to the correlation, showing that the outliers in the untransformed data have a really high contribution and determine the correlation (figure A9 in the Appendix). This is improved with the squareroot transformation and would be further improved using a log transformation, but that would mean that grid cells with 0 would be excluded. With the transformation the contribution is better distributed to all data points, it is therefore more useful for global modelling where a too strong focus on only grid cells with high burned area can be distracting.*

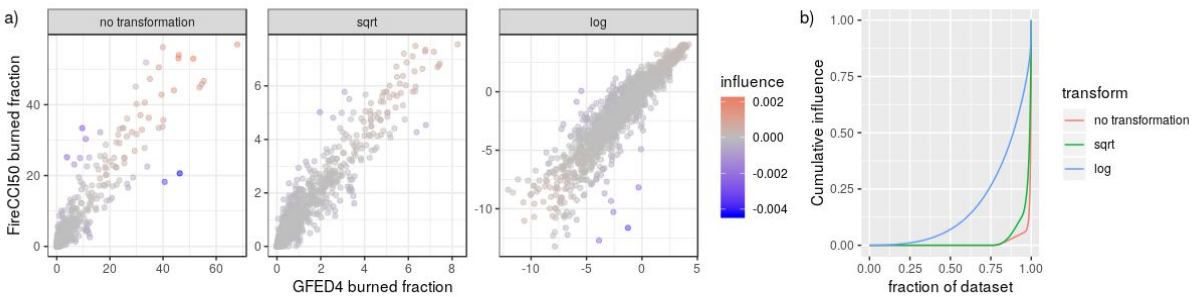

*Figure A9: Scatter plots for the GFED4 and FireCCI50 dataset without transformation, square root transformation and log transformation (a), the color indicates the influence of individual data points on the correlation (computed as the difference in the correlation with and without that datapoint). Cumulative influence of data points in the dataset on the correlation (b). Without transformation a very small fraction has a strong influence on the correlation, these are grid cells with high burned area fraction (as can be seen in a).*

*We also modify the text in the main paper:*
*We quantify the agreement between models and observations by providing the global burned area and the Pearson correlation coefficient for the between grid cell variation (see tab. 3). We choose the Pearson correlation as it quantifies the covariation of the spatial patterns, and is less sensitive to the highly uncertain absolute burned area values. Burned area has a strongly skewed distribution, with few high values and many small values close to, or equal to, zero. These few high values have a much higher contribution to the overall correlation (see figure A9 in Appendix) and therefore the metric is strongly determined by the performance of the model in areas with high burning. Square root or logarithmic transformation leads to more normally distributed values, that reduce this bias (see figure A9 in Appendix). As the logarithm transformation excludes grid cells with zero burned area, we adopt the square root transformation.*

Page 6 line 19 – major uncertainties is a subjective phrasing that requires more qualifications. Humber et al 2018 clearly discussed the nuanced and important ways that observed burned area data sets agree and disagree when using global, regional, and varying temporal scales. Looking at Figure 3 in Humber et al 2018 and Figure 1 in this paper, however, the implication is that FireMIP models have even more than "major" uncertainties in the sense that even at an annual time scale, there is more spread amongst models than amongst the observations. Furthermore, the three burned area data sets discussed in this study (GFED4, GFED4s, and FireCCI50) show that there is agreement unless the specific methodological approach is augmented with the small fires approach described in Randerson et al 2012. Is that really a major disagreement or just a difference in analysis? Please be more specific or careful in the discussion around observational uncertainties. Also, please see my comment about Figure 1 below.

*4) See also reply 9 for reviewer 1. In Figure 1, the models are largely within the range of the observations for the evaluation period. The section shows that the models are largely in the range of satellite observed burned area and have a reasonable spatial distribution (see appendix figure A1). There is methodological uncertainty in satellite burned area products and this is reflected in the variation between the products due to the methodological* *approach applied. The spread between these products still underestimates the uncertainty in the satellite products as all are based on the same sensor (MODIS). This is already mentioned in the manuscript on p.6 l. 23. We improve the paragraph with more details on the differences between the sensors and also link it to more recent burned area estimation using the high resolution Sentinel-2 data, which gives insights in the huge uncertainty of satellite products (see also reply 9 for reviewer 1).*

*To evaluate the simulations of burned area, we compare the simulated burned area with remote sensing data products. Global burned area observations from satellites still suffer from substantial uncertainty, as reflected by the considerable differences in spatial and temporal patterns between different data products (Humber et al., 2018; Hantson et al., 2016a; Chuvieco et al., 2018; van der Werf et al., 2017). Using multiple satellite products in model benchmarking is one approach to take into account these observational uncertainties (Rabin et al., 2017a). In this study, we use three satellite products: GFED4 (Giglio et al., 2013), GFED4s (van der Werf et al., 2017) and FireCCI50 (Chuvieco et al., 2018). GFED4 is a gridded version of the MODIS Collection 5.1 MCD64 burned area product. It is known that this product strongly underestimates small fires, including cropland fires (e.g.Hall et al. (2016)). In GFED4s, burned area due to small fires is estimated based on MODIS active fire (AF) detections and added to GFED4 burned area. However, this methodology may introduce significant errors related to erroneous AF detections (Zhang et al., 2018). As a complementary product, FireCCI50 was developed using MODIS spectral bands with higher spatial resolution than MCD64. A higher resolution enhances the ability to detect smaller fires; however, this improvement is partially offset by suboptimal spectral properties of the bands. Both GFED4s and FireCCI50 have larger burned area than GFED4. Since all three products are based on MODIS data, the inter-product differences probably underestimate uncertainties associated with these products. A recent mapping of burned area for Africa using higher resolution Sentinel-2 observations indicates that all three products substantially underestimate burned area (Roteta et al., 2019). For the model evaluation we use temporally averaged burned area fraction for the years 2001–2013, the interval common to all three satellite products and the model simulations.*

*Hall, J. V., T. V. Loboda, L. Giglio and G. W. McCarty (2016). "A MODIS-based burned area assessment for Russian croplands: Mapping requirements and challenges." Remote sensing of environment 184: 506-521.*

*Roteta, E., A. Bastarrika, M. Padilla, T. Storm and E. Chuvieco (2019). "Development of a Sentinel-2 burned area algorithm: Generation of a small*

*fire database for sub-Saharan Africa." Remote Sensing of Environment 222: 1-17.*

*Zhang, T., Wooster, M., de Jong, M., and Xu, W.: How Well Does the 'Small Fire Boost' Methodology Used within the GFED4.1s Fire Emissions Database Represent the Timing, Location and Magnitude of Agricultural Burning?, Remote Sensing, 10, 823, https://doi.org/10.3390/rs10060823, 2018.*

*Moreover we now include a new publication (Forkel et al. 2019) in the discussion which shows that the trends as observed by satellites are still highly uncertain and not robust.*

*Satellite records show a decline in global burned area since 1996 (Andela et al., 2016). However, as Forkel et al. (2019b) have shown, the significance of the observed global decline is strongly affected by the length of the sampled interval because of the high interannual variability in burned area and trends between products show only a low correlation (Forkel et al., 2019b).*

*No observations document the longer term trends in burned area. Charcoal records (Marlon et al., 2008, 2016) and carbon monoxide data from ice-core records (Wang et al., 2010) are a proxy for biomass burning and show a global decrease in biomass burning over most of the 20th century. However, the charcoal records show an increase in burning since 2000 CE, but this discrepancy might reflect regional undersampling (for instance in Africa) or taphonomic issues of the charcoal record. A recent fire emission dataset (van Marle et al., 2017) merges information from satellites, charcoal records, airport visibility records and if no other information was available uses simulation results of the FireMIP models. This dataset is not included to evaluate the models here as it is partly based on the simulations of the FireMIP models and as it provides only estimates for emissions not burned area.*

*The understanding of the drivers on simulated trends that we give below provides insights on what causes the simulated trends and which assumptions control the trend. These insights will help to understand which observational constraints and process understanding is required to improve global fire models.*

Page 6 line 20-21 – please explain what is meant by 0.01 and 0.2%. I am not following what the values refer to.

*5) We clarify in the manuscript, see also reply 11 for reviewer 1:*

*[...] yields uncertainty estimates of 0.01 % (GFED4) and 0.2% (Fire CCI50)*

Figure 1 would benefit from being split into a two-part plot: one part could remain asis, but the other would show the present day subset of the full analysis period. This is the evaluation period, but it is buried under too many curves.

*6) Unfortunately this suggestion would lead to us exactly reproducing the figure number 3 of the Andela et al 2017 paper and contradicts the general suggestion of the reviewer to go beyond previous studies. We do agree, however, that the satellite datasets are buried under the curves in our plot. We now include a shaded area for the range of the satellite datasets as this is the main point we wish to convey here. As well, since we do not want to focus on evaluation of the models (which has been the focus of Andela et al. 2017 and Forkel et al. 2019 already) we rephrase the heading of this section to "Simulated historical burned area" to reflect the focus on the longer term trends and understanding the reasons for the divergence between models, independent of their correctness. We add a reference to Forkel et al. (2019) for more details.*

Table 3 and page 7 – are these spatial correlation coefficients that compare the gridcell to grid cell agreement on a map? Or are they temporal correlation coefficients? It does not seem that Figure 1 temporal correlation is this high, but please clarify in the text. If this is a spatial correlation, please include the figure in the Appendix as it could be valuable to modelers in identifying regional weaknesses in the FireMIP simulated burned area.

*7) We conduct a gridcell to gridcell comparison here, however spatial correlation coefficient is not a statistical term and may be confused with spatial auto-correlation. It implies some consideration of the geographical location. For table 3, we average burned area fraction over 2001 - 2013 (compare figure A1) and then correlate all individual grid cells of the remotely sensed product with the respective model. Therefore there is only one value, we did not analyse the spatial distribution or regional variation. For example, the first value in table 3, column 'R(GFED4, model)' is the Pearson correlation coefficient between the square root-transformed burned area fraction averaged over 2001 - 2013 in GFED4 and the square root-transformed burned area fraction averaged over 2001 - 2013 in CLASS-CTEM. We now include the "correlation over grid cells" to indicate it is not over time and change the caption of table 3 to "Global burned area averaged over 2001–2013 in Mha yr-1 and the Pearson correlation coefficients between burned area fraction averaged over 2001 - 2013 in the baseline experiment SF1 for all FireMIP-models and the respective observation data over all grid cells. We use a square root transformation on both model and observations. All correlation coefficients are significant (p-value < 0.05).*

Table A2 is missing statistics relative to GFED4s.

*8) GFED4s does not provide uncertainty estimates and therefore is not included in table A2. (We change the table caption from 'GFED4 and FireCCI50 provide uncertainty estimates' to 'Only GFED4 and FireCCI50* *provide uncertainty estimates, therefore GFED4s is not included' to clarify this.)*

Page 9 – the first sentence on this page highlights a major problem in the approach with modeling. Aiming at trends without a full understanding of the drivers in the simulations is .

> *9) One sentence in this comment is incomplete. It refers to the following sentence „The better understanding of the drivers of simulated trends that we provide below can inform us on how certain trends can be achieved in models." We speculate that the reviewer wants to indicate, that the possibility to achieve a trend based on a certain driver, does not necessarily mean that this is correct. Being aware however of how trends can be achieved is a useful information for model development. Whether the changes are plausible still needs to be addressed before implementing them.*
> *We add:*
> *The understanding of the drivers on simulated trends that we give below provides insights on what causes the simulated trends and which assumptions control the trend. These insights will help to understand which observational constraints and process understanding is required to improve global fire models.*

Table 4 – while the M-K test is likely fine, the uncertainties (standard error or confidence intervals) in the slopes need to be included to understand the results better.

> *10) We include the uncertainties of the slope parameter. However the Mann-Kendall test is better suited to understand whether the trend is significant.*

Page 9 and Section 3.2.4 – I thought that FireMIP only used a repeated lightning scaled to changes in modeled convection? While there is likely something to gain in the lightning sensitivity experiment, I would like to see some clearer discussion of the important caveats in interpreting the results. For example, would it be safe to surmise that there is no sensitivity to lightning changes since 1900 only if the modeled lightning is anything close to reality? Determining a lightning climatology from an untestable climate-model based parameterization and then drawing conclusions from that testing is prone to some circular or flawed logic.

> *11) The limitation of uncertainty in the lightning data is already included on p.20 line 10 where we see a major problem in conserving the correlation between lightning and other climate variables. We include now that the CAPE anomalies are derived from a global numerical weather prediction model. However, we don't see a flawed logic in showing that although the imposed lightning was strongly increasing the model results don't necessarily show*

*increases. That the present trend in the imposed lightning leads to a small change in burned area shows that the models have a low sensitivity to lightning. Lightning parameterizations of climate models are tested (see for instance Krause et al. (2014)). Krause et al. (2014) only show a decrease of lightning of 3.3% in pre-industrial times compared to present day. We add this information to give the reader an insight on the uncertainty. The results in Krause et al. (2014) however support our conclusion of the low sensitivity as they also only find small influences on burned area. Using the lightning dataset from Krause et al. (2014) instead of ours would likely reduce the response in burned area.*

*We add in the manuscript:*

*Most of the models show a low response of burned area to lightning (see fig. 2), although lightning rates increase by 20% over the simulation period - an increase that is much larger than the 3.3% change between pre-industrial times and the present estimated from a recent modelling study (Krause et al., 2014)*

Figure 2 – please retitle these with something that is easier to quickly interpret without cross-referencing the table. For example, I suggest (a) Constant CO2 (SF2_CO2), (b) Constant Population (SF2_FPO), (c) Constant Land Cover (SF2_FLA), (d) Constant Lightning (SF2_FLI), (e) Constant climate (SF2_CLI). Also please make figure 2 much wider to avoid the visual clutter of overlaid zigzagging lines. & Figure 2 – change the y-axes ranges so they are constant. It is hard to understand the sensitivity if the plotted range is variable.

*12) We changed the Figure according to the suggestions.*

Page 11 line 9 – I agree that the statistics suggest individual trends are significant but this does not preclude the massive spread (both positive and negative) in the trends amongst models (table 4). I think this statement needs to include that caveat for an honest accounting of the FireMIP output.

*13) The preceding sentence in the manuscript describes the details of the directions of the trends, including positive and negative trends.*

Section 3.3 – the first paragraph makes no sense. What I am reading in this study is that the models barely agree on any trend, but yet the authors propose here that the models are important for understanding projected trends and supporting land management strategies. To me, a land management practice cannot be based on model trends that do not agree on trend and cannot be of much use if there is lack of agreement at country scales, let alone finer spatial scales.

*14) We agree to some extent, that is why we wrote that the models need to be improved to be useful. We rephrase the paragraph and remove the reference to land management.*

*Global vegetation models are an important tool for examining the impacts of climate change and are used in policy-relevant contexts (IPCC, 2014; Schellnhuber et al., 2014; IPBES, 2016). Given the various influences of fire on the ecosystems (Bond et al., 2015), the carbon cycle and climate (Lasslop et al., 2019), improvements of global fire models are particularly important.*

Section 3.3, second paragraph – the results presented in the manuscript clearly show that models only agree in magnitude in the present day, but the quick microscope analysis of the present day trends show that observations and models do not agree in trends. Some models predict a positive slope, some negative. Unless the authors intend to propose that one FireMIP model is more physically realistic than another, then the results of the sensitivity studies are inconclusive.

*15) We agree with the reviewer that we cannot conclude from these analyses how the drivers caused real trends in fire regimes as the divergence between the models is too big. Only a few years ago it was not possible to detect any trends in the satellite data, the satellite estimate is still far from robust. The result of our sensitivity study is an improved understanding of how the trends are caused in the models and how certain trends can be achieved. We have rephrased the paragraph substantially, see reply 1.*

Section 3.3 or 4 – it would be useful if these authors were to comment directly on fire models that did not contribute to FireMIP but that have contributed significantly to discussions of human-driven fire both in the present day and over the more distant past. This includes studies by Pfeiffer et al https://www.geosci-model-dev.net/6/643/2013/, Rabin et al https://www.geosci-model-dev.net/11/815/2018/, and Hantson et al https://journals.ametsoc.org/doi/full/10.1175/BAMS-D-15-00319.1 . All of these either echo or predict the results discussed by Andela et al 2017 and Bistinas et al 2014 related to a need to quantitatively represent the human use of fire on our planet in the modeling framework.

*16) The previous papers acknowledged that the understanding of the human-fire relationship was rather low. However they could not provide the insight that this causes the largest divergence between global fire models as they were not based on a systematic comparison of simulation results. Moreover, we attribute specific model behaviour to the underlying model assumptions. We agree that some of these previous models give important information regarding incorporation of human-fire relationships (but Hantson et al. 2016 only summarizes the discussions of a workshop). Pfeiffer et al. (2013) deal with pre-industrial fire regimes. Rabin et al. (2018) is limited to the period of satellite observations, as they prescribe the agricultural burning based on satellite observations.*

*We integrate these earlier studies in section 3.3 and improve the discussion of the implications for model development. For the full context, see reply 1.*
*Our analysis shows which parts of the models are particularly important to simulate changes in burned area and need additional observational constraints or improved process understanding. In line with previous research (Bistinas et al., 2014; Hantson et al., 2016a, b; Andela et al., 2017), the large divergence in the response to human activities between the FireMIP models shows that the human impact on fires is still insufficiently understood and therefore not constrained in current models.*
*[...]*
*Fires on pasturelands have been estimated to contribute over 40% of the global burned area (Rabin et al., 2015). Pasture fires are not treated explicitly in any of the models, although some models slightly modify the vegetation on pastures by harvesting or changing the fuel bulk density (see tab. 5). Expansion of pastures is mostly implemented by simply increasing the area of grasslands. Information on how fuel properties differ between pastures and natural grasslands could therefore help to improve model parametrisations. Prescribing fires on anthropogenic land covers can be a solution for certain applications of fire models (Rabin et al., 2018).*
*[...]*
*Regional analysis of remote sensing data could be highly useful, as a global relationship between burned area and individual human factors as assumed in many models and also statistical analysis is not likely. Assumptions on how different human groups (hunter-gatherers, pastoralists, and farmers) use fire have been included in a paleofire model (Pfeiffer et al., 2013). The development of such an approach for modern times would be highly valuable for fire models that aim to model the recent decades and future.*
*[...]*

Conclusions – the conclusions are already evident in the Andela et al 2017 paper,so I do not see what we gain in this study. The authors conclude “further analyses are required to better disentangle” factors, but this is the same conclusion so many firemodel and FireMIP papers have arrived at. Could the authors make a clearer argument about what we gain in this manuscript?

*17) The cited phrase is not part of our conclusion sections, but part of the discussion. We delete it as it was not a substantial remark. For the gains of the manuscript see reply 1, 9, 16.*

# ~~Sensitivity~~ Response of simulated ~~historical~~ burned area to historical changes in environmental and anthropogenic ~~controls~~factors: A comparison of seven fire models

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**Abstract.** Understanding how fire regimes change over time is of major importance for understanding their future impact on the Earth system, including society. Large differences in simulated burned area between fire models show that there is substantial uncertainty associated with modelling global change impacts on fire regimes. We draw here on sensitivity simulations made by seven global dynamic vegetation models participating in the Fire Model Intercomparison Project (FireMIP) to understand how differences in models translate into differences in fire regime projections. The sensitivity experiments isolate the impact of the individual drivers ~~of fire~~on simulated burned area, which are prescribed in the simulations. Specifically these drivers are atmospheric $CO_2$ concentration, population density, land-use change, lightning and climate.

The seven models capture spatial patterns in burned area. However, they show considerable differences in the burned area trends since ~~1900.~~ 1921. We analyse the trajectories of differences between the sensitivity and reference simulation to improve our understanding of what drives the global ~~trend~~ trends in burned area. Where it is possible, we link the inter-model differences to model assumptions.

Overall, these analyses reveal that the ~~strongest differences leading to diverging trajectories~~ largest uncertainties in simulating global historical burned area are related to the ~~way~~ representation of anthropogenic ignitions and suppression ~~, as well as the~~ and effects of land-use on vegetation and fire~~, are incorporated in individual models. This points to a~~. In line with previous studies this highlights the need to improve our understanding and model representation of the relationship between human activities and fire to improve our abilities to model fire ~~for global change~~ within Earth system model applications. Only two models show a

strong response to atmospheric $CO_2$ ~~and the~~ concentration. The effects of changes in atmospheric $CO_2$ concentration on fire are complex and quantitative information of how fuel loads and flammability change due to this factor is missing. The response to lightning on global scale is low~~for all models. The sensitivity to climate shows a spatially heterogeneous response and globally only two models show a significant trend. It was not possible to attribute the climate-induced changes~~. The response of burned area to climate is spatially heterogeneous and has a strong interannual variation. Climate is therefore likely more important than the other factors for short term variations and extremes in burned area~~to model assumptions or specific climatic parameters. However, the strong influence of climate on the inter-annual variability in burned area, shown by all the models, shows that we need to pay attention to the simulation of fire weather but also meteorological influences on biomass accumulation and fuel properties in order to better capture extremes in fire behavior~~. This study provides a basis to understand the uncertainties in global fire modelling and the necessary improvements in process understanding and observational constraints to reduce uncertainties in modelling burned area trends.

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## 1 Introduction

~~About 4of the global vegetated area burns each year (Giglio et al., 2013) , but between 30-40of the land surface is affected by fire regularly (Chapin et al., 2002; Chuvieco et al., 2008) . Thus, over large parts of the world, wildfires~~ Wildfires are an important ~~cause of vegetation disturbance~~driver of vegetation distribution, and regulate ecosystem functioning, biodiversity and carbon storage over large parts of the world (Bond et al., 2005; Hantson et al., 2016a). Fire has strong impacts on climate through changing land surface properties, atmospheric chemistry and hence radiative forcing, as well as biogeochemical cycling ~~(Bowman et al., 2009; Randerson et al., 2012; Ward et al., 2012; Yue et al., 2016; Li and Lawrence, 2017; Li et al., 2017)~~ (Bowman et al., 2009; Randerson et al., 2012; Ward et al., 2012; Yue et al., 2016; Li and Lawrence, 2017; Li et al., 2017; Lasslop et al., 20 Estimates of the net effect of fire on the Earth system vary. Analyses based on observations of the pre-industrial period suggest that the contribution of fire to the overall climate–carbon-cycle feedback is substantial ~~(~~with 5.6 ± 3.2 ppm K-1 $CO_2$ ~~per degree of land temperature change; Harrison et al., 2018 )~~(Harrison et al., 2018) while the strength of the global land climate–carbon-cycle feedback estimated from Earth system simulations (Arora et al., 2013) is 17.5 ppm K-1 (Harrison et al., 2018) . However, comparing potential fire-induced losses from terrestrial carbon pools and stocks of solid pyrogenic carbon in soils and ocean, fire may also be a net sink of carbon and Earth system simulations show a negative effect of fire on radiative forcing (Lasslop et al., 2019) . In addition to these consequences for the Earth System, wildfires directly impact society and economy (Gauthier et al., 2015) and human health can be seriously impaired (Johnston et al., 2012; Finlay et al., 2012).

Given the various impacts ~~that fire has~~ of fire on natural and human systems and the large uncertainties, it is important to ~~understand~~ improve the understanding on what controls the occurrence of wildfires and to know how fire regimes might change in the future.

~~The fire model intercomparison project (FireMIP, Hantson et al., 2016a; Rabin et al., 2017a ) provides simulations for a systematic comparison of fire-model behaviour based on outputs from a large range of multiple model runs with identical forcing inputs. Sensitivity simulations were conducted for individual forcings, specifically $CO_2$, population density, land-use change, lightning and climate.~~Based on current process understanding ~~these drivers may influence burned area in the following ways~~the following drivers influenced burned area over the last decades to centuries:

Increasing atmospheric $CO_2$ concentration leads to increases in net primary production ~~(Hickler et al., 2008; Knorr et al., 2016)~~ (Hickler et al., 2008) and decreased stomatal conductance reduces the plant transpiration and enhances water conservation in plants (Morison, 1985). It can lead to ~~changes in vegetation composition~~ an increase in the abundance of woody plants ('woody thickening'; Wigley et al., 2010; Bond and Midgley, 2012; Buitenwerf et al., 2012) because $C_3$ plants are generally more competitive than $C_4$ plants under higher atmospheric $CO_2$ concentration (e.g. Ehleringer and Björkman, 1977; Ehleringer et al., 1997; Wand et al., 2001; Sage and Kubien, 2007). The impact of these various changes on burned area is complex. Increased productivity can lead to increased fuel availability, which can lead to increased burned area in water- and fuel-limited regions (Kelley and Harrison, 2014). On the other hand, decreased stomatal conductance and lower transpiration can lead to ~~increased soil and~~ enhanced water conservation in plants. This increases the moisture content of soil as well as vegetation moisture content and consequently live and dead fuel moisture contents~~and hence to a reduction in burned area in more humid regions~~, which decreases flammability and in consequence reduces burned area. Woody thickening can lead to a reduction in burned area through changing the nature of fuel loads (Kelley and Harrison, 2014).

There is still controversy about whether humans increase or decrease fire overall: Although there is broad agreement that humans suppress fires in regions with high population density, observational studies are less clear about what happens in areas of low population density and show both increases or ~~decrease~~ decreases due to human activities (see for instance Marlon et al., 2008; Bowman et al., 2011; Marlon et al., 2013; Vannière et al., 2016; Andela et al., 2017; Balch et al., 2017). Studies of the covariation between population density and number of fires have shown that increasing population density leads to an increase in the number of ignitions or in the number of individual fires until peaking at ~~inter-mediate~~ intermediate population densities and drop subsequently (Syphard et al., 2009; Archibald et al., 2010). Burned area can be expressed as the number of fires multiplied by their fire size. The increase in burned area ~~for low population density~~ due to changes in ignitions is expected to differ ~~from the one found for number of fires~~ between regions with varying population density as the largest fires occur in unpopulated areas (Hantson et al., 2015a)~~and burned area can be expressed as number of fires times fire size. Global analysis~~. Global analyses find that the net effect of population density is a decrease in burned area (Bistinas et al., 2014; Knorr et al., 2014), with high uncertainties for low population density if the method allows for non-monotonic relationships (Knorr et al., 2014). Regional ~~analysis tends~~ analyses tend to confirm this, but positive relationships between burned area and population density have been shown, for instance, for the least disturbed areas in the USA (Parisien et al., 2016).

Fire was used to manage croplands in pre-industrial times (e.g. Dumond, 1961; Otto and Anderson, 1982; Johnston, 2003) and ~~it~~ is still common practice ~~in~~ mainly in non-industrialized areas (i.e. Sub-Saharan Africa, parts of South East Asia, Indonesia and Latin America; e.g. Conklin, 1961; Rasul and Thapa, 2003). However fires in agricultural areas are common ~~on~~

all over the world (Korontzi et al., 2006). ~~The influence of land-use on fire on global scale is not well studied. Severe data gaps and an unsatisfactory level of understanding characterize our knowledge on how humans use fire in land management (Erb et al., 2017) . Analysis of satellite data~~ Global analyses indicate a decrease of burned area (Bistinas et al., 2014; Andela and van der Werf, 2014) and fire size (Hantson et al., 2015b) with increases in cropland fraction. Fires on ~~pastures~~ pasturelands have been estimated to contribute over 40% of the global burned area (Rabin et al., 2015). ~~Analysis~~ Analyses of global datasets find an increase of burned area with increases in ~~pasture cover fraction Bistinas et al. (2014)~~ grazing land cover (Bistinas et al., 2014) but reduced burned area on intensely grazed areas (Andela et al., 2017). Despite these analyses, the severe data gaps limit our level of understanding on how humans use fire in land management (Erb et al., 2017) .

Lightning is the main source of natural ignitions (Scott et al., 2014). It is connected to convective activity and is therefore expected to change with global warming (Krause et al., 2014). Most of ~~total~~ the burned area in boreal regions ~~, for example,~~ results from a few large fires (Stocks et al., 2002); these large fires are frequently ignited by lightning (Peterson et al., 2010). Veraverbeke et al. (2017) have shown that lightning ignitions drive the interannual variability as well as the long-term trends of ~~the~~ ignitions in boreal regions.

Climate ~~can influence~~ influences burned area through weather conditions and through its influence on vegetation (Bistinas et al., 2014; Forkel et al., 2017). Weather conditions (precedent precipitation, temperature and wind ~~speeds~~speed) influence fuel drying, ~~while wind speed~~ wind speed additionally affects the rate of fire spread (Harrison et al., 2010; Scott et al., 2014). ~~Fuel loads and vegetation type are also~~ Vegetation type and fuel load are driven by climate and both strongly ~~determine~~ influence fire occurrence (Chuvieco et al., 2008; Pettinari and Chuvieco, 2016). ~~As fires are limited at low moisture~~ Fires are limited under dry conditions due to low vegetation productivity and therefore insufficient fuel, and ~~at high moisture conditions due to the fuel being~~ under wet conditions because the fuel is too wet to burn~~, the~~ . The highest burned areas are therefore found in areas with ~~medium~~ intermediate moisture conditions (Krawchuk and Moritz, 2011). There is no obvious ~~controversy in literature on~~ disagreement in literature about how specific climatic factors ~~drive~~ influence fire. However, the ~~strength of single factors and balance between factors~~relative importance of each factor, e.g. weather vs. vegetation, is still uncertain and varies spatially (Forkel et al., 2017). Fire models are sensitive to the meteorological forcing, different forcing datasets already lead to large differences in simulated burned area (Rabin et al., 2017a; Lasslop et al., 2014). ~~Wind speed for instance strongly varies between datasets and although wind~~ The importance of factors also varies between small and large scales. Wind speed is an obvious driver of fire spread ~~,~~ on the local scale, but it is difficult to extract this influence on the spatial resolution of global models (Lasslop et al., 2015).

Fire-enabled vegetation models ~~generally~~ simulate fire regimes in response to the combination of individual forcings, including atmospheric $CO_2$ concentration, population density, land-use change, lightning and climate. Individual fire-enabled vegetation models have been shown to simulate observed global patterns of burned area and fire emissions reasonably well (Kloster et al., 2010; Prentice et al., 2011; Li et al., 2012; Lasslop et al., 2014; Yue et al., 2014), but there are large differences between models in terms of regional patterns, fire seasonality and interannual variability, ~~and~~ historical trends (Kelley et al., 2013; Andela et al., 2017) and responses to individual factors (Kloster et al., 2010; Knorr et al., 2014, 2016; Lasslop and Kloster, 2017, 2015) . The fire model intercomparison project (FireMIP, Hantson et al., 2016a; Rabin et al., 2017a ) provides a systematic framework to consistently analyse and understand the causes of these differences and to relate them to differences in the treatment of key drivers of fire in individual models. The FireMIP project provides simulations for a systematic comparison of fire-model behaviour based on outputs of a large range of models with identical forcing inputs. In addition to a reference historical simulation, sensitivity simulations were conducted for individual forcings, specifically atmospheric $CO_2$ concentration, population density, land-use change, lightning and climate. A recent evaluation of the FireMIP models indicates that the relationship with climatic parameters is captured well by models, the response to human factors is captured by some models and the response to vegetation productivity or the allocation of carbon to fuels needs refinement for most models (Forkel et al., 2019a). Comparisons of the FireMIP historical simulations found differences in transient model behaviour in the 20th century (Andela et al., 2017; van Marle et al., 2017) . The causes of the differences and the reasons why different models show different responses are not yet understood.

In this ~~study we briefly assess how well the FireMIP models simulated present day burned area~~ multi-model study we use the historical simulation to show the overall modelled response of burned area to changes in environmental and human factors. We then compare the sensitivity experiments of the five most commonly used driving factors to document how simulated burned area responds to the individual forcing factors and relate inter-model differences of the burned area response to differences in model assumptions or parametrisation. We finally ~~discuss the model limitations and~~ suggest implications of our results for model development and application.

## 2 Methods

The baseline FireMIP experiment (SF1) is a transient simulation from 1700–2013, in which atmospheric $CO_2$ concentration, population density, ~~land–use~~land-use, lightning, and climate change through time according to prescribed datasets. The baseline and sensitivity simulations start from the end of a spin-up simulation with equilibrated carbon pools (see Rabin et al. (2017a) for details of the experimental protocol). The five sensitivity experiments (SF2) are designed to isolate differences in model behaviour associated with individual forcing factors. The model inputs and setup are the same as in SF1, but one of the forcings is kept constant at the value used in the spin-up throughout the ~~simulation in each~~ experiment (see tab. 1). Thus, for example, in SF2_CO2, population density, ~~land–use~~land-use, lightning and climate inputs change each year, but atmospheric $CO_2$ concentration is held constant at 277.33 ppm for the whole of the simulation. The resulting difference in burned area between the simulations is then a combination of the changes in the forcing and the sensitivity of the model to that forcing factor. Not all models performed every sensitivity experiment due to limitations in model structure (see tab. 2). Detailed model descriptions can be found in the corresponding literature listed in table A1. Two of the models (CLASS–CTEM and CLM) started the simulations later than the others (1861 and 1850, respectively) ~~. Since our analyses are confined to differences in behavior during the 20th century, this difference in the length of the simulations between the models should have little impact~~ and due to limitations in data availability the reference year of the forcings used in the spin-up varies (see tab. 1). We account for these differences in starting years between models and of the forcing factors by limiting our analysis to the period where all factors are different from the ones used in the spin-up (after 1921). These differences still influence the absolute differences, we therefore quantify the strength of the impact through the slope of a regression line and do not interpret the offset.

**Table 1.** Overview over the sensitivity experiments conducted by FireMIP-models (Rabin et al., 2017a). Rptd indicates the forcing was repeated over the given years. SF2_CO2 stands for fixed ~~CO2~~atmospheric $CO_2$ concentration, SF2_FPO for fixed population density, SF2_FLA for fixed ~~land use~~land-use, SF2_FLI for fixed lightning, and SF2_CLI for fixed climate.

| Driving factor | Sensitivity Experiments | | | | |
|---|---|---|---|---|---|
| | SF2_CO2 | SF2_FPO | SF2_FLA | SF2_FLI | SF2_CLI |
| $CO_2$ | 277.33 ppm | transient | transient | transient | transient |
| Population density (PD) | transient | Fixed Year 1 | transient | transient | transient |
| Land-use change (LUC) | transient | transient | Fixed Year 1 | transient | transient |
| Lightning | transient | transient | transient | Rptd: 1901–1920 | transient |
| Climate | transient | transient | transient | transient | Rptd: 1901–1920 |

**Table 2.** Sensitivity experiments conducted by FireMIP models.

| Model | Sensitivity Experiments | | | | |
|---|---|---|---|---|---|
| | SF2_CO2 | SF2_FPO | SF2_FLA | SF2_FLI | SF2_CLI |
| CLASS–CTEM | x | x | x | x | x |
| CLM | x | x | x | x | x |
| INFERNO | x | x | x | | |
| JSBACH–SPITFIRE | x | x | x | x | x |
| LPJ–GUESS–SIMFIRE–BLAZE | x | x | x | | x |
| LPJ–GUESS–SPITFIRE | x | x | x | x | ~~x~~ |
| ORCHIDEE–SPITFIRE | x | x | x | x | x |

~~Detailed model descriptions can be found in the corresponding literature listed in table A1.~~

### 2.1 Data processing and analysis of simulation results

Our analyses of the SF1 and SF2 simulations focus on the simulation of burned area but are complemented by effects on vegetation carbon pools for the SF2_CO2 simulation. We focus on the time series of global burned area over the historical simulation and the spatial patterns of differences in burned area between ~~1900~~ 1921 and 2013, as in this period all forcings are transient and different from the values used in the spin-up. Annual global values are an area weighted average using the grid cell area. We quantify the ~~sensitivity~~ response of the models to each driving factor using the ~~relative~~ absolute difference in burned area between the baseline and the respective sensitivity experiment (SF1-SF2_i~~/SF2_i~~, with i in CO2, FPO, FLA, FLI, CLI). Positive differences mean that the transient change of the factor lead to an increase in burned area. We use the climate data operators (CDO version 2018: Climate Data Operators. Available at: http://www.mpimet.mpg.de/cdo) to process and remap the simulated outputs. We test the ~~relative~~ difference time series for trends over the period from ~~1900~~ 1921 to 2013 using the Mann-Kendall test, implemented in the R package Kendall (McLeod, 2011). We quantify the global trend as the slope of a linear regression and summarize the spatial distribution of trends by quantifying the area with significant positive trends and the area with significant negative trends.

Due to a postprocessing error, INFERNO lacks two years in SF2_CO2 (~~2002 and 2003~~2001 and 2002).

### 2.2 Model-data comparison

To evaluate the ~~realism of the~~ simulations of burned area, we compare the simulated burned area with remote sensing data products. ~~We used~~ Global burned area observations from satellites still suffer from substantial uncertainty, as reflected by the considerable differences in spatial and temporal patterns between different data products (Humber et al., 2018; Hantson et al., 2016a; Chuvieco et al., 2018; van der Werf et al., 2017 ). Using multiple satellite products in model benchmarking is one approach to take into account these observational uncertainties (Rabin et al., 2017a) . In this study, we use three satellite products: GFED4 (Giglio et al., 2013), GFED4s ~~(Randerson et al., 2012)~~ (van der Werf et al., 2017) and FireCCI50 (Chuvieco et al., 2018). ~~These three data sets use different retrieval algorithms, which cause differences in spatial and temporal patterns in burned area (Hantson et al., 2016a; Humber et al., 2018) . Since there is no agreement about which is most reliable, using~~ GFED4 is a gridded version of the MODIS Collection 5.1 MCD64 burned area product. It is known that this product strongly underestimates small fires, including cropland fires (e.g. Hall et al., 2016 ). In GFED4s, burned area due to small fires is estimated based on MODIS active fire (AF) detections and added to GFED4 burned area. However, this methodology may introduce significant errors related to erroneous AF detections (Zhang et al., 2018) . As a complementary product, FireCCI50 was developed using MODIS spectral bands with higher spatial resolution than MCD64. A higher resolution enhances the ability to detect smaller fires; however, this improvement is partially offset by suboptimal spectral properties of the bands. Both GFED4s and FireCCI50 have larger burned area than GFED4. Since all three products ~~provides a measure of the uncertainty in the observations~~are based on MODIS data, the inter-product differences probably underestimate uncertainties associated with these products. A recent mapping of burned area for Africa using higher resolution Sentinel-2 observations indicates that all three products substantially underestimate burned area (Roteta et al., 2019) . For the ~~comparison~~ model evaluation we use temporally averaged burned area fraction for the years ~~2001–2013, which is~~ 2001–2013, the interval common to all three satellite ~~data sets~~ products and the model simulations. ~~For this comparison, we scale~~ We resample the model outputs to the lowest model resolution (CLASS-CTEM: 2.8125 x 2.8125°) with first order conservative remapping. ~~Due to the strongly skewed distribution of burned area fraction we apply a square root transformation on both~~

~~observations and model output.~~ We quantify the agreement between models and observations ~~with~~ by providing the global burned area and the Pearson correlation coefficient for the between grid cell variation (see tab. 3). We choose the Pearson correlation as it quantifies the covariation of the spatial patterns, and is less sensitive to the highly uncertain absolute burned area values. Burned area has a strongly skewed distribution, with few high values and many small values close to, or equal to, zero. These few high values have a much higher contribution to the overall correlation (see figure A9 in Appendix) and therefore the metric is strongly determined by the performance of the model in areas with high burning. Square root or logarithmic transformation leads to more normally distributed values, that reduce this bias (see figure A9 in Appendix). As the logarithm transformation excludes grid cells with zero burned area, we adopt the square root transformation.

In spite of major advances in mapping burned area based on satellite data, these data products include major uncertainties. GFED4 and FireCCI50 provide uncertainty estimates for the burned area. Applying Gaussian error propagation, which assumes that errors are independent and normally distributed, yields uncertainty estimates of 0.01% (GFED4) and 0.2% (FireCCI50) of the global burned area, which is certainly an underestimation. The assumptions of normal distribution and independence are likely violated. The spread between global burned area data sets is probably a more realistic estimate. Since all the products rely on the MODIS sensor, this approach will ~~, however, also~~ not capture the full uncertainty. Nevertheless, to investigate the effect of data quality in the observations on the model-data comparison we use the burned area product uncertainty estimates (aggregated to model resolution assuming independence) to group the observations into points with low, medium and high uncertainty (low: within the 0–33rd percentile, medium: within the 33rd–66th percentile, and high: within the 66th–99th percentile of the relative uncertainty estimates = uncertainty / burned area). We then compute the correlations for data points with low, medium and high uncertainty separately.

## 3 Results and discussion

### 3.1 ~~Evaluation of the baseline experiment~~Simulated historical burned area

The models show magnitudes of annual global burned area between ~~354–530~~ 354–531 Mha/yr for present day. This is comparable to the estimates obtained from the satellite products, which range from 345–480 Mha/yr (see fig. 1, tab. 3). The correlation coefficients between all of the simulations and the satellite observations are reasonable, with values ranging from 0.51 (CLASS–CTEM, GFED4s) to 0.8 (ORCHIDEE–SPITFIRE, GFED4; see tab. 3). In general, the correlations with GFED4 are highest and with GFED4s lowest for almost all models - which may reflect the fact that most models do not explicitly simulate agricultural fires or may ~~reflect an overestimation or not sufficiently precise estimation of the contribution of such fires to burned area~~ indicate inaccuracies in the mapping of agricultural fires in the GFED4s data set. The correlation coefficients strongly decrease with increasing observational relative uncertainty (see tab. A2)~~, showing~~ . This shows that part of the mismatch in the spatial patterns between simulations and observations is a consequence of uncertainties in the satellite products themselves. The FireMIP models simulate the broad scale patterns in burned area reasonably well (see fig. A1), with maxima in the major fire-affected regions of the Sahel, southern Africa, northern Australia and the western USA. All of the models tend to overestimate the burned area in South America and also in the temperate regions of the USA. For a more detailed evaluation of the burned area see Forkel et al. (2019a) .

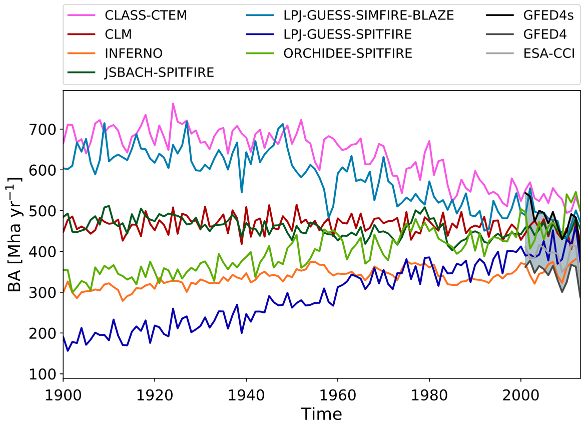


**Figure 1.** Annual global burned area (BA) in Mha yr$^{-1}$ for all FireMIP-models for ~~1900–2013~~ 1921–2013 for the baseline experiment SF1. The shaded area indicates the range of annual global burned area values for the observations.

**Table 3.** Global burned area averaged over 2001–2013 in Mha yr-1 and the Pearson correlation coefficients between the baseline experiment SF1 for all FireMIP-models and the respective observation data. ~~Due to the skewed distribution of burned area, we~~ We use a square root transformation on both model and observations. All correlation coefficients are significant (p-value $<$ ~~0.001~~0.05).

| Model | Burned Area (Mha yr-1) | R(GFED4, model) | R(GFED4s, model) | R(FireCCI50, model) |
|---|---|---|---|---|
| CLASS–CTEM | 531 | 0.58 | 0.51 | 0.56 |
| CLM | 451 | 0.73 | 0.68 | 0.74 |
| INFERNO | 354 | 0.70 | 0.64 | 0.69 |
| JSBACH–SPITFIRE | 455 | 0.66 | 0.57 | 0.62 |
| LPJ–GUESS–SIMFIRE–BLAZE | 482 | 0.67 | 0.60 | 0.62 |
| LPJ–GUESS–SPITFIRE | 404 | 0.55 | 0.56 | 0.59 |
| ORCHIDEE–SPITFIRE | 474 | 0.80 | 0.72 | 0.79 |
| GFED4 | 345 | | | |
| GFED4s | 480 | | | |
| FireCCI50 | 389 | | | |

The simulated trend in burned area ~~of the historical reference~~ in the historical simulation differs between the models (see fig. 1). All models ~~, except CLM,~~ have a significant trend over the time series from ~~1900–2013~~ 1921–2013 (see tab. 4). Models that have a relatively high total burned area initially (LPJ–GUESS–SIMFIRE–BLAZE, CLASS–CTEM) show a decline in burned area over the 20th century. Most models that have a low burned area (INFERNO, ORCHIDEE–SPITFIRE, LPJ-GUESS-SPITFIRE) show an increasing trend. JSBACH–SPITFIRE and CLM have intermediate levels in burned area and show a weak decreasing trend over the 20th century. ~~Only half of the models~~

Satellite records show a decline in ~~burned area after 2000 CE (see Andela et al., 2017 ). The global decline in satellite data is strongly dominated by savanna ecosystems and the spatial pattern of trends is very heterogeneous (Andela et al., 2017) . The short~~ global burned area since 1996 (Andela et al., 2017) . However, as Forkel et al. (2019b) have shown, the significance of the observed global decline is strongly affected by the length of the ~~satellite record leads to uncertainties in the trends, which are in most regions statistically not significant (Andela et al., 2017) .Few datasets exist for~~ sampled interval because of the high interannual variability in burned area and trends between products show only a low correlation (Forkel et al., 2019b) .

No observations document the longer term ~~trend. Charcoal data~~ trends in burned area. Charcoal records (Marlon et al., 2008, 2016) and carbon monoxide data from ice-core records (Wang et al., 2010) are a proxy for ~~fire occurrence over longer time scales (Marlon et al., 2008, 2016) . These charcoal records~~ biomass burning and show a global decrease in biomass burning over most of the 20th century~~(Marlon et al., 2008, 2016) , which is consistent with carbon monoxide data from ice-core records (Wang et al., 2010)~~ . However, the charcoal records ~~appear to~~ show an increase in burning since 2000 CE, ~~contrary to the decline shown by satellite-based records of burned area (Andela et al., 2017) . This~~ but this discrepancy might reflect ~~sampling~~ regional undersampling (for instance in Africa) or taphonomic issues of the charcoal record. ~~For instance the continents that contribute most to the global burned area (Africa) is heavily undersampled. A recently developed fire emissions~~ A recent fire emission dataset (van Marle et al., 2017) merges information from satellites, charcoal records, airport visibility records and if no other information was available uses simulation results of the FireMIP models. This dataset is not included to evaluate the models here as it is partly based on the simulations of the ~~models used in this study~~ FireMIP models and as it ~~does not provide estimates of burned area. A decline in global burned areaover the 20th century might be more realistic than the increase shown by several models. Further evaluation of historical trends in fire proxies and longer satellite time series will help to gain more confidence in observed trends of fire regimes.The better~~ provides only estimates for emissions not burned area.

The understanding of the drivers ~~of~~ on simulated trends that we ~~provide below can inform us on how certain trends can be achieved in models.~~ give below provides insights on what causes the simulated trends and which assumptions control the trend. These insights will help to understand which observational constraints and process understanding is required to improve global fire models.

### 3.2 ~~Sensitivity of models to individual drivers~~

~~There are large differences in sign and magnitude between modelsin the temporal response of global burned area from 1900–2013 to each individual driving factor when compared to the baseline experiment (see fig. 2,~~

**Table 4.** Trends (slope and standard error of a linear regression, [Mha yr$^{-1}$]) in annual global burned area for the years 1921-2013 for the baseline experiment SF1 and absolute difference time series of annual burned area. The trends for the forcing data sets are based on the the relative difference between the transient forcing and year 1920 value for SF2_CO2, SF2_FPO and SF2_FLA and the relative difference between the transient and the recycled forcing for SF2_FLI and SF2_CLI for the years 1921-2013 [%] (see tab. 1). Bold values indicate significance based on a Mann-Kendall test (p-value < 0.05). Experiments that are not available for specific models are indicated with n.a..

| Model | Sensitivity Experiments | | | | | |
|---|---|---|---|---|---|---|
| | SF1 | SF2_CO2 | SF2_FPO | SF2_FLA | SF2_FLI | SF2_CLI |
| CLASS–CTEM | **-2.238** | **-0.059** | **-0.754** | **-0.922** | 0.000 | 0.072 |
| | ± 0.116 | ± 0.008 | ± 0.052 | ± 0.049 | ± 0.001 | ± 0.134 |
| CLM | **-0.277** | **0.065** | **-1.05** | -0.065 | -0.048 | 0.046 |
| | ± 0.083 | ± 0.018 | ± 0.044 | ± 0.027 | ± 0.023 | ± 0.05 |
| INFERNO | **0.256** | **0.118** | **-0.571** | **0.303** | n.a. | n.a. |
| | ± 0.063 | ± 0.007 | ± 0.031 | ± 0.01 | | |
| JSBACH–SPITFIRE | **-0.304** | **0.574** | **-0.182** | **-0.873** | **-0.074** | 0.097 |
| | ± 0.077 | ± 0.020 | ± 0.038 | ± 0.051 | ±0.014 | ± 0.099 |
| LPJ–GUESS–SIMFIRE–BLAZE | **-2.161** | **-0.145** | **-0.847** | **-1.485** | n.a. | 0.249 |
| | ± 0.138 | ± 0.016 | ± 0.047 | ± 0.067 | | ± 0.144 |
| LPJ–GUESS–SPITFIRE | **2.351** | **0.986** | **1.345** | **1.845** | **0.015** | n.a. |
| | ± 0.087 | ± 0.032 | ± 0.050 | ± 0.044 | ± 0.006 | |
| ORCHIDEE–SPITFIRE | **1.383** | **0.035** | **0.520** | **0.859** | **0.334** | 0.033 |
| | ± 0.113 | ± 0.026 | ± 0.022 | ± 0.036 | ± 0.072 | ± 0.120 |
| | | $CO_2$ | Population density | Land cover | Lightning | Temperature |
| Forcing | | **0.946** | **13.868** | **0.903** | **0.219** | **0.086** |
| | | ± 0.033 | ± 1.363 | ± 0.033 | ± 0.037 | ± 0.009 |
| | | | | | | Wind speed |
| | | | | | | **0.012** |
| | | | | | | ± 0.006 |

### 3.2 Response of simulated burned area to individual drivers

The response of burned area to the individual factors is determined by the changes in the driving factors and the sensitivity of the model to these changes. The population density forcing dataset has the strongest trend in the relative differences between the transient forcing and the year 1920 value followed by the land-use and land cover change dataset. The trend in atmospheric $CO_2$ concentration is higher than the trend in the lightning dataset, which is more than twice as strong as in the air temperature.

Wind speed shows the lowest trend of all investigated driving factors (see tab. 4). Population density (SF2_FPO) and land-use change (SF2_FLA) cause the largest ~~inter-model spread in trends~~ divergence between models in trends of burned area (slope between ~~-0.156 and 0.441~~ -1.05 and 1.345 Mha year$^{-1}$ and between ~~-0.204 and 0.686~~ -1.485 and 1.845 Mha year$^{-1}$, respectively)~~, all trends are statistically significant~~ .All models have a statistically significant trend in burned area for SF2_FPO as well as for SF2_FLA , except for CLM for SF2_FLA (see tab. 4, fig. 2 b and c). For SF2_CO2 all models have a significant trend, however, ~~only~~ the magnitude of the trend is much smaller compared to the trend due to anthropogenic factors. LPJ–GUESS–SPITFIRE and JSBACH–SPITFIRE have ~~a clear positive trend~~ strong trends (> ~~0.13~~ 0.5 Mha year$^{-1}$), for all other models the slope is close to zero (< ~~0.03~~ 0.15 Mha year$^{-1}$; see tab. 4, fig. 2 a). The differences between models are increasing over the 20th century for these first three experiments. The response to changes in lightning and climate generally shows much smaller trends ~~: only two models have~~ but high inter-annual variability: none of the models has a significant trend for climate~~, with increases in burned area due to changing climate (0.054 and 0.028 year$^{-1}$)~~. Three models show significant (but inconsistent ~~-0.017, 0.005 and 0.074~~ 0.014, 0.334 and -0.074 Mha year$^{-1}$) trends for lightning (see tab. 4). The ~~time series of differences between these latter two experiments and the baseline experiment show a strong inter-annual variability. This~~ interannual variability is stronger for climate~~(up to~~ . The mean standard deviation of the absolute differences averaged over all models is 30 ~~in several years) than lightning (up to 20for very few years and only one model~~ Mha for climate and 7 Mha for lightning (only 3 Mha if the model with the strongest response is excluded; see fig. 2 d and e).

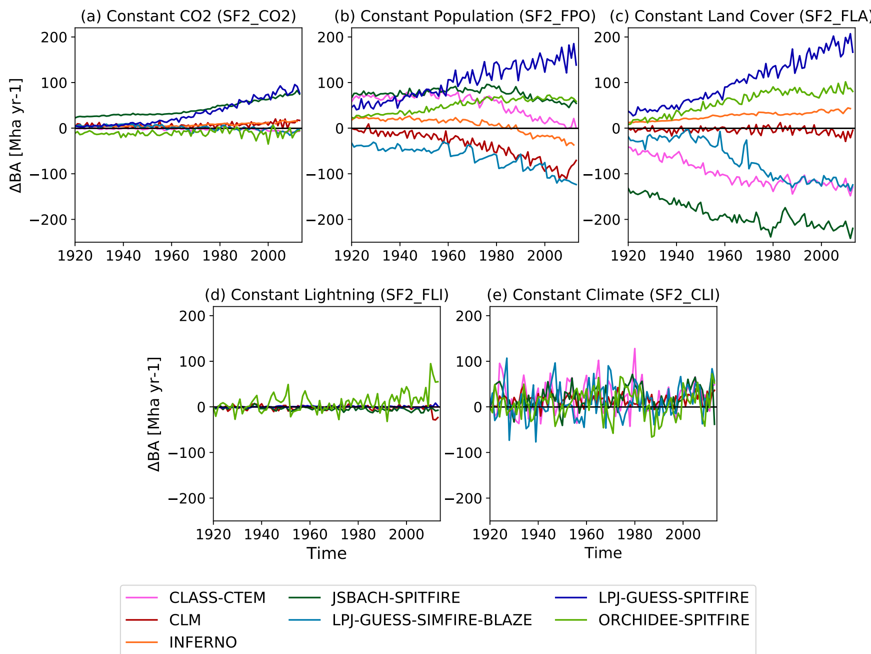


**Figure 2.** ~~Relative~~ Absolute difference in annual global burned area (ΔBA) in Mha across ~~1900~~ 1921 to 2013 between the baseline experiment SF1 and and the sensitivity experiments SF2_CO2 (a), SF2_FPO (b), SF2_FLA (c), SF2_FLI (d) and (e) SF2_CLI , where the specific forcing factors were set to the values used during the spin-up simulation (see tab. 1).~~Note that the y-axis range differ between the panels.~~

The spatial patterns of trends in burned area are mostly heterogeneous (see supplement figures A3–A7). ~~Limited~~ The global trend can be dominated by changes in limited areas of the world~~can dominate~~ , while the lack of a global trend ~~or the trends can cancel out when aggregating to the global burned area sum. A~~ can reflect opposing trends in different regions. A detailed regional analysis is beyond the scope of this study, but we provide an alternative global view ~~on the trends~~ by quantifying the area affected by positive or negative trends (see fig. 3). This comparison shows that for most models larger areas show significant positive trends for the reference simulation (5 models), ~~rising~~ increasing atmospheric $CO_2$ concentration (5 models) and varying climate (~~all models ), whereas there~~ 5 models and 1 equal areas). There is no clear signal ~~across models~~ of either positive or negative trends across the models for the other simulations. For climate and lightning smaller areas ~~show~~ have significant trends (see fig. 3). For ~~ORCHIDEE– and LPJ–GUESS–SPITIFRE~~ ORCHIDEE–SPITFIRE and LPJ–GUESS–SPITFIRE all factors but climate cause a significant positive trend globally (see tab. 4) and larger areas have positive trends for all factors, except lightning for LPJ–GUESS–SPITFIRE (see fig. 3). On the other end of the model range LPJ–GUESS–SIMFIRE–BLAZE only shows a positive global trend for climate ~~(see tab. 4), $CO_2$ and climate induce~~ and atmospheric $CO_2$ concentration induced positive trends in larger areas than negative trends (see fig. 3).

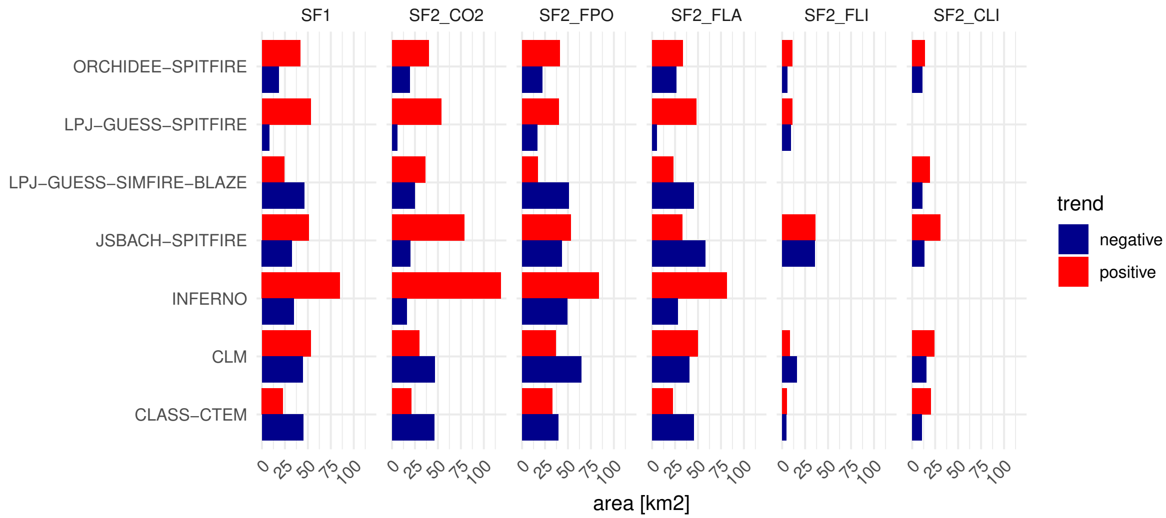


**Figure 3.** Area with a significant positive trend (red bar) or with a significant (Mann-Kendall test $p<0.05$) negative change (blue bar) in burned area fraction averaged over ~~1901–2013~~ 1921–2013 for the baseline experiment SF1 and for the absolute differences in burned area fraction between the sensitivity experiments SF2 and SF1 (see tab. 1). Compare fig. A2 - A7.

In the following paragraphs we detail the inter-model differences and their causes for each sensitivity experiment.

### 3.2.1 ~~Sensitivity~~ Response of ~~models~~ simulated burned area to atmospheric $CO_2$ concentration

The overall changes in burned area in individual simulations as a result of atmospheric $CO_2$ concentration changes are a complex response to multiple changes in vegetation: changes in land cover, fuel load, fuel characteristics and fuel moisture. Burned area can either increase due to higher availability of fuel loads or decrease due to changes in flammability caused by different fuel ~~characteristics including moisture (Rabin et al., 2017a)~~ properties. The FireMIP-models react to increasing atmospheric $CO_2$ concentration in different ways: some models (JSBACH–SPITFIRE and LPJ–GUESS–SPITFIRE) show a strong increase in burned area, some (CLM and INFERNO) show a moderate increase, CLASS–CTEM shows a slight decrease, and LPJ–GUESS–SIMFIRE–BLAZE and ORCHIDEE–SPITFIRE show a non-monotonic response (see fig. 2, a)). For all models, the trends over the 20th century are significant (see tab. 4).

We use changes in vegetation carbon to understand changes in fuel load and composition because information on the amount of fuel used within the fire models was not available for individual plant functional types (PFTs). All models show an increase in total vegetation biomass ('total', solid lines; see fig. 4), as expected because of higher productivity (Farquhar et al., 1980; Hickler et al., 2008) and increased water use efficiency (De Kauwe et al., 2013). The response of specific types of vegetation carbon to increasing atmospheric $CO_2$ concentration varies between the vegetation models. The biomass of $C_3$ vegetation (trees and $C_3$ grasses) increases in all of the models. The biomass of $C_4$ grasses increases in CLASS–CTEM, INFERNO, and JSBACH–SPITFIRE, but does not change in ORCHIDEE–SPITFIRE. Since ORCHIDEE–SPITFIRE was run with fixed vegetation distribution, changes in the extent of different PFTs can be ruled out as a cause of changes in vegetation carbon. There is a decrease in burned area in regions with abundant $C_4$ grasses (Sahel and North Australia) in this model, suggesting that changes in fuel type (increased $C_3$ tree biomass) results in changes in flammability in these regions. The carbon stored in $C_4$ grasses is reduced in response to increasing atmospheric $CO_2$ concentration in CLM and LPJ–GUESS–SIMFIRE–BLAZE and is fairly constant in LPJ–GUESS–SPITFIRE. This can be a result of a decrease in $C_4$ grass cover in LPJ–GUESS–SIMFIRE–BLAZE and LPJ–GUESS–SPITFIRE. However, since CLM was run with prescribed vegetation cover, the reduction in $C_4$ carbon must reflect the fact that any increase in $C_4$ grass biomass due to higher atmospheric $CO_2$ concentration is offset by greater losses through burning due to the increased total fuel load.

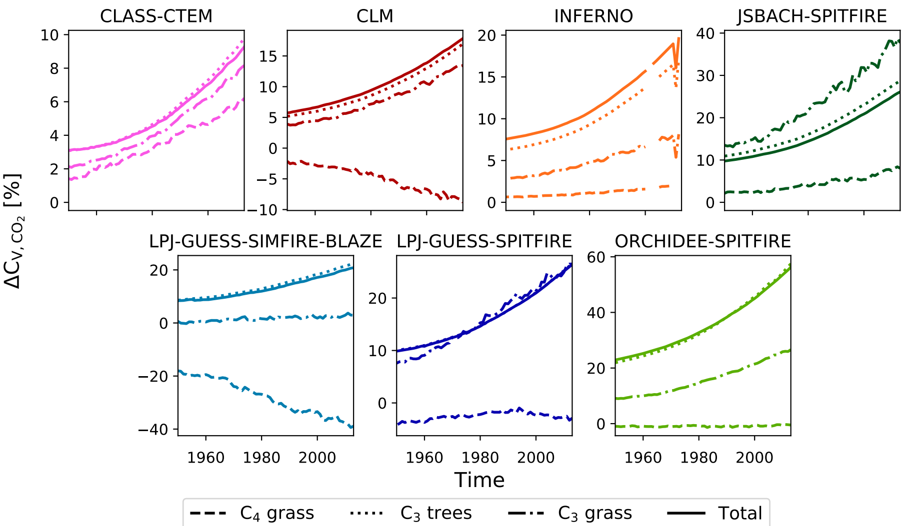


**Figure 4.** Relative difference in global carbon stored in $C_4$ grasses (dashed lines), in $C_3$ trees (dotted lines), in $C_3$ grasses (dash-dotted lines) and in total global carbon stored in vegetation (solid lines) between the baseline experiment SF1 and the sensitivity experiment SF2_CO2 (see tab. 1; $C_{V,CO_2}$) for 1950–2013 in % (annual averages). $C_4$ and $C_3$ grasses as well as $C_3$ trees only include natural PFTs (pastures and croplands excluded). Note that the y-axis limits differ between the panels. Due to a postprocessing error, INFERNO lacks two years (2001 and 2002) ~~(2002 and 2003~~ .

CLM and LPJ–GUESS–SIMFIRE–BLAZE include an interactive nitrogen cycle, CLASS–CTEM a non-interactive nitrogen down-regulation. Effects of atmospheric $CO_2$ concentration on vegetation biomass for these three models are therefore at the lower end of the model ensemble. The strength of atmospheric $CO_2$ concentration effects on productivity is still uncertain and quantitative information about effects on fuel loads is not available. Comparisons with experimental data suggest that models that do not include the nitrogen cycle overestimate the effect on productivity (Hickler et al., 2015) . However, an analysis using an observation-based emergent constraint on the long-term sensitivity of land carbon storage shows that models from the Coupled Climate Model Intercomparison Project (CMIP5) ensemble that included an interactive nitrogen cycle underestimate the impact of atmospheric $CO_2$ concentration on productivity (Wenzel et al., 2016) .

Soil moisture is used by several models to compute fuel moisture (see fig. 5). Soil moisture can be influenced by different atmospheric $CO_2$ concentration as reductions in stomatal conductance can lead to increases in soil moisture, whereas increases in ~~LAI~~ the leaf area index (LAI) caused by increased biomass of increased tree cover lead to higher transpiration and therefore lower soil moisture. Soil moisture increases slightly in four models (INFERNO, CLASS–CTEM, CLM, JSBACH–SPITFIRE), and decreases slightly in ORCHIDEE–SPITFIRE. Only LPJ–GUESS–SPITFIRE shows a strong decrease (5% in global average) in soil moisture (see fig. 6).

Models which include fuel load and moisture effects through threshold functions (see fig. 5, CLASS–CTEM, INFERNO, CLM) tend to show muted responses. Decreases in burned area appear to be largely caused by increases in soil moisture or tree cover. Increases associated with increasing fuel load are limited to regions with low biomass. The balance between these effects differs between the models. CLASS-CTEM shows a small decrease in burned area globally, and the spatial pattern is dominated by areas with negative trends in burned area, but there are positive trends in dry regions (see fig. A3). The small global increase of burned area in INFERNO is likely related to increased fuel loads, negative trends in burned area only occur in the tropical regions (see fig. A3). INFERNO uses a constant burned area per PFT that is set to 0.6, 1.4 and 1.2 km$^2$ for trees, grass and shrubs, respectively. CLM shows increased global burned area, but increases are located in dry areas while the boreal regions show decreases. JSBACH–SPITFIRE and LPJ-GUESS–SPITFIRE respond to elevated atmospheric $CO_2$ concentration with a strong increase in burned area, likely driven by increases in fuel load. LPJ–GUESS–SPITFIRE additionally shows a strong decrease in soil moisture, which might explain why this model shows the strongest increase in burned area. ORCHIDEE–SPITFIRE shows lower burned area in response to elevated atmospheric $CO_2$ concentration but the decreases are mainly localized in the regions with very high burned area (Sahel and Northern Australia; see fig. A3) and are likely driven by the increase in $C_3$ woody biomass (see fig. 4) as SPITFIRE is very sensitive to the type of fuel (Lasslop et al., 2014). LPJ–GUESS–SIMFIRE–BLAZE shows an initial increase and a decrease in burned area at the end of the simulation. The spatial pattern is mixed, the decrease in $C_4$ grass biomass indicates that woody thickening, either due to changes in land cover fraction or fuel composition is the reason for this reduction in burned area. ~~The higher vegetation biomass shown by all models is expected as studies showed that elevated~~ ~~$CO_2$~~ ~~increases the productivity (Farquhar et al., 1980; Hickler et al., 2008) and water-use efficiency (De Kauwe et al., 2013) . Increased productivity and vegetation storage leads to higher and faster fuel build-up. The higher water-use efficiency can decrease flammability through increased soil moisture. Additionally an~~ An increase in woody plants with higher atmospheric $CO_2$ concentration is expected (Wigley et al., 2010; Buitenwerf et al., 2012; Bond and Midgley, 2012)~~, which have~~ . Their coarser and less flammable fuel ~~. Decreases in flammability~~ can lead to reduced burned area. ~~The strength of~~ ~~$CO_2$~~ ~~effects on productivity and allocation is still uncertain. Comparisons with experimental data suggest that models that do not include the nitrogen cycle overestimate the effect on productivity (Hickler et al., 2015) . However, an analysis using an observation-based emergent constraint on the longterm sensitivity of land carbon storage shows that models from the Coupled Climate Model Intercomparison Project (CMIP5) ensemble that included an interactive nitrogen cycle underestimate the impact of~~ ~~$CO_2$~~ ~~on productivity (Wenzel et al., 2016) .~~ A recent study using an optimized empirical model indicates that increases in biomass led to decreases in burned area in regions with high fuel loads, likely due to increases in coarser fuels and increases in burned area in fuel limited regions (Forkel et al., 2019b) .

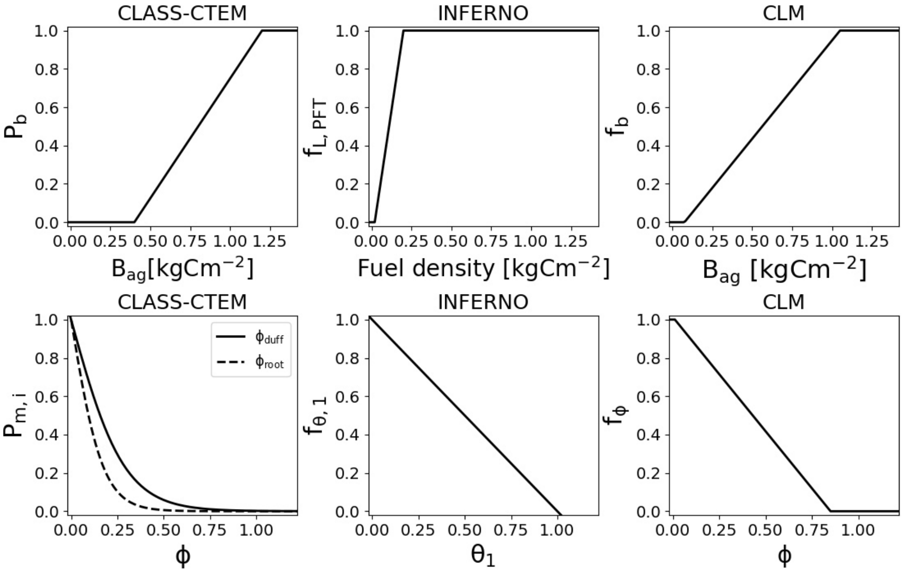


**Figure 5.** Impact of fuel load on the probability of fire ($P_b$) for CLASS-CTEM, on the fuel load index ($f_{L,PFT}$) for INFERNO and on fuel availability ($f_b$) for CLM (top panels). Impact of soil moisture content and soil wetness on fire for CLASS-CTEM, CLM, and INFERNO (bottom panels). In order to facilitate comparability, the soil moisture function for CLM is scaled to the value range [0,1].

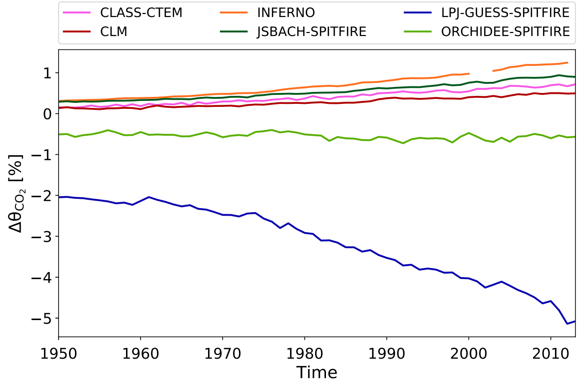


**Figure 6.** Annual average of the relative difference in volumetric soil moisture (CLM) and total soil moisture content (remaining models) between the baseline experiment SF1 and and the sensitivity experiment SF2_CO2 (see tab. 1; $\Delta\theta_{CO_2}$) for 1950–2013 in %. Due to a postprocessing error, INFERNO lacks two years (2001 and 2002) ~~(2002 and 2003~~ .

### 3.2.2 ~~Sensitivity~~ Response of ~~models~~ simulated burned area to population density

The population density forcing used for FireMIP increases in every region of the globe over time as well as in annual global values (Goldewijk et al., 2010). This increasing population density is associated with a monotonic increase of global burned area for LPJ–GUESS–SPITFIRE, and a monotonic decrease for LPJ–GUESS–SIMFIRE–BLAZE and CLM. The remaining models show a peak in the impact of population density on burned area around 1950 and a subsequent decline (see fig. 2, b). Models however largely agree on a decreasing trend due to population density since 1921 (see tab. 4) and the ones that show a positive trend did not reproduce the relationship between population density and burned area in a multivariate model evaluation (Forkel et al., 2019a) . Changes in population density therefore very likely contributed to a decrease in global burned area since 1921.

All the models, except LPJ–GUESS-SIMFIRE–BLAZE, include the number of anthropogenic ignitions ($I_A$) or the probability of fire due to anthropogenic ignitions ($P_{i,h}$ in CLASS–CTEM) in the calculation of burned area. Most of the models represent the number of anthropogenic ignitions with an increase up to a certain threshold number and then a decline, implicitly assuming that for high population densities humans ~~tend to~~ suppress fires (SPITFIRE–models, INFERNO and CLM; see fig. 7). CLASS–CTEM, JSBACH–SPITFIRE and CLM include explicit terms to account for the effects of suppression not only on ignitions but also on fire size, or duration, or both (see fig. 8). The combination of the ignition and suppression term in CLASS–CTEM leads to a maximum impact of humans on burned area at intermediate population density. The combination of ignition and suppression mechanisms dependant on population thresholds explains why most of the models have non-monotonic changes in burned area as population increases during the 20th century. LPJ–GUESS–SPITFIRE is the only model that shows a monotonic increase in burned area in response to increasing population density; other models that include the SPITFIRE fire module (JSBACH, ORCHIDEE) show the non-monotonic trajectory that results from the shift from the dominance of ignitions to that of suppression on burned area. ORCHIDEE–SPITFIRE has a much lower contribution from anthropogenic ignitions than LPJ–GUESS–SPITFIRE and therefore different spatial patterns of burned area (see fig. A1); JSBACH–SPITFIRE has an additional suppression term based on fire size data (Hantson et al., 2015a) . The inclusion of additional suppression mechanisms may also explain the behavior of CLM, which shows a monotonic decrease in burned area over the 20th century.

LPJ–GUESS–SIMFIRE–BLAZE does not include anthropogenic ignitions explicitly but rather treats the net effect of changes in population density, which was optimized using burned-area satellite data (Knorr et al., 2014). This optimized net effect is a monotonic decrease of burned area with increases in population density. This explains why this model shows a monotonic decrease overall ~~and indeed is the only model that shows almost no grid cell with a positive trend in burned area~~ (see fig. ~~3,~~ A4).

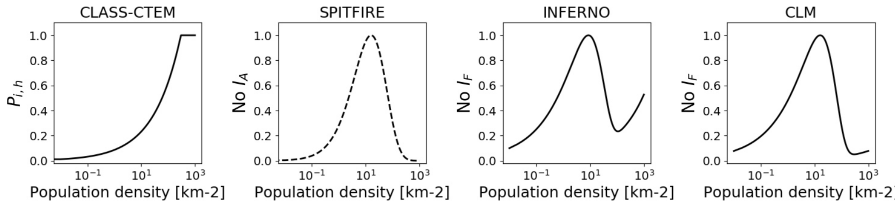


**Figure 7.** Variation in probability of fire due to human ignitions ($P_{i,h}$), anthropogenic ignitions (No $I_A$) or number of fires (No $I_F$) for changes in population density. Since all models use different units, the values are scaled to the value range [0,1].

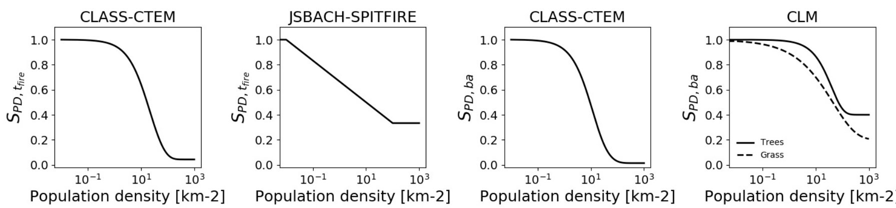


**Figure 8.** ~~Suppressive~~ Suppression effects of population density on fire duration ($S_{PD,t_{fire}}$) for CLASS-CTEM and JSBACH SPITFIRE and ~~suppressive~~ suppression effects on fire size ($S_{PD,ba}$) for CLASS-CTEM and CLM. All models are scaled to the value range [0,1].

The models all agree that ~~for~~ at high population density fire is suppressed~~, but differ on their assumptions what happens~~. This leads to similarities in the spatial patterns of the effect of population changes (see fig. A4) but they differ in their assumptions for low population density~~and~~, the threshold where humans start to suppress fire and whether explicit suppression is included. ~~This leads to some similarities in the spatial patterns of the effect of population changes (see fig. A4).~~ The net or emerging effect of humans on burned area in models, however, also depends on the presence of lightning ignitions. ~~As~~ The presence of lightning ignitions reduces the limiting effect of a lack of human ignitions on burned area. For the CLASS-CTEM model as soon as lightning ignitions are present, the net effect of humans is to suppress fires, even ~~when~~ though the underlying relationship assumes an increase in ignitions with population density (Arora and Melton, 2018, supplement). This may explain why global models assuming an increase of ignitions with increases in population density are able to capture the burned area variation along population density gradients (Lasslop and Kloster, 2017; Arora and Melton, 2018) ~~although global statistical analysis support~~ and why global statistical analyses find a net human suppression also for low population density (Bistinas et al., 2014).

### 3.2.3 ~~Sensitivity~~ Response of ~~models~~ simulated burned area to land-use change

The land-use change imposed in SF2_FLA ~~over the recent centuries~~ is characterized by a strong decrease in forested areas, and an increase in pastures and croplands (Hurtt et al., 2011). The FireMIP-models do not show a uniform response of burned area to land-use change. LPJ–GUESS–SPITFIRE shows the strongest reaction with a monotonic increase in burned area with land-use change. INFERNO and ORCHIDEE–SPITFIRE also show an increasing trend, but of lower magnitude. CLASS–CTEM, JSBACH–SPITFIRE and LPJ–GUESS–SIMFIRE–BLAZE show a decreased burned area due to increased land-use. CLM also shows a decrease in burned area but this change is ~~comparatively muted~~ not significant (see fig. 2, c)).

The FireMIP-models handle land-cover dynamics, the expansion of agricultural areas and fire in agricultural areas differently. Some of the models (CLASS–CTEM, CLM, JSBACH–SPITFIRE, ORCHIDEE–SPITFIRE) prescribe the vegetation distribution, so that the land cover fraction for all PFTs does not change through time in SF2_FLA while in the SF1 simulation the cover fractions of natural PFTs are reduced according to the expansion of agricultural areas. The other models simulate the distribution of the natural vegetation dynamically, but prescribe the agricultural areas. All models decrease the tree cover to represent the expansion of croplands over time. Land conversion due to the expansion of pasture is not represented in CLASS–CTEM. Only CLM includes cropland fires, INFERNO treats croplands as natural grasslands and all the other models exclude croplands from burning (see tab. 5). Therefore for all models except CLM and INFERNO, increases in cropland area lead to a reduction in burned area and the reasons for the divergence ~~of~~ between the other models must be caused by the treatment of pastures.

**Table 5.** Treatment of agricultural fires (Rabin et al., 2017b). 'None' indicates the vegetation type does not burn or that deforestation fires are not represented in the model. The models treating pasture fire the same as grassland do not treat pasture as a specific PFT. The indication 'no pasture' means that there is no land cover change due to pastures.

| Model | Cropland fire | Pasture fire | Deforestation fire |
|---|---|---|---|
| CLASS-CTEM | None | no pasture | None |
| CLM | Yes | Same as grassland | Yes |
| INFERNO | Same as grasslands | Same as grassland | None |
| JSBACH-SPITFIRE | None | Higher fuel bulk density than grasslands | None |
| LPJ-GUESS-SIMFIRE-BLAZE | None | Harvest of biomass | None |
| LPJ-GUESS-SPITFIRE | None | Same as grassland | None |
| ORCHIDEE-SPITFIRE | None | Same as grassland | None |

In LPJ–GUESS–SIMFIRE–BLAZE pastures are harvested; this reduction in biomass leads to a decrease in burned area in addition to the decrease caused by exclusion of fire in croplands. In JSBACH–SPITFIRE, the expansion of pastures occurs preferentially at the expense of natural grassland and does not affect tree cover until all the natural grassland has been replaced (Reick et al., 2013). This assumption decreases the effect of land cover conversion on tree cover. Additionally, in JSBACH–SPITFIRE the fuel bulk density of pastures is higher than that of natural grass by a factor of two, which decreases fire spread and thus burned area (Rabin et al., 2017b). This difference reduces burned area in pastures compared to natural grassland. In CLASS–CTEM, which also shows a decline, pastures are not included, the only land conversion is due to the expansion of croplands.

LPJ–GUESS–SPITFIRE and ORCHIDEE–SPITFIRE react with an increase in burned area to the expansion of land-use since they treat pastures as natural grasslands. The SPITFIRE fire module is very sensitive to the vegetation type with very

high burned area for natural grasslands due to higher flammability compared to woody PFTs (Lasslop et al., 2014, 2016). Fuel bulk density is an important parameter but additionally grass fuels dry out faster leading to an increase in flammability and therefore burned area if forested areas are converted to grasslands. LPJ–GUESS–SPITFIRE computes the vegetation cover dynamically, so that an increase in burned area reduces the cover fraction of woody types, which might explain the stronger response compared to ORCHIDEE–SPITFIRE. In CLM, pastures are represented by increased grass cover. The biomass scaling function does not distinguish fuel types (see fig. 5), therefore the lower fuel amount of grasslands could lead to a decrease in fire probability, while the maximum fire spread rate depends on the vegetation type and is higher for grasslands (Rabin et al., 2017b). The inclusion of cropland and deforestation fires dampen the effect of land-cover change on global burned area. In INFERNO, agricultural regions are not defined explicitly. Instead, woody PFT types are excluded on agricultural area (Clark et al., 2011). INFERNO includes an average burned area for each PFT in the calculation of the burned area per PFT which leads directly to increasing grass cover resulting in higher burned area (Mangeon et al., 2016; Rabin et al., 2017b).
Land-use was already identified as a main reason for inter-model spread in the CMIP5 ensemble (Kloster and Lasslop, 2017). We ~~have shown~~ show that this largely reflects the way pastures are treated, as most models used here (except CLM and INFERNO) simply exclude croplands from burning.

### 3.2.4 ~~Sensitivity~~ Response of ~~models~~ simulated burned area to lightning

Most of the models show a low ~~sensitivity of burning rates~~ response of burned area to lightning (see fig. 2), although lightning rates increase by 20% over the simulation period – an increase that is much larger than the 3.3% change between pre-industrial times and the present estimated from a recent modelling study (Krause et al., 2014) . ORCHIDEE–SPITFIRE shows an increase in burned area between 1940–1960 and towards the end of the simulation. ~~The reason can most reasonably be found in~~ In comparison to the other SPITFIRE-models ~~and seems~~ the differences seem to be related to two points. Firstly, ~~it~~ ORCHIDEE–SPITFIRE uses a 12 times higher factor to convert lightning strikes to actual ignitions and anthropogenic ignitions that are 100 times lower than for the other models ~~. Therefore, the partitioning of natural and anthropogenic ignitions is different from other SPITFIRE models~~ (see Rabin et al., 2017b). Secondly, although a partitioning factor (SGFED) varies regionally, the ~~per-capita~~ per capita ignition frequency is constant; in JSBACH–SPITFIRE and LPJ–GUESS–SPITFIRE, the ~~per-capita~~ per capita ignition frequency varies regionally. This results in strong differences in the spatial patterns of burned area (see fig. A1). In consequence, the strength of regions contributing to the global burned area varies between the models; ORCHIDEE–SPITFIRE shows much more burning in the tropical and far less burning in the temperate region. Whether a lightning turns into a fire depends on the local conditions at the time of the lightning strike. Differences in the spatial distribution and timing of fires can therefore lead to different responses between models even if lightning is used in the same way within the model. Our results show that even a substantial increase (20%) in lightning has little influence on simulated global burned area. ~~However, lightning is known to be an important cause of ignitions regionally and is potentially involved in more complex interactions between fire, vegetation and climate, which can speed up the northward expansion of trees to the north in boreal regions (Veraverbeke et al., 2017) . Thus, although we have shown that the influence of increasing lightning is negligible at a~~

~~global scale, it is a potentially important factor for regional impacts~~This is consistent with (Krause et al., 2014) who found that the pre-industrial to present increase in lightning, although this increase is much smaller, had little impact on burned area.

#### 3.2.5 ~~Sensitivity~~ Response of ~~models~~ simulated burned area to climate

Simulated burned area in FireMIP responds to changes in climate with strong interannual variability but only weak trends in burned area (see fig. 2, e). Only three models show a statistically significant trend in the global burned area according to a Mann-Kendall test (CLM, LPJ–GUESS–SIMFIRE–BLAZE,ORCHIDEE–SPITFIRE; see tab. 4). However, in all models the area showing an increased burned area in response to climate is higher than the area with decreased burned area (see fig. 3). Agreement in spatial patterns of trends between the models is however low (see fig. A7).

The influence of climate on burned area is complex; it influences burned area through the meteorological conditions and through effects on vegetation conditions that influence fuel load and fuel characteristics (Scott et al., 2014). We therefore correlated for each grid cell changes in physical parameters (precipitation, temperature, wind speed and soil moisture) and vegetation parameters (litter, vegetation carbon and grass biomass) with changes in burned area. We find that the correlation between the individual parameters and burned area is low (see fig. A8). The absolute rank correlations are lower at the monthly scale than at the annual scale. However, at the monthly scale the number of grid cells showing significant correlations with physical parameters is higher than the number showing significant correlations with vegetation parameters, indicating that changes in physical parameters have more influence at shorter time scales than changes in vegetation parameters. This difference disappears with the aggregation to annual time scale. On the annual time scale, however, the mean absolute rank correlation is slightly higher for the vegetation parameters. Soil moisture which is also influenced by vegetation has a slightly higher correlation compared to precipitation~~and temperature~~ , temperature and wind speed too. This indicates that vegetation parameters are more influential on the longer annual time step and physical parameters on the monthly time step. The relationship between precipitation or soil moisture and burned area is expected to be negative, while the impact of temperature is expected to be positive. This is clearly reflected in the percentage of positively significant correlations at the annual scale, but is less clear at the monthly time step. This might reflect that the seasonality of temperature, precipitation and vegetation ~~parameter~~ parameters is often synchronized and therefore the effects of the parameters cannot be separated. The low correlation between individual parameters and burned area reflects the complex interactions between the climatic drivers, vegetation conditions and fire weather.

The impact of climate on the interannual variability~~is~~, however, is strongly expressed in the simulated burned area. This is consistent with the finding that recent precipitation changes influence interannual variability in fire but have little impact on recent longer-term trends ~~(Andela et al., 2017)~~(Andela et al., 2017) . To fully understand the impact of the changes in climate, a number of simulations would be necessary, where only individual climate parameters change while the others are kept constant. In addition, simulations where combinations of variables change, might give further insights on the synergies between the variables. An alternative approach, given the complex interactions between climate ~~variables~~and vegetation parameters, might be to disentangle the model signals using multivariate analysis ~~(see e.g. Forkel et al., 2019a)~~ (see e.g. Forkel et al., 2019a; Lasslop et al., 2018) .

### 3.3 Implications for model development and applications

~~The huge spread of simulated burned area trends for any of the forcing factors indicates the high uncertainties in burned area trajectories. With the current state of knowledge, the use of a model ensemble that covers the model structural uncertainties is clearly the best approach for projections. Nevertheless, our analyses suggest a number of promising avenues for further model development and indicates which analysis of observational data would be useful to constrain global models. Improvements of global~~ Global vegetation models are an important tool for examining the impacts of climate change and are used in policy-relevant contexts (IPCC, 2014; Schellnhuber et al., 2014; IPBES, 2016) . Given the various influences of fire on the ecosystems (Bond et al., 2005) , the carbon cycle and climate (Lasslop et al., 2019) , improvements of global fire models are particularly important.

The main concern for model applications is the large spread of the historical simulated burned area. It remains difficult to evaluate and optimize the transient burned area simulations as the period observed by satellites is still short and the trends are not robust (Forkel et al., 2019b) . Fire proxies (charcoal and ice-cores) give information on biomass burning over longer time scales. They do not confirm the recent decrease in burned area detected by satellites, but also only contain very few datapoints for that period (Marlon et al., 2016) . For a valid comparison with the long term fire proxies, including estimates of deforestation fires in the models will be ~~particularly important to improve the future projections of fire-enabled models to support land management strategies for instance in the context of climate change mitigation. Representing human influence on fire is the major challenge for long-term projections. Our analyses of the controls on the variability of fire suggest that human activities drive the long term (decadal to centennial) trajectories, while considering climate variability may be sufficient for short-term projections. The~~ crucial, as land-use change fire emissions likely have a strong contribution to the signal (Marlon et al., 2008) . An improved understanding of uncertainties in observed trends of fire regimes is therefore necessary. Only robust information should be included in models.

Our analysis shows which parts of the models are particularly important to simulate changes in burned area and need additional observational constraints or improved process understanding. In line with previous research (Bistinas et al., 2014; Hantson et al., 2016a, b; Andela et al., 2017) , the large divergence in the response to human activities between the FireMIP models shows that the human impact on fires is still insufficiently understood and therefore ~~poorly represented~~ not constrained in current models. ~~There is strong inter-model agreement that burned area is suppressed at high population densities, which means that most models show a similar spatial distribution of fire-prone areas (see fig. A4) and a reduction of the burned area in the last decades of the simulation due to increases in population density. However, the reduction in global burned area in the reference simulation is for most models still much smaller than shown by satellite observations (Andela et al., 2017) . This could be solved by increasing the suppression effect of humans through population density in the models, however, it could also be related to land-use and for LPJ-GUESS-SPITFIRE and JSBACH-SPITFIRE to overestimation of the $CO_2$ fertilization effect. The level of socioeconomic development also modifies the relationship between population density and burned area (Andela et al., 2017; Forkel et al., 2017) ; further analyses are required to better disentangle the balance of the different driving factors.~~

We ~~have identified~~ identify land-use change as the major cause of inter-model spread. Only one model ~~included~~ explicitly includes fires associated with ~~land use~~ land-use and land cover change (cropland and deforestation fires), all the other models only ~~included~~ include such effects through changes in vegetation parameters and structure. ~~Croplands are simply excluded from burning in all but one model. The spread of the other models is therefore likely related to the treatment of pastures.~~ The inclusion of cropland fires is certainly important to understand and ~~predict~~ project changes in emissions, air pollution and the carbon cycle ~~(Li et al., 2018)~~ (Li et al., 2018; Arora and Melton, 2018) . Cropland fires are, due to their small extent and low intensity, still a major uncertainty in ~~remote sensing datasets (Randerson et al., 2012) .~~ our current understanding of global burned area (Randerson et al., 2012) . Biases in the spatial patterns of burned area and the relationship between cropland fraction and burned area can therefore be expected. High resolution remote sensing may help to improve the detection ~~. But increased understanding in regional differences~~ (Hall et al., 2016) . Moreover, understanding why and when ~~people burn croplands~~ humans burn croplands on a regional scale may help to find an adequate representation of cropland fires within models ~~. Pastures~~ and avoid overfitting to observational datasets. As croplands are simply excluded from burning in most models (except two), the spread of the other models is likely related to the treatment of pastures. Fires on pasturelands have been estimated to contribute over 40% of the global burned area (Rabin et al., 2015). Pasture fires are not treated explicitly in any of the models, although some models slightly modify the vegetation on pastures ~~,~~ by harvesting or changing the fuel bulk density (see tab. 5). ~~Since most models implement expansion of pastures simply by~~ Expansion of pastures is mostly implemented by simply increasing the area of grasslands~~, information~~ . Information on how fuel properties differ between pastures and natural grasslands could therefore help to improve model parametrisations. Prescribing fires on anthropogenic land covers can be a solution for certain applications of fire models (Rabin et al., 2018) . Grazing intensity was found to be related to decreases in burned area (Andela et al., 2017). ~~It therefore may be necessary to include information on grazing intensity , or better information on pasture management in general, to represent pastures realistically within global fire models~~ Models so far represent the area that is converted due to land cover change but not the intensity of land-use. This was partly due to the lack of global data regarding land use intensity which is now becoming available and provides new opportunities for fire model development (e.g. the LUH2 dataset; Hurtt et al., 2017 ). In the sensitivity simulations shown here, even models that decrease burned area due to land-use and land cover change do not show a further decrease over the last decade. This indicates that model input datasets, explicit in time and space, for land-use intensity and grazing intensity are necessary for fire projections. The level of socioeconomic development also modifies the relationship between humans and burned area (Andela et al., 2017; Forkel et al., 2017) . Regional analysis of remote sensing data could be highly useful, as a global relationship between burned area and individual human factors as assumed in many models and also statistical analysis is not likely. Assumptions on how different human groups (hunter-gatherers, pastoralists, and farmers) use fire have been included in a paleofire model (Pfeiffer et al., 2013) . The development of such an approach for modern times would be highly valuable for fire models that aim to model the recent decades and future. Deforestation fires are only included in one model (CLM). As deforestation fires are likely a strong source of biomass burning over the longer time scales, accounting for deforestation fires will be crucial for a model comparison with the charcoal record.

We also find inter-model agreement for certain aspects. For instance, burned area is suppressed at high population densities, which leads to a similar spatial response to population density (see fig. A4). Moreover, most models show a reduction of the global burned area due to changes in population density. The response functions of burned area to population density of the two models that increase burned area is less in line with response functions derived from global datasets (Forkel et al., 2019a) . As a strong human suppressive effect is well supported by satellite observations (Andela et al., 2017; Hantson et al., 2015b) , a reparametrisation of these responses would be reasonable.

We show that, although all models show an overall increase in biomass as a consequence of increasing atmospheric $CO_2$ concentration, models disagree about whether this results in an increase or decrease in burned area. The disagreement reflects the complex ways in which changes in atmospheric $CO_2$ concentration influence vegetation properties, which results in different responses in different ecosystems. For LPJ-GUESS-SPITFIRE and JSBACH-SPITFIRE the $CO_2$ fertilization effect considerably contributed to an increase in burned area. Such an effect is so far only supported for fuel limited areas (Forkel et al., 2019b) . The assumption that the influence of higher fuel load on burned area levels off for high fuel loads as used in other models could help to reduce this increase in burned area in regions with higher fuel load.

Climate and lightning have a much lower effect on the trends than the other factors. While this study focuses on the trends, research on the short term variability and extreme events will be highly useful to investigate fire risks. The influence of climate and lightning on fire are therefore important research topics even if we find a comparably low influence on the long term trends. Moreover the trends in climate parameters may increase for the future and therefore the influence on burned area might increase.

In contrast to many model simulations that use a lightning climatology based on satellite observations, the FireMIP experiments were driven by a transient dataset of lightning activity created by scaling a mean monthly climatology of lightning activity using convective available potential energy (CAPE) anomalies ~~. Although we do not detect large signals in global burned area due to changes in lightning, the impact of changes in lightning at a regional scale (and particularly in boreal regions) is considerable~~of a global numerical weather prediction model. Since climate changes can be expected to cause changes in lightning, it will be important to develop transient lightning datasets for climate change studies on fire. Using present day lightning patterns, for example, will certainly lead to an overestimation of lightning strikes in regions with drier climate projected in the future. ~~The covariation~~ But not only spatial patterns of lightning are important, the co-variation with climate as well as the temporal resolution ~~are important (Felsberg et al., 2018) . The FireMIP dataset was developed using only a limited amount of information about the covariation of precipitation, CAPE and lightning; further analyses of these relationships would be useful.~~ of the input dataset determine the influence on burned area (Felsberg et al., 2018) . Although we do not detect large signals in global burned area due to changes in lightning, lightning is known to be an important cause of ignitions regionally and is potentially involved in more complex interactions between fire, vegetation and climate, which can speed up the northward expansion of trees to the north in boreal regions (Veraverbeke et al., 2017) . Thus, although our results suggest that the influence of increasing lightning is negligible at a global scale, it is a potentially important factor for process-based models that aim to model interactions between fire, vegetation and climate.

~~It is obvious that~~ Recent advances in remote sensing products have high potential to support model development. However, remotely sensed burned area datasets alone are not a sufficient basis to evaluate fire models as many model structures can lead to reasonable burned area patterns. ~~It is important to test how well current models represent the number of fires, the size of individual fires and fire intensity. Both the effects of fire on vegetation (combustion of biomass and tree mortality; Williams et al., 1999; Wooster et al., 2005 ) and of plume heights for fire emissions to the atmosphere (Veira et al., 2016) are a function of fire intensity.~~ The emergence of longer records of burned area and the increasing availability of information on other aspects of the fire regime ~~should~~ considerably improve opportunities to evaluate and improve our models. The FRY database (Laurent et al., 2018) and the global fire atlas (Andela et al., 2018), for example provide information on fire size, numbers of fire, rate of spread, and the characteristics of fire patches. ~~Exploiting such datasets should help toconstrain the internal mechanisms of fire models and hopefully allow to improve the balance of different drivers.~~ These datasets will be useful to, for instance, separate effects of ignition and suppression. Rate of spread equations in global fire models are at present either very simple empirical representations tuned to improve burned area or based on laboratory experiments (Hantson et al., 2016a) . The mentioned datasets now offer the opportunity to derive parameters for rate of spread equations at the spatial scales these models operate on. Fire size and rate of spread are important target variables besides burned area that can determine the impacts of fire. The effects on vegetation (combustion of biomass and tree mortality; Williams et al., 1999; Wooster et al., 2005 ) and on the atmosphere (Veira et al., 2016) are a function of fire intensity, which is also included in the FRY database (Laurent et al., 2018) . A better evaluation of such parameters can enhance the usability of fire model simulations.

The specific model application has a strong influence on judging the validity of a model. Our analyses of the controls on the variability of fire suggest that human activities drive the long term (decadal to centennial) trajectories, while considering climate variability may be sufficient for short-term projections. Changes in the trends of the driving factors may change this balance. For instance, stronger changes in climate into the future may increase the relative importance of climate for long term fire projections in the future.

## 4 Summary and conclusions

~~The analysis presented here improves our understanding of global modelling of burned area and uncertainties associated with specific drivers and process representations in the models. The identified differences in fire models also provide information to focus analysis of observations that aim to provide constraints for global fire models. Although burned area in most models compares reasonably well with satellite observations, there is a huge spread in transient simulations before the satellite era and a huge spread in the influence of the driving factors between models.~~ This comprehensive analysis of the influences of climate, lightning, atmospheric $CO_2$ concentration, population density and land-use and land cover change provides improved understanding of the relation between simulated historical trends in burned area and process representations in the models. It shows in detail which model responses of burned area to environmental factors can be understood, how these are related to the model equations, and how these translate into trends of burned area for the historical period.

The analysis of the sensitivity experiments ~~showed that: (1)~~ shows that: The increase in atmospheric $CO_2$ concentration over the 20th century leads to increased burned area in regions where fuel loads increase, but to decreased burned area in regions where tree density or coarse fuels with lower flammability increase or ~~increases~~ elevations in soil moisture decrease flammability. Although models agree that the amount of available fuel increases, the type of fuel and vegetation composition are ~~, however,~~ critical to understand the influence of atmospheric $CO_2$ concentration on simulated burned area.

~~(2)~~ Most models agree on a decrease in burned area due to increases in population density. Most models link the number of ignitions to population in a way that ignitions increase initially at low population densities. In densely populated regions, all models assume that the effect of anthropogenic ignitions is outweighed by fire suppression and the increased fragmentation of the landscape by anthropogenic ~~land use. Whether the model shows an overall increase, a decrease or an initial increase followed by a decrease in burned area over the 20th century depends largely on the population threshold assumed for the transition from increasing ignitions to increasing suppression, and the complexity of the treatment of fire suppression~~land-use. It would be useful to develop an approach that represents local human-fire relationships, but this will likely remain a long term challenge and requires the synthesis of knowledge from various research fields.

~~(3)~~ The simulated response of burned area to land-use and land cover change depends on how fires in cropland and pastureland are treated in each model. Most models simply exclude croplands from the burnable area, therefore the treatment of pastures ~~contributes~~ causes the largest part of the model spread. Models that do not allow fire in croplands, and either harvest biomass in pastures or assume specific vegetation parameters, show a reduction in burned area. Models that treat pastures as natural grasslands and distinguish different fuel types or strongly increase burned area for grasslands show an increase in burned area. Improved knowledge on the effects of land-use intensity on burned area and the development of appropriate forcing datasets could strongly support model development.

~~(4)~~ The models are comparatively insensitive to changes in lightning, likely because lightning ignitions are not a limiting factor in many regions with very high burning activity. Previous studies however show the importance of lightning and changes in lightning for burned area in the boreal region. Therefore especially regional studies should pay attention to this factor.

~~(5)~~ None of the models shows a strong trend due to changing climate but all of them show a strong influence of climate on the interannual variability. Climatic and ecosystem parameters are only able to explain a rather small part of this variation, with stronger correlations for the ecosystem parameters on the longer annual time scale and stronger relationship with climatic parameters on the monthly time scale.

Different drivers of burned area affect different time scales: the anthropogenic factors influence long term variability, while climate, and lightning affect short-term variability. Understanding the influence of climate and lightning is especially important for interannual variability and extreme events. On the other hand understanding the impact of anthropogenic drivers are likely more important for the longer term changes of fire as for instance needed ~~, for instance,~~ in Earth system models. Changes in the trends of the forcing parameters might however affect the balance between them.

The uncertainties in global fire models need to be taken into account in model applications, for instance if model simulations are to be used to ~~design~~ support climate adaptation strategies. ~~Using model ensembles can be suitable to provide estimates of the uncertainties~~Model ensemble simulations can give indications of such uncertainties. Therefore the results of this study provide a basis to interpret uncertainties in global fire modelling studies. The spatial patterns of burned area and its drivers are already well explored and understood. We here provide a summary of which model assumptions need additional constraints to efficiently reduce the uncertainty in temporal trends.

*Code availability.* TEXT

*Data availability.* Datasets will be available after acception of the paper

*Code and data availability.* TEXT

*Sample availability.* TEXT

**Appendix A**

**A1**

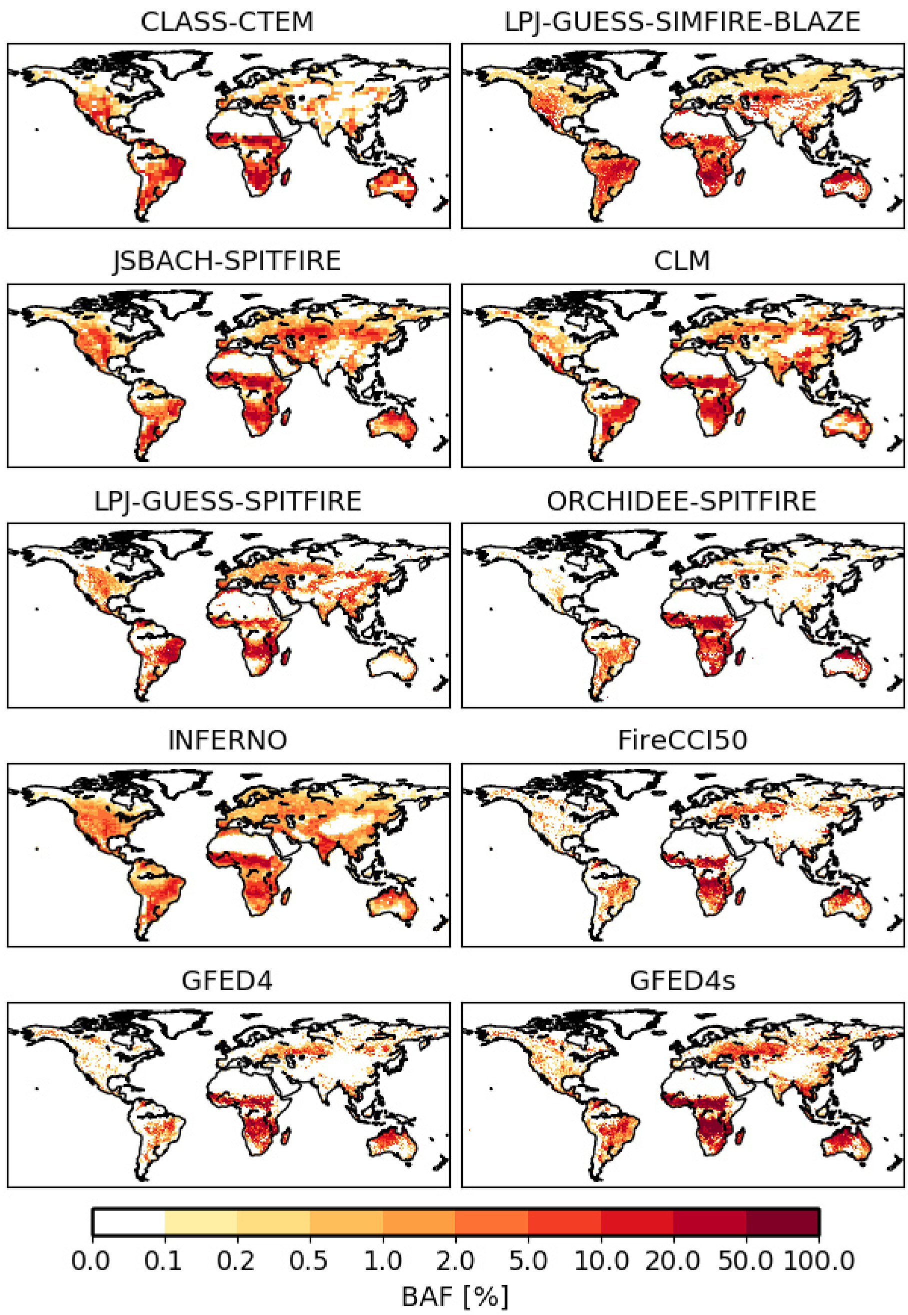


**Figure A1.** Spatial distribution of annual burned area fraction (BAF) ~~of a grid cell~~ in % for the baseline experiment SF1 and observation data, averaged over 2001-2013.

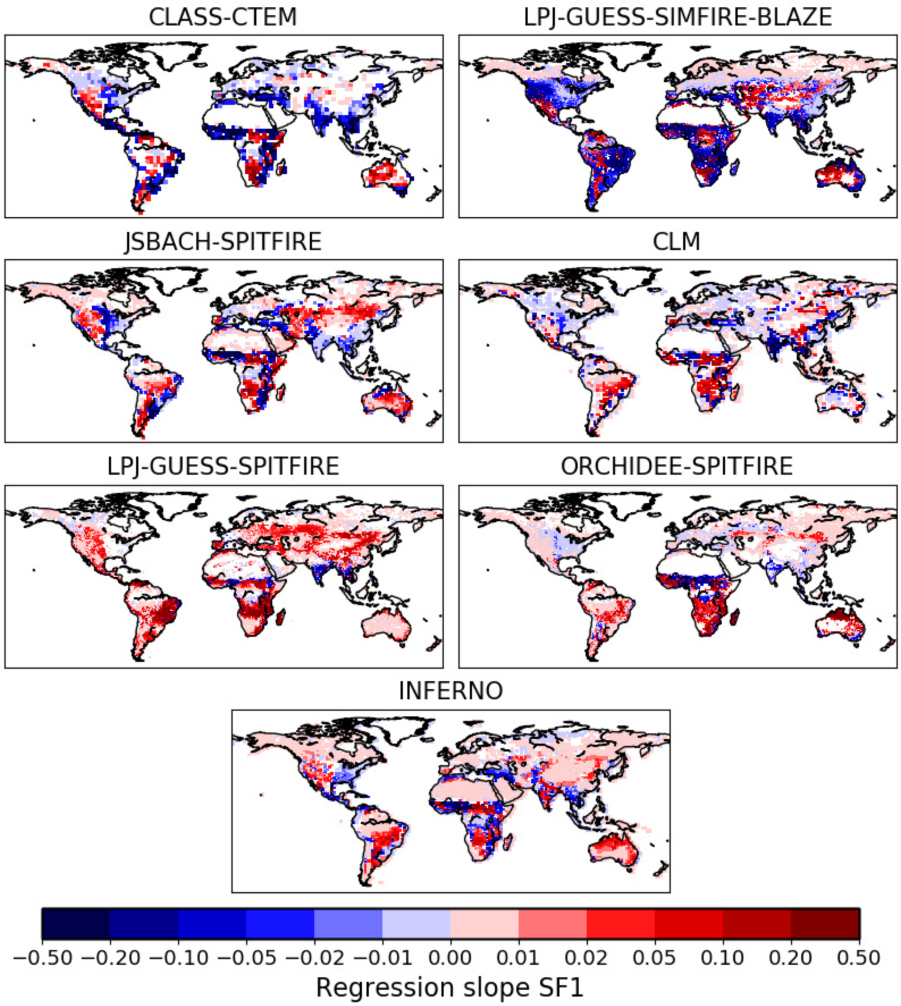


**Figure A2.** ~~Regression slope~~ Spatial distribution of ~~a grid cell~~ regression slopes for the baseline experiment SF1 over ~~1901-2013~~1921-2013.

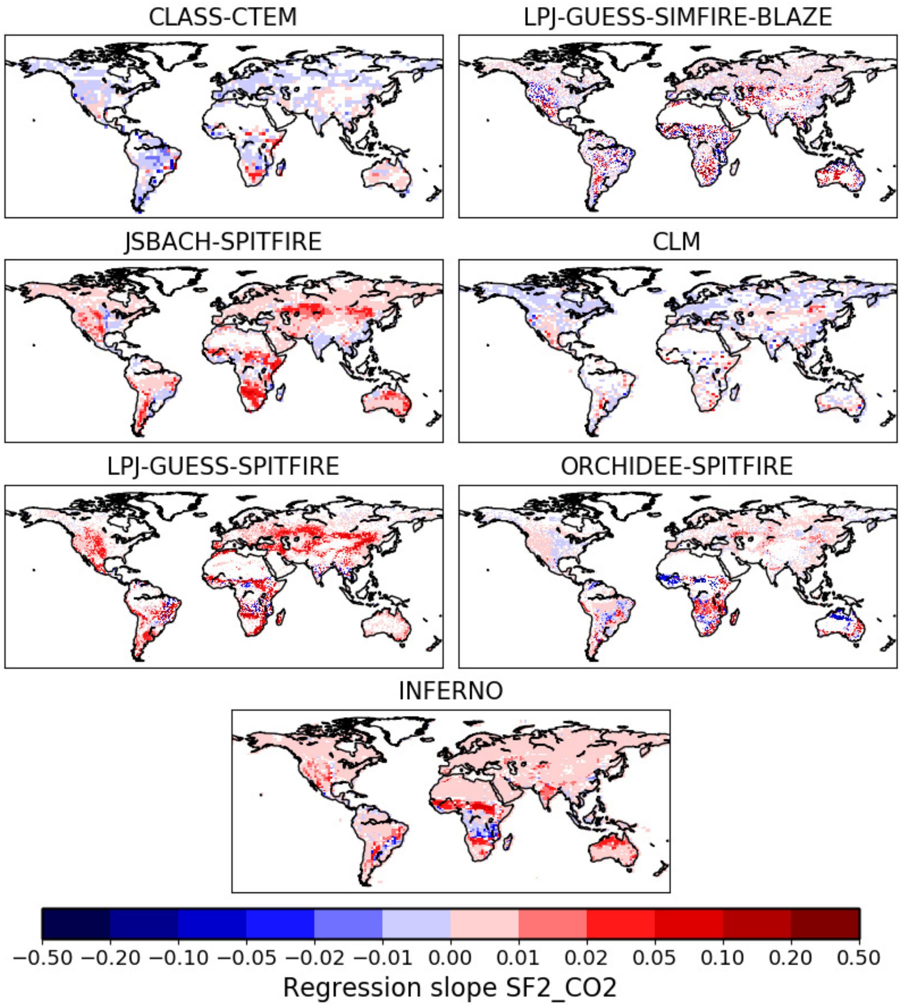


**Figure A3.** ~~Regression slope~~ Spatial distribution of ~~a grid cell~~ regression slopes for the difference between the baseline experiment SF1 and the sensitivity experiment SF2_CO2 (SF1–SF2_CO2; see tab. 1) over ~~1901-2013~~1921-2013.

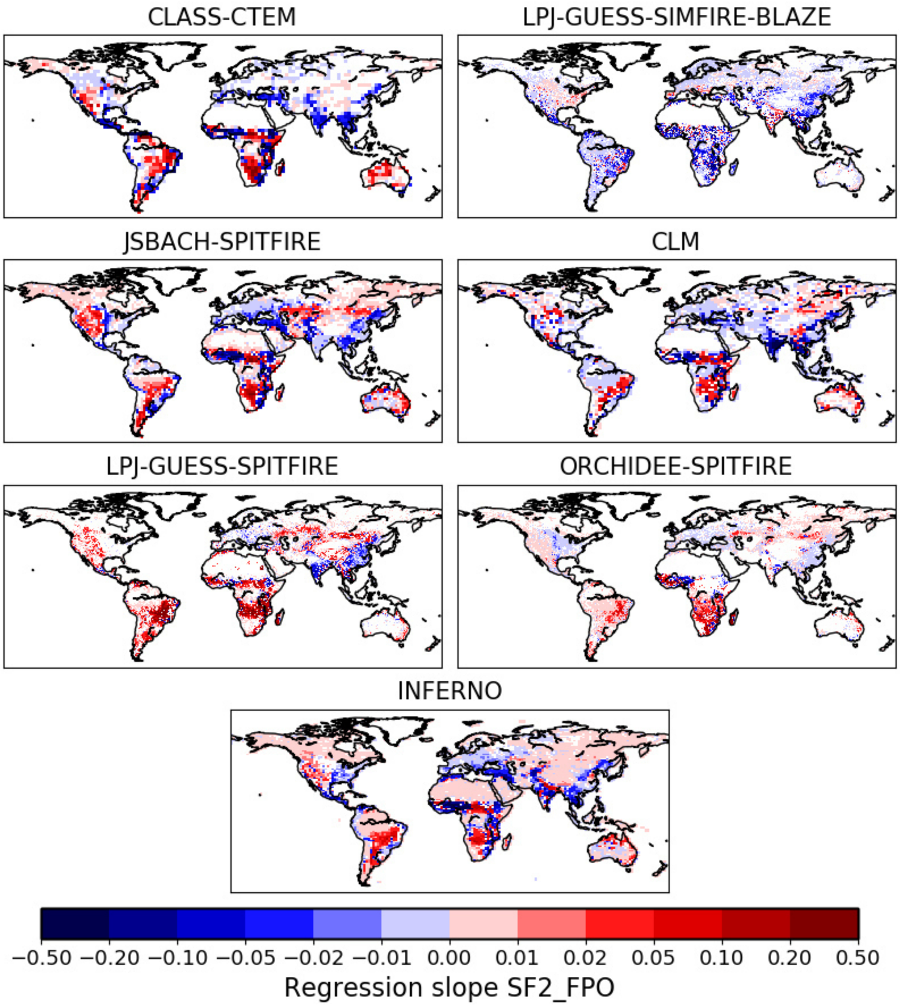


**Figure A4.** ~~Regression slope~~ Spatial distribution of ~~a grid cell~~ regression slopes for the difference between the baseline experiment SF1 and the sensitivity experiment SF2_FPO (SF1–SF2_FPO; see tab. 1) over ~~1901-2013~~1921-2013.

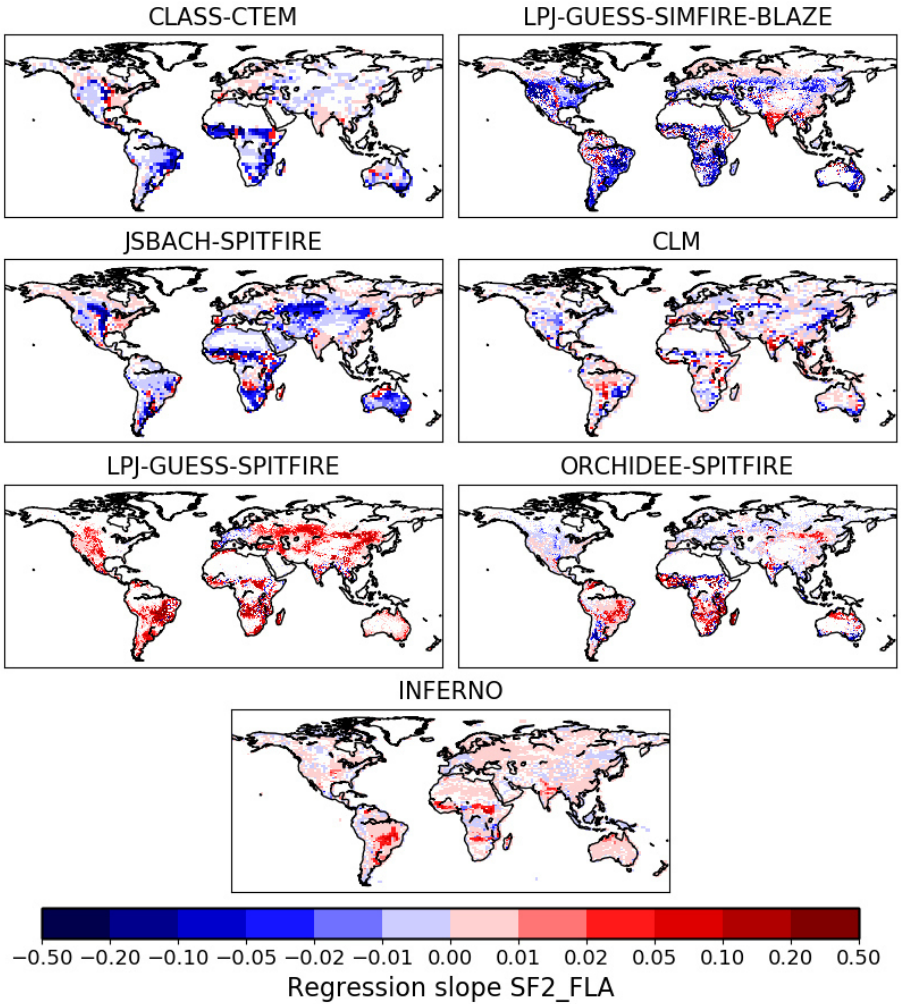


**Figure A5.** ~~Regression slope~~ Spatial distribution of ~~a grid cell~~ regression slopes for the difference between the baseline experiment SF1 and the sensitivity experiment SF2_FLA (SF1–SF2_FLA; see tab. 1) over ~~1901-2013~~1921-2013.

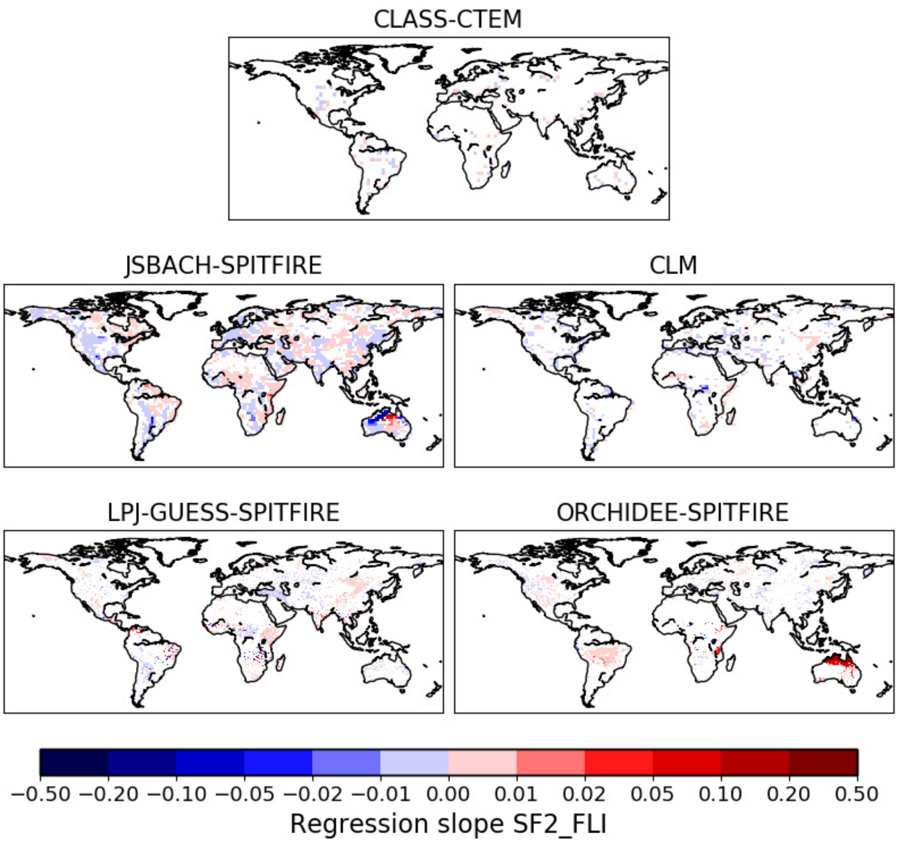


**Figure A6.** ~~Regression slope of a grid cell~~ Spatial distribution or regression slopes for the difference between the baseline experiment SF1 and the sensitivity experiment SF2_FLI (SF1–SF2_FLI; see tab. 1) over ~~1901-2013~~1921-2013.

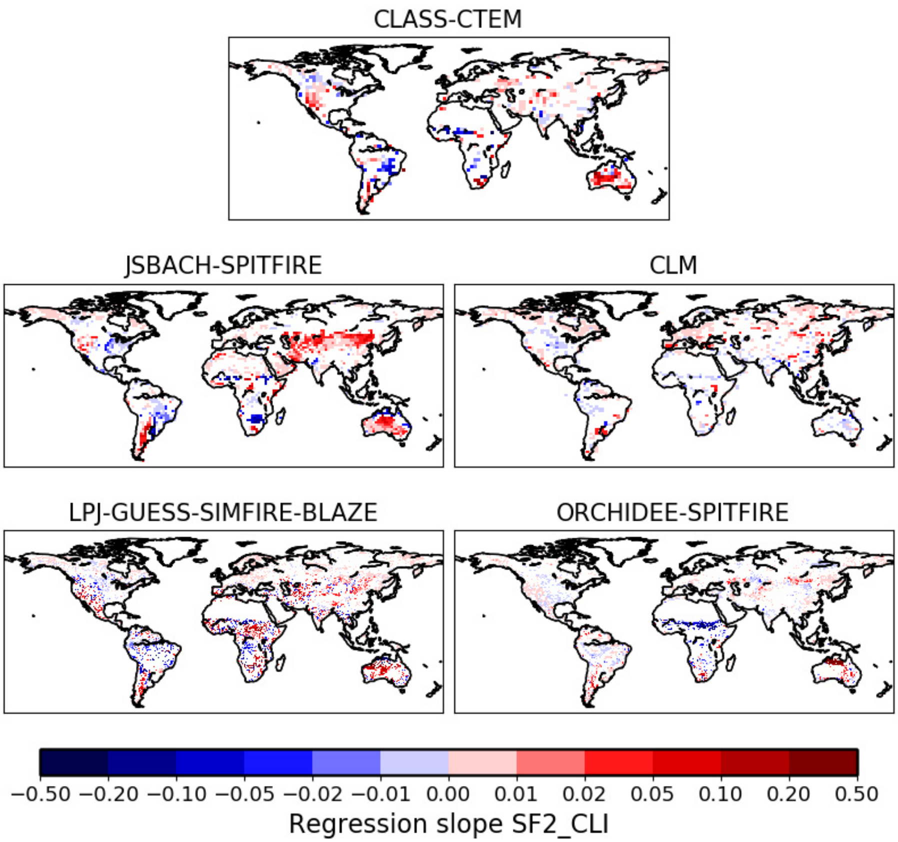


**Figure A7.** ~~Regression slope~~ Spatial distribution of ~~a grid cell~~ regression slopes for the difference between the baseline experiment SF1 and the sensitivity experiment SF2_CLI (SF1–SF2_CLI; see tab. 1) over ~~1901-2013~~1921-2013.

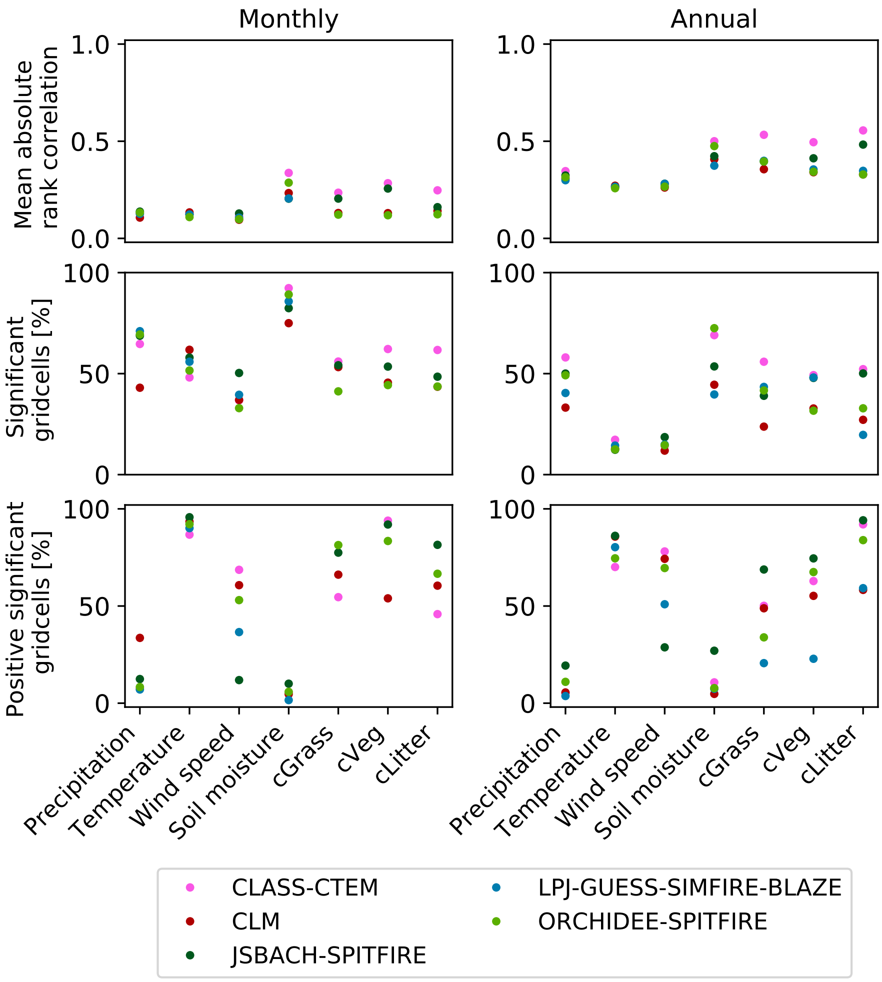


**Figure A8.** Spearman rank-order correlation coefficient for each grid cell over ~~1901–2013~~ 1921–2013 between the ~~relative~~ difference between the baseline experiment SF1 and the sensitivity experiment SF2_CLI (see tab. 1) for annual burned area fraction and precipitation, temperature, wind speed, carbon stored in litter, carbon stored in vegetation, carbon stored in grass and in soil moisture, respectively. The upper panel shows the mean absolute rank correlation, i.e. the spatial average over the absolute and significant (p-value $< 0.05$) Spearman rank-order correlation coefficients where the relative difference in burned area fraction is $> 0.1$. The second panel shows the proportion of grid cells with a significant correlation. The lowest panels indicate the percentage of significant grid cells with a positive correlation.

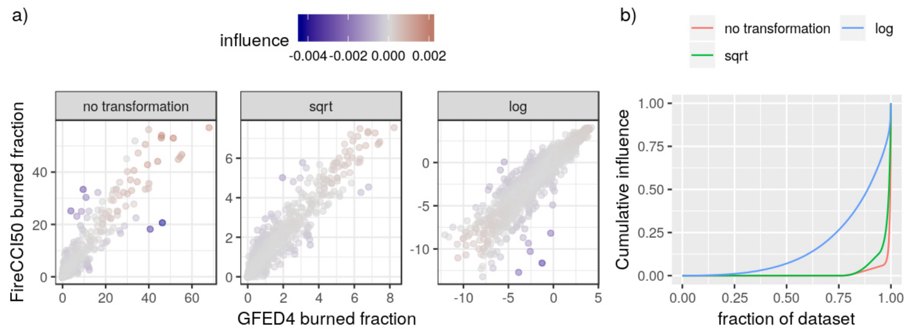


**Figure A9.** Scatter plots for the GFED4 and FireCCI50 dataset without transformation, square root transformation and log transformation (a), the color indicates the influence of individual data points on the correlation (computed as the difference in the correlation with and without that datapoint). Cumulative influence of data points in the dataset on the correlation (b). Without transformation a very small fraction has a strong influence on the correlation, these are grid cells with high burned area fraction (as can be seen in a).

**Table A1.** Reference literature for FireMIP models.

| Model | Land/ Vegetation model | Fire model |
|---|---|---|
| CLASS-CTEM | Arora and Boer (2005)<br>Melton and Arora (2016) | Arora and Boer (2005)<br>Melton and Arora (2016) |
| CLM | Oleson et al. (2013) | Li et al. (2012, 2013, 2014) |
| INFERNO | J. Best et al. (2011), Clark et al. (2011) | Mangeon et al. (2016) |
| JSBACH-SPITFIRE | Reick et al. (2013) | Lasslop et al. (2014)<br>Hantson et al. (2015a) |
| LPJ-GUESS-SIMFIRE-BLAZE | Smith et al. (2001, 2014)<br>Lindeskog et al. (2013) | Knorr et al. (2016) |
| LPJ-GUESS-SPITFIRE | Smith et al. (2001)<br>Sitch et al. (2003)<br>Ahlström et al. (2012) | Lehsten et al. (2009, 2015) |
| ORCHIDEE-SPITFIRE | Krinner et al. (2005) | Yue et al. (2014, 2015) |

**Table A2.** Correlation coefficients between burned area simulated by the FireMIP-models within the baseline experiment SF1 and the respective observation data. Due to the very skewed distribution of burned area, we use a square root transformation on both model and observations. Numbers in brackets show the Pearson correlation coefficients for not-transformed data. Only GFED4 and FireCCI50 provide uncertainty estimates, therefore GFED4s is not included. Correlation coefficients for 33% show the correlation between all grid points that lie within the 0–33% percentile of the relative standard error; values for 66% lie within the 33–66% percentile of the relative standard error and values for 99% lie within the 66–99% percentile. Bold numbers indicate correlation coefficients that are significant (p-value $<$ ~~0.001~~0.05).

| Model | GFED4 | | | FireCCI50 | | |
|---|---|---|---|---|---|---|
| | 33% | 66% | 99% | 33% | 66% | 99% |
| CLASS–CTEM | **0.59** (**0.41**) | **-0.08** (-0.07) | 0.04 (-0.03) | **0.58** (**0.38**) | -0.02 (-0.04) | 0.06 (0.003) |
| CLM | **0.78** (**0.72**) | **0.13** (**0.14**) | 0.09 (-0.03) | **0.80** (**0.73**) | **0.11** (**0.10**) | **0.09** (-0.03) |
| INFERNO | **0.76** (**0.68**) | **-0.18** ( **-0.13**) | 0.05 (-0.02) | **0.77** (**0.64**) | -0.01 (0.01) | 0.05 (0.03) |
| JSBACH–SPITFIRE | **0.69** (**0.62**) | -0.08 ( **-0.11**) | 0.02 (-0.05) | **0.68** (**0.56**) | -0.01 (-0.04) | 0.06 (0.01) |
| LPJ–GUESS–SIMFIRE–BLAZE | **0.70** (**0.55**) | -0.06 (-0.07) | -0.05 (**-0.10**) | **0.67** (**0.48**) | 0.03 (0.04) | -0.04 (-0.08) |
| LPJ–GUESS–SPITFIRE | **0.56** (**0.46**) | **0.42** (**0.41**) | **0.31** ( **0.17**) | **0.61** (**0.48**) | **0.40** (**0.33**) | **0.47** (**0.34**) |
| ORCHIDEE–SPITFIRE | **0.82** (**0.74**) | **0.51** (**0.35**) | **0.48** (**0.36**) | **0.81** (**0.74**) | **0.49** (**0.31**) | **0.47** (**0.30**) |

*Author contributions.* LT and GL designed the study and performed the analysis with input from SPH, AH and SH. CY, GL, JM, LF, MF, SH provided simulations. LT, GL and SPH wrote the manuscript with contributions from all authors.

*Competing interests.* TEXT

*Disclaimer.* TEXT

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